Ubiquitous and Wearable Computing Solutions for Enhancing Motor Rehabilitation of the Upper Extremity Post-Stroke

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Declaration of Authorship

I, Aodhan Coffey, declare that this thesis titled, 'Ubiquitous and Wearable Computing Solutions for Enhancing Motor Rehabilitation of the Upper Extremity Post-Stroke' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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"Let your mind take you places your feet can not carry you"

Anonymous

Abstract

A stroke is the loss of brain function caused by a sudden interruption in the blood supply of the brain. The extent of damage caused by a stroke is dependent on many factors such as the type of stroke, its location in the brain, the extent of oxygen deprivation and the criticality of the neural systems affected. While stroke is a non-cumulative disease, it is nevertheless a deadly pervasive disease and one of the leading causes of death and disability worldwide. Those fortunate enough to survive stroke are often left with some form of serious long-term disability. Weakness or paralysis on one side of the body, or in an individual limb is common after stroke. This affects independence and can greatly limit quality of life.

Stroke rehabilitation represents the collective effort to heal the body following stroke and to return the survivor to as normal a life as possible. It is well established that rehabilitation therapy comprising task-specific, repetitive, prolonged movement training with learning is an effective method of provoking the necessary neuroplastic changes required which ultimately lead to the recovery of function after stroke. However, traditional means of delivering such treatments are labour intensive and constitute a significant burden for the therapist limiting their ability to treat multiple patients. This makes rehabilitation medicine a costly endeavour that may benefit from technological contributions. As such, stroke has severe social and economic implications, problems exasperated by its age related dependencies and the rapid ageing of our world. Consequently these factors are leading to a rise in the number living with stroke related complications. This is increasing the demand for post stroke rehabilitation services and places an overwhelming amount of additional stress on our already stretched healthcare systems.

Therefore, new innovative solutions are urgently required to support the efforts of healthcare professionals in an attempt to alleviate this stress and to ultimately improve the quality of care for stroke survivors. Recent innovations in computer and communication technology have lead to a torrent of research into ubiquitous, pervasive and distributed technologies, which might be put to great use for rehabilitative purpose. Such technology has great potential utility to support the rehabilitation process through the delivery of complementary, relatively autonomous rehabilitation therapy, potentially in the comfort of the patient's own home. This thesis describes concerted work to improve the current state and future prospects of stroke rehabilitation, through investigations which explore the utility of wearable, ambient and ubiquitous computing solutions for the development

of potentially transformative healthcare technology. Towards this goal, multiple different avenues of the rehabilitation process are explored, tackling the full chain of processes involved in motor recovery, from brain to extremities. Subsequently, a number of cost effective prototype devices for use in supporting the ongoing rehabilitation process were developed and tested with healthy subjects, a number of open problems were identified and highlighted, and tentative solutions for home-based rehabilitation were put forward.

It is envisaged that the use of such technology will play a critical role in abating the current healthcare crisis and it is hoped that the ideas presented in this thesis will aid in the progression and development of cost effective, efficacious rehabilitation services, accessible and affordable to all in need.

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There are a significant amount of other friends who have helped and supported me through this thesis. I wish I could name and thank you all personally here but I cannot. But know that I am eternally grateful to all of you, for those conversations of support, the laughs we've had and the good times we've shared. Such moments made those times of difficulty easier to bear and helped me focus and stay on the path to finishing my thesis.

Finally, I owe the greatest debt of gratitude to my girlfriend Deborah. Thank you for taking this journey with me and for sticking by my side during the best and worst of times. You kept me sane and without your constant support, council, sacrifice and love, I would not have finished this thesis. From the deepest recesses of my heart, thank you for everything, I am eternally grateful!

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Abbreviations

AAM	**A**ctive **A**ppearance **M**odel
AAN	**A**ssist-**as**-**n**eeded
AAROM	**A**ctive **A**ssist **R**ange of **M**otion
AT	**A**ssitive **T**echnology
ABMS	**A**gent-**b**ased **M**odelling and **S**imulation
ACA	**A**nterior **C**erebral **A**rtery
ADC	**A**nalog to **D**igital **C**onversion
ADL	**A**ctivities of **D**aily **L**iving
AMPA	**A**lpha-Amino-3-Hydroxy-5-**M**ethyl-4-Isoxazole **P**ropionic **A**cid
ANOVA	**An**alysis **O**f **V**ariance
API	**A**pplication **P**rogram **I**nterface
AR	**A**ugmented **R**eality
AVM	**A**rterio**v**enous **M**alformation
BCI	**B**rain **C**omputer **I**nterface
BPS	**B**its **P**er **S**econd
BT	**B**lue**t**ooth
BVH	**B**io**v**ision **H**ierarchical
CIMT	**C**onstraint **I**nduced **M**ovement **T**herapy
CMS	**C**ommon **M**ode **S**ense
CNS	**C**entral **N**ervous **S**ystem
CSM	**C**ortical **S**timulation **M**apping
CSP	**C**ommon **S**patial **P**atterns
CVA	**C**erebro**v**ascular **A**ccident
CVD	**C**ardio**v**ascular **D**isease
CVI	**C**erebro**v**ascular **I**ncident
DDA	**D**ynamic **D**ifficulty **A**djustment
DRL	**D**riven **R**ight **L**eg
ECG	**E**lectro**c**ardio**g**ram
EEG	**E**lectro**e**ncephalo**g**raph
EMG	**E**lectro**m**yo**g**raph

EDR	**E**lectrodermal **R**esponse
ESD	**E**arly **S**upported **D**ischarge
FMS	**F**acial **M**otor **S**ystem
FPS	**F**rames **P**er **S**econd
fMRI	**F**unctional **M**agnetic **R**esonance **I**maging
GSR	**G**alvanic **S**kin **R**esponse
GRASP	**G**raded **R**epetitive **A**rm **S**upplementary **P**rogram
HB	**H**ouse **B**rackmann
HBR	**H**ome **B**ased **R**ehabilitation
HEG	**H**emo**e**ncephalo**g**raphy
IMU	**I**nertial **M**easurement **U**nit
IMMS	**I**nertial **M**agnetic **M**easurement **S**ystem
IoT	**I**nternet **o**f **T**hings
IR	**I**nfra**r**ed
KP	**K**nowledge of **P**erformance
KR	**K**nowledge of **R**esults
LDA	**L**inear **D**iscriminate **A**nalysis
LED	**L**ight **E**mitting **D**iode
LIS	**L**ocked-**i**n **S**yndrome
LTD	**L**ong **T**erm **D**epression
LTP	**L**ong **T**erm **P**otentiation
MCA	**M**iddle **C**erebral **A**rtery
MDF	**M**e**d**ian **F**requency **A**nalysis
MEMS	**M**icro **E**lectrical **M**echanical **S**ystems
MNF	**M**ean **F**requency **A**nalysis
MUAP	**M**otor **U**nit **A**ction **P**otential
MVC	**M**aximum **V**oluntary **C**ontraction
NMDA	**N**-**M**ethyl-**D**-aspartic **A**cid
PROM	**P**assive **R**ange **o**f **M**otion
PID	**P**roportional **I**ntegral **D**erivative
PSD	**P**ower **S**pectral **D**ensity
PCA	**P**rincipal **C**omponent **A**nalysis
PWM	**P**ulse **W**idth **M**odulation
PCB	**P**rinted **C**ircuit **B**oard
PET	**P**ositron **E**misson **T**omography
PNS	**P**eripherial **N**ervous **S**ystem
PPG	**P**hoto**p**lethysmo**g**raph
RCT	**R**andomised **C**linical **T**rials
RGS	**R**ehabiliation **G**aming **S**ystem

SAR	**S**ocially **A**ssistive **R**obotics
SMR	**S**ensori**m**otor **R**hythm
TIA	**T**ransient **I**schaemic **A**ttack
UART	**U**niversal **A**synchronous **R**eceiver/**T**ransmitter
VR	**V**irtual **R**eality

Symbols

Matrix Notation	
$\mathbf{X}$	Two-dimensional matrix
$\mathbf{X}^T$	Transpose of $\mathbf{X}$
x_{ij}	Element at row i, column j, of matrix $\mathbf{X}$

This thesis is dedicated to my parents, Ciarán and Mary. For the endless opportunities, encouragement, support and most of all love they have given me throughout my life.

I would be lost without you.

Chapter 1

Introduction

The average age of the world's population is increasing at an unprecedented rate. A report commissioned by the U.S. National Institute on Aging estimates that the current number of people worldwide age 65 and older is 524 million. By the year 2050, that number will have reached 1.5 billion [354]. To put these figures into perspective, in just under 40 years, the proportion of older people will double from 7% to 14% of the world's total population. While this shift in population demographics will have many unforeseeable effects on society, it will inevitably lead to a rise in the number of people living with chronic illnesses such as cardiovascular diseases (CVD), cancer, chronic obstructive pulmonary disease, dementia and diabetes.

Of such diseases, stroke a subtype of CVD is of particular concern, being the second leading cause of death above the age of 60 [396] and the leading cause of long-term disability worldwide [254]. Globally, 15 million people suffer a stroke each year, one-third die, one-third make a reasonable recovery and one-third are left with moderate to severe disability [237] with major impact on their quality of life. Given that age is one of the most substantial risk factors for stroke, with the risk of stroke doubling each decade after 55, the ageing of the world population implies a growing number of people at risk [49].

A stroke is a brain attack, characterised by the sudden interruption of blood flow to the brain causing the loss of brain function. Each stroke is unique and can effect physical, cognitive and emotional functioning. The affects of stroke are dependent on the type of stroke, the location in the brain and the extent of the resulting brain injury. The most common impairment caused by stroke is motor impairment [390], which can be regarded as a loss or limitation of function in muscle control or movement. More specifically, weakness in the upper limbs is the most common impairment after stroke effecting approximately 80% of patients [200]. Movement impairment is categorised according to severity of deficit, e.g. from weakness in an individual limb, movement weakness on one side of the body (hemiparesis) or the inability to move one side of the body (hemiplegia). The loss of functional ability is a significant impairment for an individual, limiting their ability to engage in activities of everyday living, reducing their quality of life and their independence. Therefore, much emphasis is put on the restoration of motor function and the recovery of functional movement skills during stroke rehabilitation.

The mechanisms of recovery after stroke are complicated. In general, motor recovery depends on the plasticity of neurons and circuits within the motor system [187]. The brain has some innate capacity to recover following the stroke, known as spontaneous recovery [310], during this period improvement in physical, cognitive, and communication deficits may occur on their own. However, the brain can also extensively remodel after stroke, primarily through a process called neuro-plasticity [321]. Neuro-plasticity is defined as the ability of the brain to change its structure and/or function in response to internal and external constraints and goals [150]. Fundamental research has demonstrated that reorganization is not driven simply by increased use and instead that expansion of cortical representations requires skill dependent motor learning behaviour. As a result, it is well established that rehabilitation therapy comprising task-specific, repetitive, prolonged movement training with learning can have a significant impact on recovery outcomes [112],[131]. In most cases, stroke rehabilitation begins while the patient is still in acute care and continues long after returning home. The duration of rehabilitation differs from patient to patient, some stroke survivors recover quickly, however most need some form of stroke rehabilitation long term, possibly months or years after their stroke.

Positive outcome of physical rehabilitation after neurological impairment depends heavily on the onset, duration, intensity and task-orientation of the training. Treatment of motor defects after stroke is subsequently labour intensive, requiring extensive, protracted one-to-one manual interactions with a physical therapist, constituting a significant burden for the therapist and decreasing the availability of rehabilitation services. Subsequently, stroke imposes a major economic burden on healthcare systems worldwide. A recent study comparing international stroke cost showed that on average, 0.27% of gross domestic product is spent on stroke by national health systems, and that post stroke care accounts for approximately 3% of total national health care expenditures [102]. These problems will most likely exacerbate in the future as life expectancy continues to increase [260], resulting in an increase in the incidence of stroke, accompanied by a growing population of elderly people with moderate and severe motor disabilities. In addition, the rising disproportion of older people will also result in there being a smaller "working age" population to care for those afflicted with disability and to contribute taxes to pay for national healthcare services.

Consequently, healthcare providers are actively investigating alternative approaches to providing healthcare services post stroke. Early supported discharge (ESD) accompanied by home-based rehabilitation (HBR) is one such intervention under consideration which has gained much appraisal. Studies suggest that ESD can provide a cost-effective alternative in the management of stroke care and can reduce the amount of time patients spend in hospital [109],[310],[28]. Advocates of such programs suggest that in addition to economic benefits there are several additional advantages to moving towards a HBR paradigm including; reduced risks of nosocomial acquired illnesses and less distress caused from prolonged hospital stay [11]. In addition, the home centred treatment paradigm gives people the advantage of practising skills and developing compensatory strategies in the context of their own home. However, to be successful, such programs will need to deliver results which are comparable to that of conventional clinical rehabilitation. Currently, there are some distinct disadvantages to home based rehabilitation programs. First, there is a dearth of affordable specialised equipment available to support home based rehabilitation programs. Second, there is evidence to suggest that adherence to rehabilitation programs is poor in the absence of supervision [26],[370]. As a result, there is both an imminent need and an opportunity to develop new technology that can supplement the efforts of healthcare specialists, through the addition of devices that can augment the benefits of therapeutic intervention and which can encourage continuous adherence with unsupervised exercise programs.

Computing technology is pervasive, each decade bringing smarter, cheaper and more powerful devices to the market place. It may be hard to believe but by today's standards the computer NASA used to put a man on the moon is no more powerful than some pocket calculators [130]. It is estimated that there are approximately 2 billion personal computers (PCs) actively in use as of 2014, with countless more office based and autonomous systems in use world-wide [116]. Indeed, computers have become much more than simple tools of labour and now play an active role in how we live, socialise and even identify ourselves. The internet has created a global connectedness of unimaginable proportion allowing us to instinctively interact with systems, purblind to the reality that such information might be stored on a machine half a world away. Technology is also advancing rapidly, capturing the imagination of a world desperate for more connectivity, desiring smarter, more intuitive means of interacting with their world, which is rapidly becoming more and more digital. While the driving force behind much of this technology is commercial products, this technology also represents great hope for millions of people worldwide suffering from illness and disease. The evolving concepts of pervasive computing, ubiquitous computing and ambient intelligence are increasingly influencing health care and medicine [278, 387, 387]. Such technology has the potential to be supportive, diagnostic and analytical in an unobtrusive and even inconspicuous manner [70]. Wearable sensors and ubiquitous computing applications have tremendous capabilities, such as remote, autonomous patient monitoring and diagnosis. While not applicable to all illnesses, such technology can play a major role in assistance healthcare, offering enhancements to unsupervised forms of physical therapy in the comfort of a patient's own home. In addition, smart systems can take measurements, quantify and assess on-going rehabilitation efforts and automatically adjust parameters of training programs according to patient progress. From the perspective of healthcare, there is great potential to utilise such technology to improve the efficacy of home-based rehabilitation. Capabilities such as these will no doubt help advance the paradigm shift from hospital/clinical rehabilitation towards home care, and may also enhance patient self-care and independent living.

1.1 Objective

The objective of this thesis is to contribute towards improving the efficacy of home-based rehabilitation after stroke, with focus on interventions for the upper extremity. This objective is approached from two perspectives. First, through the design and development of novel, low cost devices suitable for the home setting which can help facilitate recovery, support the ongoing rehabilitation process and to improve adherence through the provision of extrinsic feedback.

Second, to investigate the interaction dynamics of supervised assisted therapy, through the application of novel modelling techniques, with the view towards designing more effective controllers for human unsupervised assisted movement therapy.

1.2 Contributions

In its entirety, this thesis has produced a number of contributions which are described below.

1. A comprehensive literature review of the state of the art in technology assisted home-based rehabilitation. The review consists of a short description of the key

domains pertaining to home-based solutions for stroke rehabilitation; wearable sensors, ubiquitous computing, ambient intelligent environments, low cost robotics and brain computer interfaces.

2. Development of a novel, affordable, open source, autonomous sensor glove system for gesture based control of home environments.

3. Investigations into the potential application of Game Theory and agent based modelling as a novel approach to modelling patient/therapist interaction dynamics with a view toward developing more efficient assistance control strategies.

4. Development of a low cost, digital hand dynamometer for measuring grip strength.

5. Development of a novel feedback platform for investigating the effects of extrinsic feedback on motor performance.

6. Modification of an open source Electroencephalograph (EEG) platform for use as an Electromyography (EMG) acquisition platform.

7. Collection and presentation of data highlighting the effects of "slacking" by the motor system during obfuscated feedback driven exercises.

8. Design and development of an affordable, brain computer interface (BCI) driven pneumatic exercise glove system for home-based neuro-rehabilitation.

9. Demonstration of machine learning techniques for automatic facial paralysis scoring and the synthesis of images with successive grades of facial motor paralysis, towards the development of an intelligent feedback mirror for stroke.

1.3 List of Publications

A list of the publications produced from the thesis is presented below.

1. Coffey, A. L., Ward, T. E., & Middleton, R. H. (2011). Game Theory: A Potential Tool for the Design and Analysis of Patient-Robot Interaction Strategies. International Journal of Ambient Computing and Intelligence, 3(3), 43–51.

2. Coffey, A. L., & Ward, T. E. (2013). A Sensor Glove System for Rehabilitation in Instrumental Activities of Daily Living. In Communications in Computer and Information Science (Vol. 374, pp. 135–139). Las Vegas, NV, USA: International Conference, HCI International 2013,.

3. Coffey, A. L., Leamy, D. J., & Ward, T. E. (2014). A Novel BCI-Controlled Pneumatic Glove System for Home-Based Neurorehabilitation. In 36th Annual International IEEE EMBS Conference of the IEEE Engineering in Medicine and Biology (pp. 3622 – 3625). Chicago, IL: IEEE.

4. Coffey, A. L., & Ward, T. E. (2014). Slacking in the Context of Agent-based Assessment in Virtual Rehabilitation Systems. In 36th Annual International IEEE EMBS Conference of the IEEE Engineering in Medicine and Biology (pp. 5844–5847). Chicago, IL: IEEE.

5. Coffey, A. L., & Ward, T. E. (2015). Combined Ambient and Wearable Sensors for Gesture-Based Environmental Control in the Home. In Recent Advances in Ambient Intelligence and Context-Aware Computing (1st ed., pp. 1–21). IGI Global.

6. Hurtier, J., Van Dokkum L., Dalhoumi S., Coffey A., Perrey S., Jourdan C., Dray G., Ward T., Froger J., Laffont I. (2016). A closed-loop BCI system for rehabilitation of the hemiplegic upper-limb: A performance study of the systems ability to detect intention of movement. Annals of Physical and Rehabilitation Medicine.

1.4 Outline of the Thesis

This thesis is comprised of seven subsequent chapters, the content of which is described below.

Chapter 2 provides a background to the physiological systems and functions of interest in this thesis, including a detailed discussion of the nervous system, (both central and peripheral), the anatomical structure of the brain, the cerebral circulatory system, as well as an in-depth discussion of the components of neural plasticity, neurons, synapses and action potentials. In addition, specific details pertaining to the underlying cause, effects and recovery mechanisms of stroke are given. Finally, details of the physiological signals that are most commonly measured for clinical purposes and which are used through this thesis are given, including Electroencephalogram (EEG), Electromyogram (EMG) and grip strength.

Chapter 3 details the current state of the art in assisted upper extremity interventions and the current challenges for technology assisted solutions. The review is separated into 4 distinct areas of interest, which are prevalent throughout this thesis. (1), a literature review of sensor gloves for the capture of hand motion data (2), a literature review of robotic devices for rehabilitation of the upper extremity, including a detailed discussion about current approaches to control systems and control strategies. (3), a literature review of extrinsic feedback, highlighting the role of extrinsic feedback on implicit motor learning and discussing its capacity for enhancing participant motivation and self-efficacy after stroke. And (4), a literature review of physiological sensed feedback (i.e. biofeedback and neurofeedback) approaches to rehabilitation, discussing the potential of such systems for enhancing motor rehabilitation in chronic stroke patients with severe movement weakness.

Chapter 4 introduces the design of a novel, autonomous sensor glove system for gesture based control of personal electronic appliances (TV, radio, etc.) and describes its potential for integrating repetitive, therapeutic practise of functional hand skills into the activities of daily living.

Chapter 5 explores the development of a virtual therapist for stroke rehabilitation. The chapter begins with the exploration of the interaction dynamics between a patient and therapist during a typical assisted movement task. After which the concept of modelling these interaction dynamics using "Game Theory" is discussed. A rudimentary demonstration of such an implementation is demonstrated and through simulations some interesting behavioural patterns are identified and exposed (motor "slacking" and learned dependency). Finally, a discussion follows about the potential use of such an approach for modelling patient/therapist interaction dynamics towards developing more sophisticated control systems for technology assisted movement therapy.

Chapter 6 introduces the design of a novel experimental platform for investigating the effects of obfuscated feedback on motor performance during a repetitive grip and release task. Towards this goal, the design and development of two independent low-cost tools (a digital hand dynamometer and an EMG acquisition unit) for motor function assessment are described. Using the experimental platform an experiment is performed in healthy subjects investigating the use of extrinsic feedback on performance for delivering semi-automated rehabilitation therapy. Experimental results are presented which suggest the visibility of motor "slacking" as a result of error obfuscation and a discussion of the implications of theses finding for designing feedback driven therapy solutions follows.

Chapter 7 describes efforts to utilise aspects of machine learning techniques for the development of enhanced biofeedback driven rehabilitation applications. The chapter is split into two sections. The first section describes the development of a compact, inexpensive solution for home-based motor-neurorehabilitation comprising an EEG-based brain computer interface and simplified haptic feedback system based on a pneumatic glove solution. Preliminary results are presented of a pilot study conducted with health subjects to test the system. The second section describes the application of machine vision techniques, in particular the use of active appearance models for the tracking of key facial features, automatic scoring of facial paralysis and the synthesis of subdued feedback imagery.

Chapter 8 concludes the thesis by providing a summary of the novel contributions of the work therein and discusses future directions for research arising from the work performed.

Chapter 2

Physiological Background

2.1 Introduction

The brain is without doubt the most complex organ in the human body. To understand just how complex the brain is, consider that the brain is made up of a network of billions of interconnected nerve cells called neurons. A neuron is an electrically excitable cell that processes and transmits information through electrical and chemical signals. Neurons have a large number of extensions, in the order of thousands, called dendrites, which can reach out and form connections with other neurons. There are approximately 100 billion neurons in the human brain, of which 30 billion are situated in our cerebral cortex, the highest functioning portion of our brain. The cerebral cortex is capable of generating 1 million billion synaptic connections. If we consider the number of possible neural circuits which could be constructed we would be dealing with hyper astronomical numbers, i.e. 10 followed by at least a million zeros. In comparison, there are 10^{97} atoms in the known universe [89].

The connection fidelity between neuron pairs is not immutable but instead is ever changing, depending on experience and stimulus from the outside world. In this way, many neurons can form together to create neural pathways and even more complicated structures such as neural circuits and networks. It is these neural structures which give rise to extremely complex functions of the brain. Stimulus from the world around us, received by our sensory organs and passed through out peripheral nervous system to our brains modulate how these networks form and grow. From leaning how to crawl, to walking upright, to swinging a tennis racket, all of these tasks rely on highly sophisticated neural circuits, developed over years, through practise and experience. These circuits not only control how our bodies respond and function, they also mould our sense of self, defining who we are. They form our personalities, our perceptions, our thoughts, both waking and sleeping, they shape our goals and desires and even constitute our dreams.

However, like all living cells, neurons require a constant steady stream of metabolic fuel (oxygen and nutrients) in order to function correctly. In fact, neurons are highly metabolically active and therefore particularly susceptible to cell death if deprived of oxygen and nutrients for even a short period of time. The blood flow to the brain must therefore be extremely well regulated in order to keep the cells alive and hence the neural circuits intact and functioning correctly, a property referred to as homoeostasis. A disruption of the blood supply to the brain, known as a stroke, can result in rapid and widespread cell death, causing significant damage to the structure of neural circuits and therefore a cease in related neural functioning.

Fortunately, the brain can heal itself after damage through reorganisation and restructuring of damaged neural pathways, a process known collectively as neural plasticity. Further, it is well established that the process of recovery after brain injury can be facilitated and even enhanced through rehabilitation therapy comprising task-specific, repetitive, prolonged movement training with learning. The question of how best to facilitate and promote such neural plastic changes in the brain, through the application of affordable technology, is the key aspiration of this thesis. However, prior to discussing how modern technology may help treat stroke and improve the lives of survivors, the physiology of the brain and the mechanics of stroke must first be introduced in more detail. The following chapter provides the background knowledge required to understand and contextualise the problems explored in this thesis. In addition, the physiological recording technologies and techniques used to collect data throughout this thesis are also described.

2.2 The Nervous System

The nervous system is essentially the means through which we experience and interact with the world. The nervous system is made up of the brain, spinal cord and a network of fibres and nerve cells which transmits message to and from all other parts of the body, see Figure 2.1[1]. The nervous system can be subdivided into two main parts, the central nervous system (CNS) and the peripheral nervous system (PNS).

The CNS contains the brain and spinal cord, it is the command center of the body and is where information is processed and decisions are made, see Section 2.3.

[1]Source: Public domain

The PNS consists mainly of nerves (neurons) and ganglia, which are fibre bundles that connect the CNS to every other part of the body. The purpose of the PNS is to connect the CNS to the limbs and organs, essentially acting as a communication network between the brain and the rest of the body, see Section 2.4.

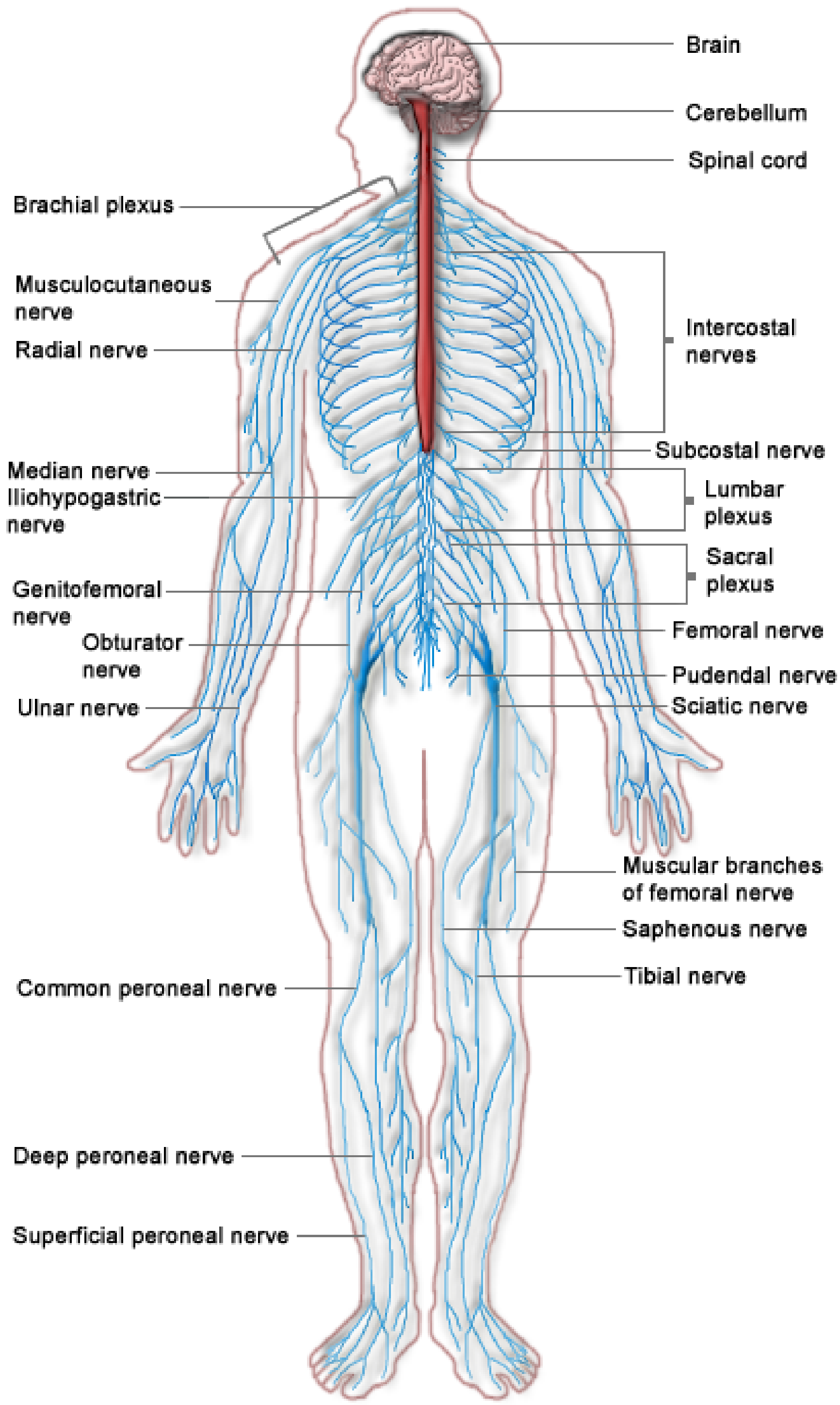

FIGURE 2.1: The nervous system including both the central nervous system (Red) and the peripheral nervous system (Blue).

At the cellular level, the nervous system is comprised primarily of a special type of cell, called the neuron, also refereed to as a "nerve cell", see Section 2.5. There are many different types of neurons. Neurons differ from one another structurally, functionally and genetically, as well as in how they form connections with other cells. As well as neurons, the nervous system also contains other specialized cells called glial cells, also known simply as glia which provide structural and metabolic support. Glial cells transport nutrients to neurons, clean up brain debris, digest parts of dead neurons and also help keep neurons in place and add insulation between them.

2.3 Central Nervous System (CNS)

2.3.1 The Spinal Cord

The spinal cord is the main pathway for information between the brain and the rest of the body. The main body of the spinal cord is a long thin strand of nerve fibres which stretch from the occipital bone down to the space between the first and second lumbar vertebrae, see Figure 2.1. The cord consists primary of two types of fibres, an efferent pathway for motor neurons, which travel from the brain towards the body to control muscle movement, and an afferent pathway for sensory neurons, which carry information from the body's sensory organs back to the brain. The cord is segmented distally into 31 sections called nerve roots which are fundamentally clusters of nerve endings which branch off the central cord into the body. The spinal cord is protected by an outer column of bone called vertebrae. Between each two vertebrae is a disk of cartilage which helps add flexibility to the spine and to absorb shocks. The spinal cord has three main functions, it carries motor neurons from the brain to the body, it carries sensory information from the sensory organs to the brain and it coordinates certain autonomous reflexes [91].

2.3.2 The Brain

The human brain is an incredibly complex structure which until recently was considered incomprehensible. Most of what we now know about the brain was only discovered in the last 50 years and is in part because of the accelerating pace of research in neurological science and the development of new functional mapping techniques. The advent of brain imaging techniques, including positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) has enabled us to peak inside the brain and glance at its inner workings. Using this technology researchers can examine in a non-invasive manner human brain functions, by study the temporal and spatial changes in the brain as a function of various stimuli.

The brain is composed of three main parts; the cerebrum, cerebellum, and brainstem, see Figure 2.2[2].

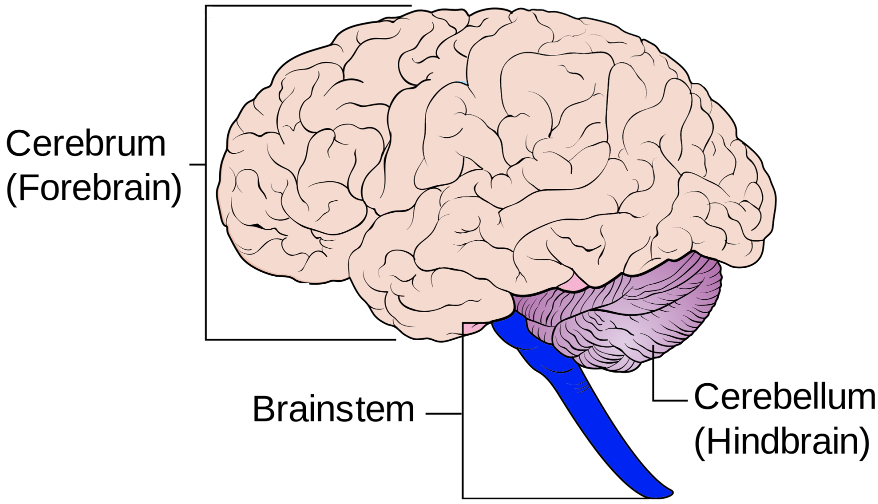

FIGURE 2.2: Sagittal view of the brain showing three main parts, cerebellum (Purple), cerebrum (Pink) and brainstem (Blue).

2.3.2.1 Cerebellum

The cerebellum is located posterior to the upper part of the brain stem. The cerebellum is relatively small, only accounting for 10% of the brains overall mass, however it contains approximately half of the brains neurons. Functionally the cerebellum plays an assisted role in motor control, while it does not initiate movement the cerebellum assists in the coordination and planning of voluntary movements such as; posture, balance, and speech. In addition, the cerebellum also plays an important role in motor learning, most notably in learning to adjust to dynamic changes in sensorimotor relationships [162]. The cerebellum also appears to be involved in a variety of linguistic functions [81].

2.3.2.2 Brainstem

The brainstem is located in the posterior of the brain, conjoining the brain with the spinal cord. The brainstem includes the midbrain, pons, and medulla. Though relatively small, the brainstem plays the important role of interfacing the brain with the nerve

[2]Source: Diagram showing some of the main areas of the brain (cropped, colors modified and re-labelled). licensed under Creative Commons Attribution-Share Alike 4.0 International

connections of the motor and sensory systems which spread out into the rest of the body. The brainstem is also responsible for autonomic, involuntary functions of the body including basic vital life functions such as, blood pressure regulation, breathing and heart rate. The brainstem is also involved with a series of complex reflective motor functions including swallowing, chewing, posture adjustment and locomotion [171].

2.3.2.3 Cerebrum

The cerebrum is the largest part of the human brain and is associated with higher brain functionality, including perception, thought, judgement, imagination and decision making. From an evolutionary perspective, the cerebrum is the newest part of the brain and is highly developed in humans compared to other species of mammals. The surface of the cerebrum is known as the cerebral cortex or simply cortex. The cortex is only a few millimetres in thickness and consists of two cortices, separated along the sagittal plane, known as the left and right hemispheres. Although thin, the cortex contains approximately 10 billion neurons and is home to the most complex functions of the human brain. The cortex has a wrinkled texture made up of ridges called gyri (singular gyrus), and grooves or fissures called Sulci (singular sulcus). Because of this configuration two-thirds of the surface of the cortex is hidden, allowing for a much larger concentration of brain matter inside the skull. Functionally, the cerebral cortex is commonly segmented into four key areas; the frontal lobe, parietal lobe, occipital lobe and temporal lobe, see Figure 2.3[3].

[3]Source: Cerebrum lobes.svg (colours modified and relabelled) licensed under CC BY-SA 3.0

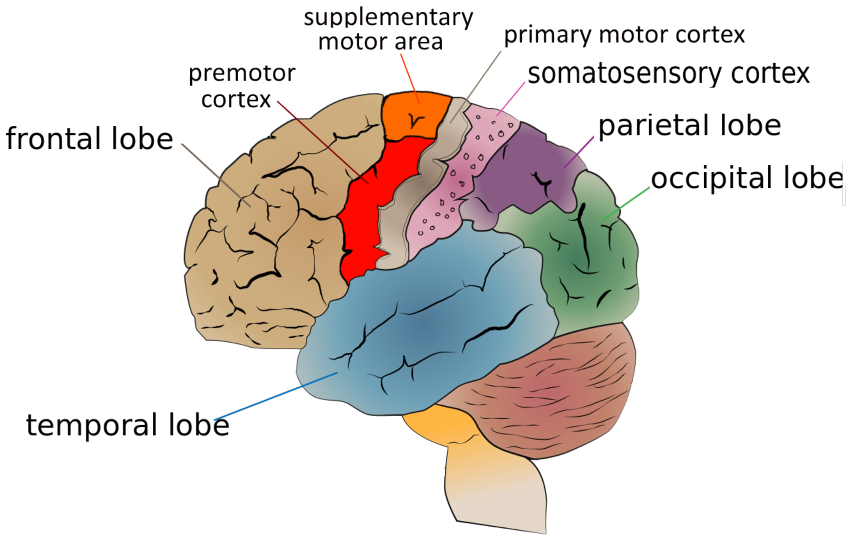

FIGURE 2.3: Cerebral cortex showing four main lobes; temporal lobe (Blue), optical lobe (Green), parietal lobe (Purple) and frontal lobe (Brown), Motor areas; primary motor cortex (Grey), premotor cortex (Red), supplementary motor area (Orange) and somatosensory cortex (Pink).

The **frontal lobe** is located in the anterior of the brain and is considered our intelligence and emotional center and home to our personality. It controls important cognitive skills such as problem solving, long term memory, language skills, judgement, impulse control, emotional expression and sexual behaviour. At the posterior of the frontal lobe, located in the dorsal precentral gyrus, lies the motor cortex, see Figure 2.3. The motor cortex is of primary interest to this thesis as it the area of the cortex responsible for planning, control, and execution of voluntary movements of the body. The motor cortex can be sub divided into three main areas; the primary motor cortex, which generates the signals that control the execution of movement. The premotor cortex, which is responsible for the preparation of movement, sensory guidance of movement and spatial guidance of movement, and the supplementary motor area, which is responsible for the planning of sequences of movement and the coordination of the two sides of the body.

The **parietal lobe** is located just behind the frontal lobe, above the occipital lobe in the upper mid section of the brain. The parietal lobe contains the somatosensory cortex which is essential to the processing of the body's senses, such as touch, pressure and pain. The main functionality of the parietal lobe is the integration of sensory information from various parts of the body. The parietal lobe also plays a part in spatial and visual perception, for example in the differentiation of size, shape and color and in language processing.

The **temporal lobe** is located at the base section of the brain, it contains the primary auditory cortex responsible for interpreting sound and the hippocampus associated with the formulation and storage of memory. The temporal lobe is responsible for processing sensory information in order to make it understandable and comprehensible, for example in the case of deciphering meaningful speech from sound and meaningful visual information from sight. The temporal lobe is also associated with the retention of language and visual memories, and association of emotion.

The **occipital lobe** is located at the rear portion of the brain, above the brainstem. The occipital contains the primary visual cortex and is the visual processing center of the brain. The occipital lobe is involved in visual-spatial processing including, the discrimination of movement and recognition of color.

Although the brain accounts for only approximately 2% of the total body weight in humans, it requires a large portion of the body's blood supply, approximately 15-20%. Normal healthy function of the brain is highly dependent upon adequate supply of oxygen and nutrients, distributed through a network of blood vessels, see Section 2.3.3 on Cerebral circulation. Without oxygen, brain cells die quickly, in the order of minutes after an oxygen-depriving event. Therefore, any decrease in the flow of blood to the brain can be catastrophic and may result in severe damage to the brain, resulting in impairment in function of the affected area.

2.3.3 Cerebral Circulation

Cerebral circulation refers to the movement of blood through the network of blood vessels which supply the brain. Arteries supply blood from the heart to the brain, rich in oxygen, glucose and other nutrients while veins carry the depleted de-oxygenated blood back towards the heart, removing by-products such as carbon dioxide and lactic acid. The blood supply towards the brain is supplied by two major artery pairs, the left and right vertebral arteries and the left and right internal carotid arteries, see Figure 2.4[4]. At the base of the brain, these four arteries become interconnected by the bilateral posterior communicating arteries, forming a circle referred to as the circle of Willis, see Figure 2.5[5]. The internal carotid arteries mainly supply the brainstem and cerebrum, while the two vertebral arteries join together forming the basilar artery which primarily supplies the posterior part of the circle of Willis.

[4]Source: Arteries beneath brain.png licensed under CC BY-SA 3.0
[5]Source: Circle of Willis en.svg licensed under Public Domain

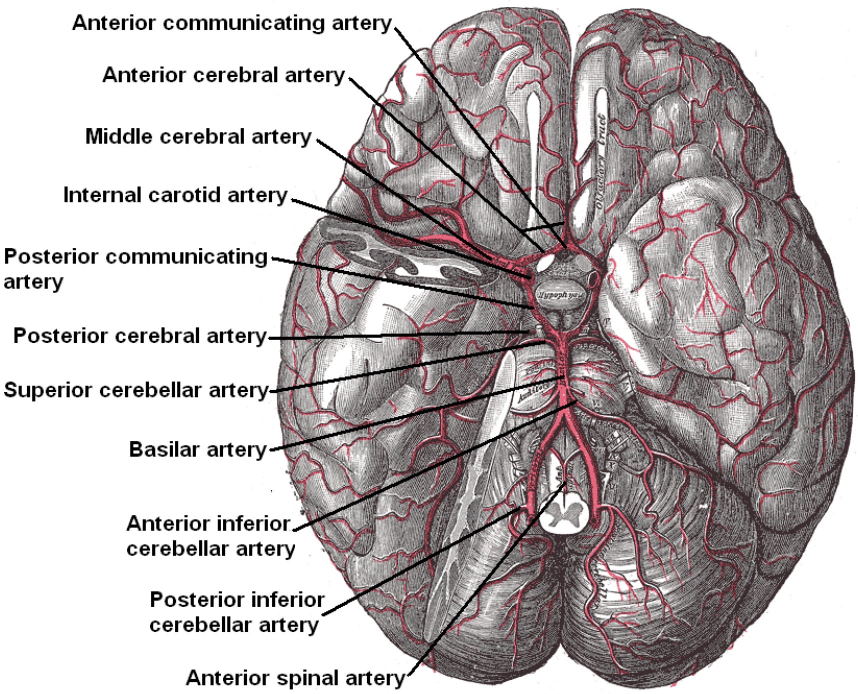

FIGURE 2.4: The major arteries of the brain.

From this circle, additional arteries branch off including, the anterior cerebral artery (ACA), the middle cerebral artery (MCA), and the posterior cerebral artery (PCA), supplying blood to all parts of the brain. The intention of the circle of Willis is to create redundancy in the cerebral circulation system which helps to maintain blood regulation to all parts of the brain, even if one of the major arteries becomes occluded.

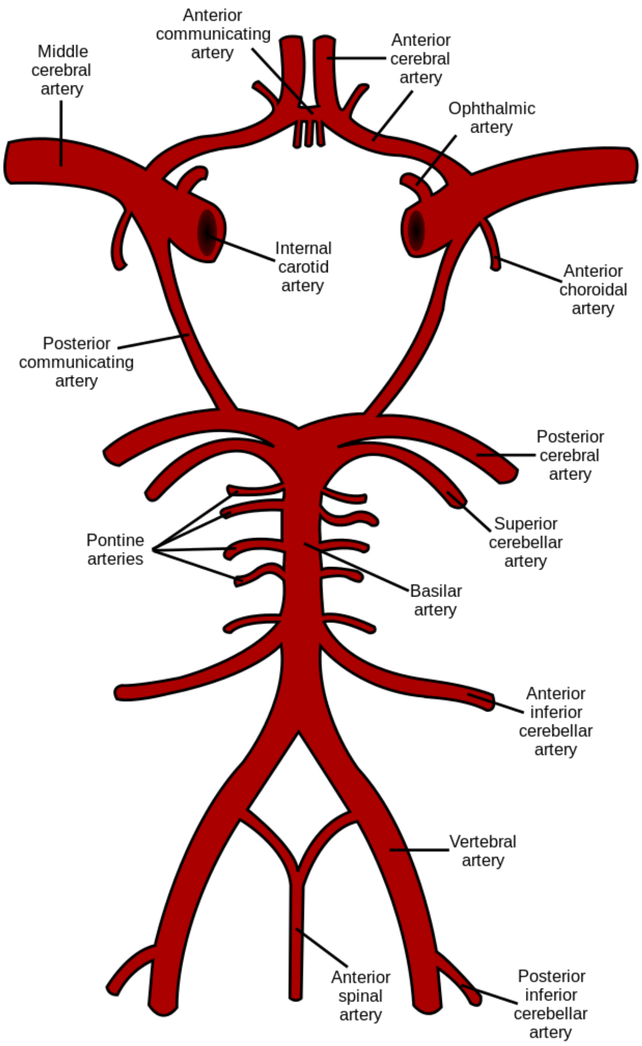

FIGURE 2.5: The Circle of Willis.

Given that regulation of blood to the brain is so important, it is of the utmost importance that the main cerebral arteries are healthy. Failure to maintain adequate blood supply to any part of the brain, typically caused by blockage or rupture of an artery, can lead to a stroke, see Section 2.6.

2.3.4 Electroencephalography (EEG)

Electroencephalography is a technique developed for recording electrical activity of the brain, the subsequent recording is referred to as an Electroencephalogram (EEG). EEG measures voltage fluctuations in the brain resulting from neural activity [76]. Neurons are constantly exchanging ions, for example while attempting to maintain resting potential and while propagating action potentials, see Section 2.5.2 on neural transmission process. While the activity of a single neuron is difficult to detect, when neurons are active together they cause a propagation effect or wave (moving ionic current) which can easily be detected by electrodes. When the wave of ions reaches the electrodes, they push or pull the electrons on its surface, which can be detected and recorded by sensitive electronic equipment. Recording these voltages over time gives us the EEG., see Figure 2.6[6].

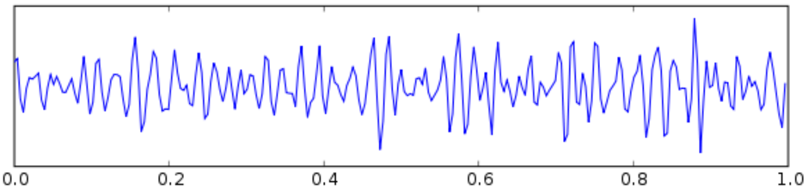

FIGURE 2.6: An EEG sample showing gamma waves.

EEG can be recorded in two main ways, from subdural electrodes surgically planted on the surface or within the substance of the brain, or in a non-invasive manner from surface placed electrodes which sit on the exterior of the scalp. The amplitude of the recorded EEG data depends on many factors and can therefore vary between subjects, however a typical adult human EEG signal is approximately between (10-20) mV when measured from subdural electrodes and approximately between (10-100) μV in amplitude when measured from the scalp [21].

EEG frequencies typically range from (1–100) Hz, however most of the interesting data lies in the lower frequencies, less than 20 Hz, as most of the cerebral signals observed in the scalp EEG fall within this range [29]. In clinical practise EEG data is typically described in terms of rhythmic activity and is therefore commonly sub-categorised into frequency bands known as alpha, beta, theta and delta, see Table 2.1.

TABLE 2.1: EEG frequency bands and associated functions.

Band	**Frequency (Hz)**	**Related Activity**
Delta	<4	adult: slow-wave sleep
Theta	4 - 7	drowsiness, idleness
Alpha	8 - 15	relaxed, eyes closed
Beta	16 - 31	active thinking, alert or stressed
Gamma	>32	perceptual functions
Mu	8 - 12	motor function activities

EEG has a wide range of applications in modern medicine, it is used to evaluate several types of brain disorders including Alzheimer's disease, epilepsy and narcolepsy.

[6]Source: Eeg gamma .svg licensed under GNU Free Documentation License

EEG is also used to quantitatively assess drug intoxication, brain trauma or the extent of brain damage in comatose patients and stroke patients. More recently EEG is finding applications in advanced research including brain computer interfacing (BCI) applications, see Chapter 3 for relevant literature on BCI.

2.4 Peripheral Nervous System (PNS)

2.4.1 Motor Unit Recruitment

A motor unit consists of one motor neuron and all of the muscle fibres it stimulates. A motor neuron is a specific type of nerve cell that controls the action of a muscle, causing it to contract or relax. A motor neuron is an efferent nerve, that is, it transmits motor commands from the brain down the spinal cord and into a muscle to produce movement. The amount of force exerted by an individual muscle fibre is dependent on two control principles; rate coding and the size principle.

2.4.1.1 Rate Coding

Rate coding relates to the frequency at which the neural signals (i.e. action potentials fired by motor neurons) get sent to a muscle telling them to contract [4]. When a single impulse is fired by a motor neuron it causes the muscle to twitch slightly and then relax again. If sufficient time elapses allowing the muscle to return to rest before a second impulse is received, the muscle will simply twitch again in the same manner as before. However, if the impulse arrives before the muscle has relaxed, it results in a greater amount of force than the first. This process can be thought of as a summation of muscle contractions. Hence, when a motor neuron increases its firing rate there is a proportional increase in the amount of force that the muscle generates. Motor unit recruitment is a measure of the number of activated motor neurons in a particular muscle, and therefore is a measure of how many muscle fibres of that muscle are activated. The larger the recruitment rate the stronger the muscle contraction will be. The maximum voluntary contraction (MVC) is known as a tetanic contraction which occurs when a motor unit has been maximally stimulated by its motor neuron, see Section 2.4.1.3.

2.4.1.2 Size Principle

The size principle refers to the systematic order in which motor units are recruited. In general, motor units are recruited in order of smallest to largest. This is known as the

Henneman's Size Principle [238]. The reasoning behind this principle is that smaller muscles are more fatigue resistant than their larger counterparts and are therefore activated when low force is required. It also permits fine control of force at all levels of output by ramping up to larger forces by recruiting more and more muscle fibres of appropriate larger size.

2.4.1.3 Maximum Voluntary Contraction (MVC)

The maximum voluntary contraction (MVC) is the upper obtainable force threshold which a muscle group can produce. This occurs when a muscle's motor unit is stimulated at a sufficiently high frequency, disallowing the muscle to return to baseline between twitches. The measure of MVC is a standardised, objective and sensitive tool for the measurement of muscle strength and plays an important role as a metric for gauging recovery during motor function rehabilitation after stroke. An increase in a patients MVC is a good indicator that they are recovering functional movement of an impaired limb. For stoke related weakness of the upper extremity, grip strength is often assessed as an indication of weakness and recovery. MVC is also used to monitor disease progression for slowly progressive conditions, such as motor neurone disease.

2.4.2 Neuromuscular Fatigue

Fatigue is a common symptom experienced in many disorders including, chronic obstructive pulmonary disease, multiple sclerosis, Parkinson's disease and post stroke [82]. Fatigue is defined as, a progressive loss of the ability to generate maximum force during, or following repeated or sustained muscle contractions, or the loss of force generation during a task [78]. Neuromuscular fatigue can be classified as either "central" or "peripheral". Central muscle fatigue can be thought of as an overall sense of energy deprivation caused by the CNS, while peripheral muscle fatigue is related to local muscle dynamics and reflects a muscle's specific inability to do work.

2.4.2.1 Central Fatigue

Central fatigue is caused by a decline in the neural signal driving a muscle group that results in an overall weakening in force output. Central fatigue is characterised by a reduction in voluntary effort unrelated to metabolic exhaustion or the indication of stress such as (elevated heart rate, blood lactate, low blood sugars, etc.). While the phenomenon of central fatigue is not entirely understood, it has been suggested that the observable reduction in neural drive during exercise may be a protective mechanism of the CNS, designed to protect against organ damage or failure, as might occur if the intensity of work was allowed to continue [31]. There is also evidence that central fatigue might be triggered by a reduction of dopamine levels in the brain and an elevation of serotonin (5-HT) [32].

2.4.2.2 Peripheral Fatigue

Peripheral fatigue results from local muscle dynamics and reflects changing internal conditions of the muscle. Peripheral muscle fatigue is primarily caused by two mechanisms, first, through anaerobic metabolism exhaustion which is an exhaustion of fuel (i.e. adenosine, triphosphate, glycogen and creatine phosphate) needed to supply the muscle in order to do work. And second, through the build up of anaerobic metabolic by-products within muscle fibres including, lactic acid and other acidic compounds which interfere with the ability of calcium to stimulate muscle contraction [182].

Peripheral muscle fatigue can be difficult to detect because compensation can be made for declining muscle fibres by increasing the innervation frequency and/or the active number of motor units. However, this activity causes a detectable change in the firing patterns of the muscle fibres, which can be detected using an Electromyography (EMG), see Section 2.4.3.

2.4.3 Electromyography (EMG)

Electromyography (EMG) is a technique for evaluating and recording the electrical activity produced by skeletal muscles. As described previously in Section 2.4.1, muscle contractions are controlled by motor units. From an electrophysiology perspective, when a motor unit fires, see Section 2.5, an impulse (called an action potential) is carried down a chain of motor neurons to the muscle it innervates. After the action potential is transmitted across the neuromuscular junction, an action potential is elicited in all of the innervated muscle fibres of that particular motor unit. The summation of this electrical activity is known as a motor unit action potential (MUAP). The corresponding electrical activity from the composition of multiple motor units makes up the signal recorded during an EMG, see Figure 2.7.

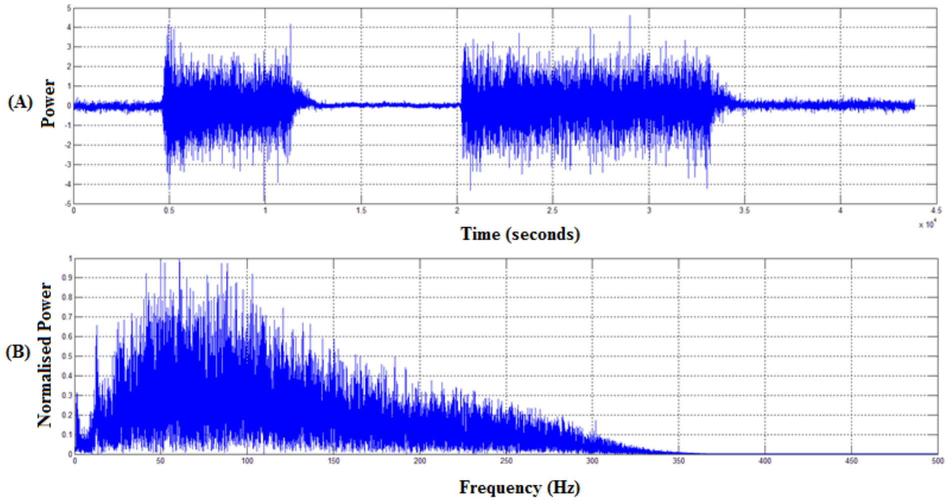

FIGURE 2.7: Example of EMG record from the forearm using Biopac MP150 acquisition system, showing A) EMG amplitude against time and B) power spectral density (PSD) of EMG.

EMG has a variety of clinical and biomedical applications. EMG is used as a diagnostic tool for identifying neuromuscular diseases and as a research tool for studying kinesiology, and disorders of motor control. EMG also plays an important role in motor function assessment during stroke rehabilitation and can be used to monitor recovery outcome and to detect peripheral muscle fatigue during intensive training, see Section 2.4.3.1.

2.4.3.1 Mean and Median Frequencies in Electromyography (EMG) Analysis

Traditionally EMG is used in the assessment of muscle fatigue and in the analysis of motor unit recruitment during incremental or constant exercise.

During maximal or prolonged exercise the majority of available motor units are recruited. According to the size principle, the smaller fast twitching muscles are recruited first. Over time these muscles become progressively fatigued and are subsequently replaced with larger slower twitching muscles. The resulting changes in muscle recruitment patterns and subsequent alteration in motor neuron firing rates cause changes in the EMG signal which can be detected by statistical frequency analysis.

Two of the most commonly used frequency domain features for the assessment of muscle fatigue in surface EMG signals are the mean frequency (MNF) and median frequency (MDF) [20, 58, 295].

The **MNF** is an average frequency which is calculated as the sum of product of the EMG power spectrum and the frequency divided by the total sum of the power spectrum. Mathematically, the MNF is expressed as Equation (2.1).

$$MNF = \frac{\sum_{i=1}^{M} f_i P_i}{\sum_{i=1}^{M} P_i} \tag{2.1}$$

where, f_i is the frequency value of EMG power spectrum at the frequency bin i, P_j is the EMG power spectrum at the frequency bin i, and M is the number of frequency bin.

The **MDF** is a frequency at which the EMG power spectrum is divided into two regions with equal amplitude. Mathematically, the MDF is expressed as Equation (2.2).

$$MDF = \frac{1}{2} \sum_{i=1}^{M} P_j \tag{2.2}$$

where, f_i is the frequency value of EMG power spectrum at the frequency bin i, P_j is the EMG power spectrum at the frequency bin i, and M is the length of frequency bin.

Both the MNF and MDF provide information regarding how the spectrum of the EMG signal changes with respect to time. Some investigations have been conducted to investigate which parameter is more suitable for evaluation of changes in neuromuscular function [365, 388]. However, findings vary between experiments and results seem to depend on the form of exercise being measured and the pertaining muscle groups being examined. For this reason many researchers include a measurement of both MNF and MDF in their studies.

2.5 Neuron

A neuron is a specialised nerve cell which transmits electro-chemical messages around the nervous system. There are various different types of neurons, however all neurons are electrically excitable cells who's function is to process and transmit information. The three main neuron types found in the nervous system are; sensory neurons, which transmit proprioceptive signals from the body's sensory organs including touch, sound, light as well as other stimuli, motor neurons, which transmit signals from the brain and spinal cord telling the skeletal muscles to contract or relax, and inter-neurons, which transmit signals between neurons within the same region of the brain.

2.5.1 Cell Structure

All neurons in the brain have broadly the same structure, illustrated by Figure 2.8 [7]. A typical neuron consists of three parts, a cell body (soma), dendrites and axon. The soma is the factory of the neuron, it produces all the proteins for the dendrites, axons and synaptic terminals. The dendrites are long extensions, often hundreds of micrometres in length, which branch off the soma giving rise to a complex "dendritic tree" structure. The function of the dendrites is to conduct electrical messages from other neurons and to transmit these signal into the cell body. The axon is fundamentally a nerve fibre which protrudes outwards from the soma, carrying electrical impulses away from the cell's body. The function of the axon is to propagate information to different cells including other neurons, muscles and glands.

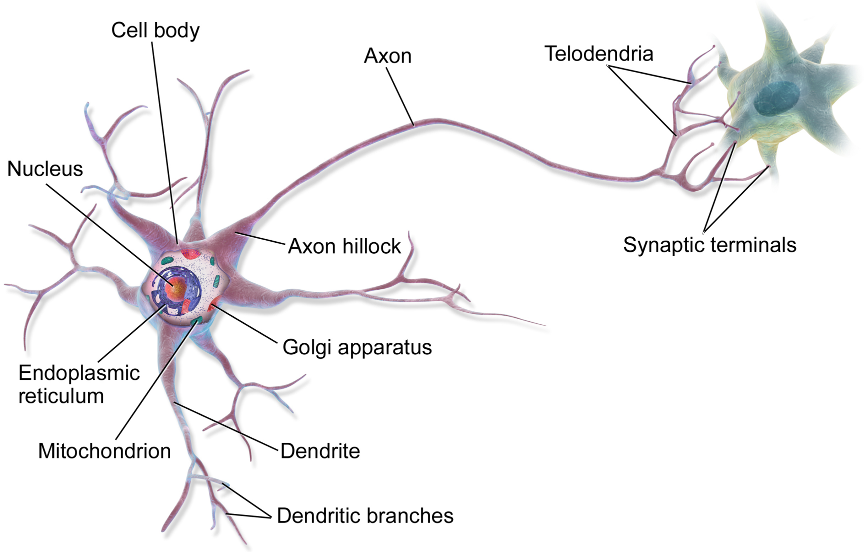

Figure 2.8: Structure of a neuron.

Neurons communicate by chemical and electrical synapses in a process referred to as neuro-transmission, also called synaptic transmission. The fundamental process that triggers the release of neurotransmitters is an electrical impulse called the action potential which is generated by exploiting the electrically excitable membrane of the neuron, see Section 2.5.2.

[7]Source: Blausen-0657-MultipolarNeuron.png licensed under CC BY 3.0

2.5.2 Action Potential

An action potential refers to the transient alteration in a cells electrical potential, caused by the propagation of an impulse along the membrane of that cell. Action potentials follow a consistent trajectory, first rapidly rising before falling sharply again, see Figure 2.9[8] for illustration.

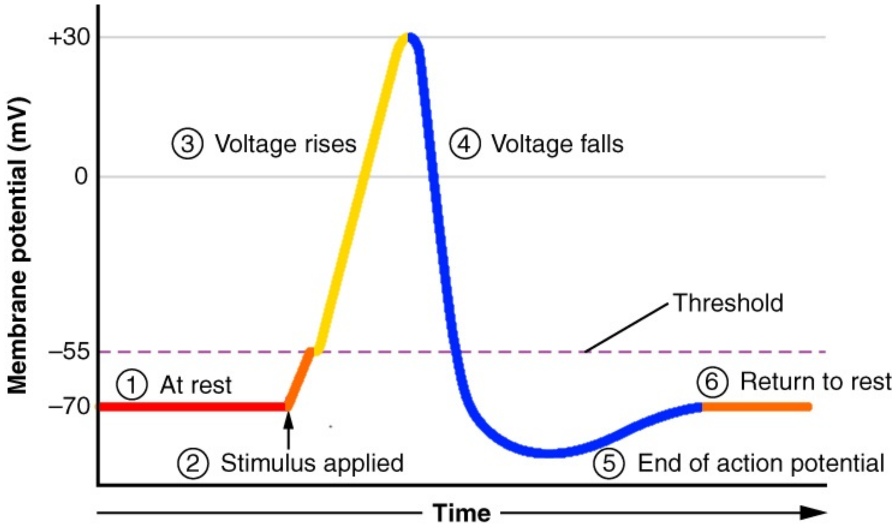

FIGURE 2.9: Illustration of the propagation of an action potential.

Action potentials are generated by special types of voltage-gated sodium (Na^+) channels that are embedded in a cell's membrane. When no stimulus is present, the Na^+ channels remain closed and the electrical potential across the membrane remains constant. If a sufficiently sized depolarising stimulus is applied to the cell causing the cells membrane potential to increase beyond a precisely defined threshold value, approximately $-55mV$, the Na^+ channels begin to rapidly open. This permits an inward flow of Na^+ ions into the cell, further depolarising the membrane and causing more Na^+ channels to open. This process continues until all of the available ion channels are open and the membrane potential reaches the equilibrium potential for Na^+, approximately $+30mV$. This results in a large increase in the cell's overall membrane potential. The rapid influx of Na^+ ions causes the polarity of the plasma membrane to reverse, at which point the Na^+ channels close, adopting an inactive state where the channels are unable to open again even though the membrane potential is still depolarised. Potassium (K^+) channels are then activated causing a subsequent outward current flow of K^+ ions, returning the electrochemical gradient to the resting state. The Na^+ channels remain in an inactive state for a few milliseconds after the membrane potential returns to its initial resting value, approximately $-70mV$.

[8]Source: figure-35-02-03.png licensed under CC BY 3.0

After an action potential has occurred there is a transient negative shift, called the after hyper-polarization or refractory period, due to additional potassium currents. This prevents the action potential from travelling back along the path it came. Therefore, the action potential travels along the length of the axon, in only one direction. When an action potential reaches the end of a pre-synaptic cell it causes the release of neural transmitters which cross the synaptic cleft and bind to the post-synaptic cell, see Section 2.5.3.

2.5.3 Synapse

A synapse is a minute junction which separates two nerve cells. Synaptic transmission is the process by which an electrical impulse is passed between two nerve cells by diffusion of a neurotransmitter, see Figure 2.10[9]. In the pre-synaptic neuron-membrane there are chemical neurotransmitters, packaged into small bundles called vesicles. Each vesicles can contain thousands of neurotransmitter molecules. When the pre-synaptic neuron is excited by a nerve impulse (an action potential), it causes the vesicles to fuse with the pre-synaptic membrane and to release their neurotransmitters into the synaptic cleft. After travelling across the cleft, these neurotransmitters then interact with receptors on the post-synaptic neuron and are converted back into an electrical impulse. The binding of the neurotransmitters may influence the post-synaptic neuron in either an inhibitory or excitatory way, increasing or decreasing the likelihood of the post synaptic neuron from firing respectively. See Section on synaptic plasticity 2.7.2.1.

[9]Source: synapse-diag1.svg licensed under CC BY-SA 3.0

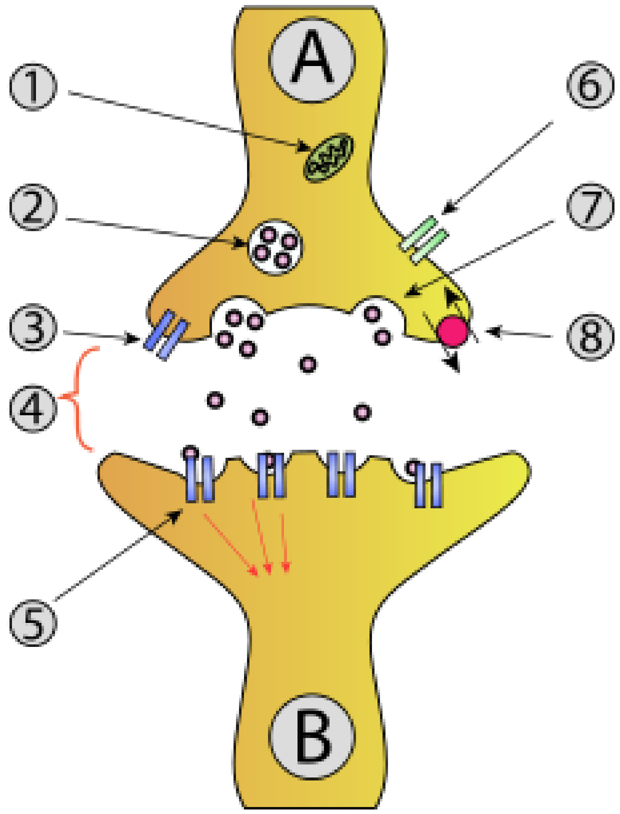

FIGURE 2.10: A: Presynaptic Neuron, B: Postsynaptic Neuron, 1: Mitochondria, 2: Neurotransmitters, 3: Receptor, 4: Synapse, 5: Postsynaptic receptors activated by neurotransmitter, 6: Calcium channel, 7: Exocytosis of a vesicle, 8: Recycling of neurotransmitter.

2.6 Stroke

A stroke, also known as a cerebrovascular accident (CVA), cerebrovascular insult (CVI), or brain attack, is a sudden loss of brain function caused by cell death, resulting from an interruption in blood flow. There are two main mechanisms by which blood supply is restricted to an area of the brain; by arterial haemorrhage, also known as a haemorrhagic stroke, see 2.6.2, or by arterial occlusion, also known as an ischaemic stroke, see 2.6.1. While not technically a stroke, a transient ischemic attack (TIA), see 2.6.3, is similar to a stroke, producing similar symptoms, but usually lasting only a few minutes and causing no permanent damage.

2.6.1 Ischaemic Stroke

Ischemic stroke is the most common type of stroke, accounting for approximately (85-90)% of all cases [10, 344]. Ischemic stroke occurs as a result of an obstruction within a blood vessel supplying blood to the brain. The underlying condition for this type of obstruction is atherosclerosis, which is the build up of fatty deposits on the inner walls of blood vessels. These fatty deposits can cause two types of obstruction, cerebral thrombosis or cerebral embolism. A cerebral thrombosis refers to the obstruction of blood flow to the brain caused by a blood clot that formed in the brain itself. In contrast, a cerebral embolism refers to an obstruction of blood to the brain resulting from a clot which has formed outside of the brain, usually in the heart and large arteries of the upper chest and neck, which breaks loose, enters the bloodstream and travels towards the brain, getting stuck when it reaches a vessel too small for it to pass. See Figure 2.11 [10].

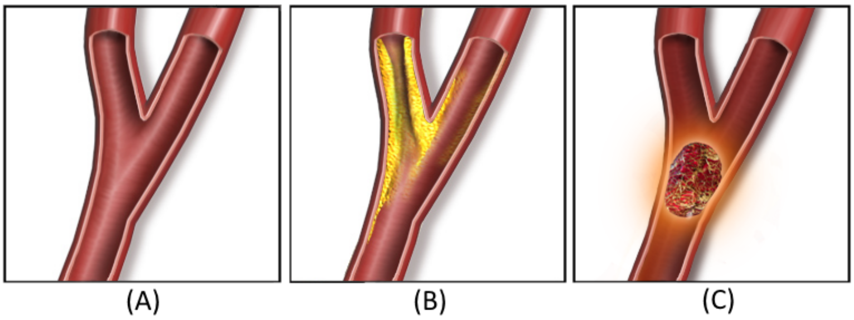

Figure 2.11: Illustration of: (A) healthy artery, (B) formation of a thrombus, and (C) an embolism.

2.6.2 Haemorrhagic Stroke

A Hemorrhagic stroke is less common than an Ischaemic stroke and accounts for approximately (10-15)% percent of stroke cases. Hemorrhagic stroke occurs when a weakened blood vessel ruptures. There are two types of weakened blood vessel conditions which typically cause hemorrhagic stroke, aneurysms and arteriovenous malformations. An aneurysms is essentially a deformation in a blood vessel or cardiac chamber, which allows blood to pool, causing it to swell. A arteriovenous malformation (AVM) is an abnormal defect in which arteries and veins are connected. The most common cause of hemorrhagic stroke is uncontrolled hypertension (high blood pressure).

2.6.3 Transient Ischaemic Attack

While not strictly a stroke, a transient ischaemic attack (TIA) is very serious and results from the temporary blockage of a blood vessel. A TIA does not typically result in acute

[10]Source: Created from two separate images, Blausen-0836-Stroke.png, Carotid-artery-stenosis.png licensed under CC BY-SA 3.0

infarction however they may be an indicator that an ischaemic stroke is imminent. According to the American stroke association, approximately 15% of major strokes are preceded by TIAs. The symptoms of TIA resemble those found early in a stroke and may include sudden onset of weakness, numbness or paralysis, typically on one side of the body. Slurred speech or difficulty understanding others. Blindness in one or both eyes. TIA's occur rapidly and are short lasting, typically lasting less than five minutes.

2.6.4 Physiological Effects of Stroke

The primary underlying mechanism for loss of function after stroke is neuronal death in the infarcted tissue but also because of cell dysfunction in the areas surrounding the infarct. In addition, the function of remote brain regions, including the contralateral areas that are connected to the area of tissue damage can be compromised due to hypometabolism, neurovascular uncoupling, and aberrant neurotransmission, jointly referred to as diaschisis [290]. When brain cells die during a stroke, abilities controlled by that area of the brain such as memory and muscle control are lost. The lasting effects of stroke are dependent on the type of stroke, the area of the brain affected and the extent of the brain injury. Each stroke is unique and can effect physical, cognitive and emotional functioning. As described in Section 2.3.2, the brain is divided into three main areas, the Cerebrum (consisting of the right and left hemispheres), the Cerebellum and brainstem. Depending on which of these regions of the brain the stroke occurs in, the effects may be very different.

If stroke occurs in the **Cerebrum**, depending on the area and hemisphere affected, any, or all, of the following body functions may be impaired; movement and sensation, speech and language, eating and swallowing, vision, cognitive (thinking, reasoning, judgement, and memory) ability, perception and orientation to surroundings, bowel and bladder control and sexual ability.

If stroke occurs in the **Cerebellum**, fine movement, coordination and balance may be effected. Common issues include; inability to walk and problems with coordination and balance (ataxia), dizziness, headaches, nausea and vomiting.

If stroke occurs in the **brainstem** it threatens vital bodily functions such as breathing, blood pressure and heart rate control. The brain stem also contains the brain's awareness center, which allows us to stay conscious of the world around us. The most common effects therefore include problems with; breathing and heart functions, body temperature control, balance and coordination, weakness or paralysis, chewing, swallowing, and speaking, vision and consciousness.

In the case of ischemic stroke, where blood circulation is impeded or restricted by occlusion of one of the main arteries supplying blood to the brain, the effects can differ greatly depending on the location of the blockage.

The **posterior cerebral artery** (PCA) supplies blood to the medial occipital lobe and the inferior and medial temporal lobes. A stroke located in the PCA can cause visual deficits, typically a decreased vision or blindness (anopsia) in half the visual field refereed to as contralateral homonymous hemianopia. Significantly larger PCA strokes may also cause contralateral hemiparesis and hemisensory loss.

The **middle cerebral artery** (MCA) is the largest vessel branching off the internal carotid artery (ICA) and is the most common site of stroke [279]. The MCA delivers blood to the regions of the brain which are responsible for motor control for the face, hand and upper extremity. A stroke located in the MCA can cause dysfunction in a large portion of the forebrain sensor-motor apparatus, including the frontal and parietal cortex and/or sub-cortical structures, resulting in deficits in motor function of the upper extremity.

The **anterior cerebral artery** (ACA) supplies the anterior medial portions of the frontal and parietal lobes. Strokes occurring in the ACA are uncommon and can easily be misdiagnosed, they usually result in contralateral leg weakness and sensory loss of the lower extremity.

2.6.5 Motor Impairment

Motor impairment can be be regarded as a loss or limitation of function in muscle control or movement. Movement impairment is categorised by severity, from weakness in an individual limb, movement weakness on one side of the body (hemiparesis) or the inability to move one side of the body (hemiplegia). Motor impairment typically occurs from damage to the motor cortex region of the cerebrum cortex. Because of the contralateral arrangement of the brain hemispheres, each cerebral hemisphere of the primary motor cortex contains a motor representation of the opposite (contra-lateral) side of the body. Injury to the left hemisphere therefore effects movement on the right hand side of the body whereas injury to the right hemisphere effects movement on the left hand side of the body. However, motor function can also be affected if stroke occurs in parts of the brain related to motor control, such as the cerebellum or brainsteam. The most severe form of motor impairment is known as locked-in syndrome (LIS) which results from a lesion to the brainstem, most frequently an ischemic pontine lesion [74].

2.7 Recovery After Traumatic Brain Injury: Mechanisms and Principles

The mechanisms of recovery after stroke are complicated. In general, motor recovery depends on the plasticity of neurons and circuits within the motor system [187]. Critical recovery after stroke is most prominent during the first 30 days but continues for at least 6 months [180, 264, 384] and is dependent on the degree of tissue loss, the preservation and/or engagement of neuronal networks which serve as substrate for the restoration of lost brain functions [393].

It is suggested that functional recovery involves 3 overlapping phases: first, reversal of diaschisis, activation of cell genesis, and repair, commonly referred to as spontaneous recovery; second, modification of existing neuronal pathways; and third, neuroanatomical plasticity leading to the formation of new neuronal connections. The second and third phases constitute the basic operations of the process known collectively as neural plasticity, which is also involved in normal learning. For this reason it is widely recognised that functional recovery after CNS injury is to an extent a relearning process.

2.7.1 Spontaneous Recovery

The brain has an innate capacity to repair itself after injury without intervention, through a process known as spontaneous recovery [270]. The principle theories of why spontaneous recovery of function occurs during the first few weeks post-stroke include: tissue reperfusion, edema reduction, reversal of diaschisis and neurogenesis [269]. In contrast, complications arising from secondary degeneration described below might help explain why spontaneous recovery does not often lead to complete recovery.

2.7.1.1 Edema Reduction

Edema (swelling) surrounding the lesion may disrupt nearby neuronal functionality. Some of the early recovery observed in stroke may be due to reduction of edema in the area surrounding the infarct [208].

2.7.1.2 Tissue Reperfusion

Reperfusion injury occurs when blood supply returns after a period of ischemic stroke causing inflammation and oxidative damage through the induction of oxidative stress rather than restoration of normal function [47]. Early recovery might be related to metabolic recovery and the reduction of tissue inflammation [23].

2.7.1.3 Reversal of Diaschisis

Diaschisis is a sudden loss or change of function in a portion of the brain connected to a remote, but damaged, brain area. There is growing evidence that recovery from diaschisis may depend on neuronal reorganisation and reconnection [332].

2.7.1.4 Neurogenesis

Neurogenesis is defined as the process of generating new neurons from precursor cells. In response to an acute ischemic insult, endogenous cells inside the cerebral cortex have been found to be able to divide at as early as 24-48 hours after ischemia to generate daughter neurons in the penumbral cortex [126].

2.7.1.5 Secondary Degeneration

Secondary degeneration is a form of degeneration occurring in nerve fibres as a result of their division. Secondary degeneration in the central nervous system involves indirect damage to neurons and glia away from the initial injury. Studies shows that secondary degeneration occurs and deteriorates not only in the fibre tract distal to but also proximal to a subcortical cerebral infarct at least 12 weeks after stroke onset, and may hamper neurological recovery [111].

2.7.2 Neural-plasticity

Until recently it was thought that developmental plasticity is mainly a characteristic of early life and that once matured the structure of the brain is fixed and immutable. This conventional view sees the brain as made up of a group of specialized processing modules, genetically hard-wired to perform specific functions, each developed and refined over millions of years of evolution. It was also believed that we were born with a finite number of neural cells and when a cell died no new cell could grow.

However, pioneering research in neurology in the late 60's and early 70's turned this notion on its head. Paul Bach-y-Rita, an American neuroscientist was one of the first to seriously study the idea of neuroplasticity and to introduce sensory substitution as a tool to treat patients suffering from neurological disorders. The first sensory substitution system was developed by Bach-y-Rita et al. in an attempt to allow congenitally blind individuals to see [373]. The result of this experiment showed that a person who has lost the ability to retrieve data from the retina, in this case due to underdevelopment of the optic nerve (optic nerve hypoplasia), can still see subjective images by instead using data gathered from additional sensory pathways such as touch or audition. The results of this study showed for the first time that the brain was indeed plastic and could rewire itself, in this case to reroute tactical vibrations representing images to the visual cortex in the brain. Bach-y-Rita went on to develop another device which enabled patients with damaged vestibular nuclei to regain their ability to remain balanced, by using an electrical stimulator placed on the tongue which reacted to a motion sensor (accelerometer) affixed to the patient's head. However, after repeated use, it was discovered that on removing the device some residual effects remained and the patient could remain balanced after the device was switched off. Bach-y-Rita hypothesized that the vestibular system was disorganized and was sending random "noisy" signals from the damaged tissue which was in turn blocking any signals sent by the remaining healthy tissue. The machine thus helped to reinforce the healthy signals and helped recruit new neuronal pathways in the brain, which with extended repetition became stronger. This idea, that the brain can reorganize and restructure itself is the fundamental principle of neural-plasticity.

Today, brain plasticity is well established and is the neurobiological foundation for recovery after brain injury. In general, neural-plasticity is defined as the ability of the brain to change its structure and/or function in response to internal and external constraints and goals [173]. This ability to adapt in response to the changing environment is the most fundamental property of the nervous tissue and constitutes the basis for motor learning. As such, neural plasticity represents an intrinsic property of the nervous system which enables modification of function and structure in response to environmental demands via the strengthening, weakening, pruning, or adding of synaptic connections (see Section 2.7.2.1 on synaptic plasticity) and by promoting neurogenesis [282].

2.7.2.1 Synaptic Plasticity

Synaptic plasticity refers to the malleability of a synapse, that is the ability of the synapse to change the connection fidelity between two neurons. A theory which describes the fundamental mechanism for synaptic plasticity was proposed by Hebb [138, 139], in which there is some growth process or metabolic change which occurs in a synaptic pathway as a result of the pre-synaptic neuron repeatedly or persistently exciting the post-synaptic neuron.

The degree of the voltage change in the post synaptic neuron is what we mean by the strength of the connection. Strengthening of the synapse is referred to as long-term potentiation (LTP), whereas weakening of synapse strength is referred to as long term depression (LTD). There is a critical window for synaptic plasticity with a peak time for changes in synaptic strength being 20 milliseconds before and after an action potential. If the pre-synaptic neuron fires before the post-synaptic neuron, within the preceding 20 milliseconds, LTP occurs. If the pre-synaptic neuron fires after the post-synaptic neuron, within the following 20 milliseconds, LTD occurs. This process is known as spike timing dependent plasticity [229].

The best example of the underlying biochemical mechanics behind LTP and LTD is synaptic plasticity in the hippopotamus neurons and is due to glutamate receptors. Glutamate is the main excitatory neurotransmitter in the brain, which activates two types of post-synaptic receptors, AMPA and NMDA that play crucial roles in hippopotamus synaptic plasticity. Both AMPA and NMPA receptors are ligand-gated ion channels and have unique properties that sub-serve different phases of synaptic plasticity. The AMPA receptor is permeable to Potassium (K+) and Sodium (Na+) and it is this inward flux through the AMPA receptor which depolarises the cell. In contrast, the NMDA receptor is blocked by magnesium and negative voltages and therefore does not significantly contribute to post synaptic depolarization. However, once the cell is depolarised, magnesium is displaced and then ions can flow through the NMDA receptor. An important property of the NMDA is that it also allows calcium to flow through it. It is the nature of this calcium current which causes spike timing dependent plasticity.

If the pre-synaptic neuron fires first it becomes depolarised and releases glutamate which binds to the AMPA receptors at the post-synaptic neuron, causing it to depolarise. As the cell becomes depolarised, NDMA receptors become unblocked and subsequently glutamate binds to them, causing a large calcium influx. In contrast, if the post-synaptic neuron fires first, it becomes depolarised, the pre-synaptic neuron then fires and releases glutamate. When the glutamate reaches the post-synaptic neuron it is still in the transition of re-polarising and therefore is at a lower voltage state. This means there are fewer NDMA receptors available to bind with and leads to a reduced calcium influx. In the cell, AMPA receptors are constantly being recycled though two process, exocytosis and endocytosis. A calcium influx large enough to cross a critical threshold will activate calcium dependent protein kinases which alter the recycling of AMPA receptors. In particular, they increase the exocytosis of them, they also change their structure and make them more permeable. This means that when glutamate crosses the synapse, more AMPA receptors are there to open, hence more current flows through and the change in potential is increased. In contrast, a lesser calcium in flux does not cross the critical threshold necessary to activate the kinases and instead only activates protein phosphatase kinases, these again alter the recycling of AMPA receptors but in the opposite way, increasing the endocytosis and therefore decreasing the number available at the post-synaptic terminal. This means that when glutamate again crosses the synapse, fewer receptors are open, less current flows through and the change in potential decreases. Thus, a large calcium influx leads to LTP and a small calcium influx results in LDP.

The operations of increasing and decreasing synaptic strength caused by coordinated neuronal firing is known as Hebbian learning, Hebbian plasticity or associative plasticity and are responsible for the fundamental neural plasticity of the brain.

2.7.2.2 Cortical Representations and Plasticity

Cortical stimulation mapping (CSM) is a type of electrocorticography used to localise functional areas in the brain through direct electrical stimulation of the cortex. CSM is used to determine which areas of the cortex are related to different body parts. Although not the first neurologists to utilise this technique, pioneering research by Penfield in the early 19th century illustrated that the primary motor and somatosensory cortices contain organised maps of the body. Penfield found that, although there were small differences between individuals due to variations in brain structure, the overall organization of these maps was basically the same across healthy individuals. Furthermore, he discovered that these maps were topologically ordered, that is, the body is represented in a highly structured fashion, with adjacent body parts mapping precisely onto adjacent areas of the brain. This is known as the cortical homunculus map, which is how the brain internally represents the body, see Figure 2.12.[11]. The size of the area devoted to any particular body part in the cortex is proportional to the amount of control that the primary motor cortex has over that part of the body. Therefore, the functional areas of the cortex occupied by both the hand and fingers is much larger than the areas acquired by the trunk or legs, since their muscle patterns are less complex.

[11]Source: 1421-Sensory-Homunculus.jpg, licensed under CC BY-SA 3.0

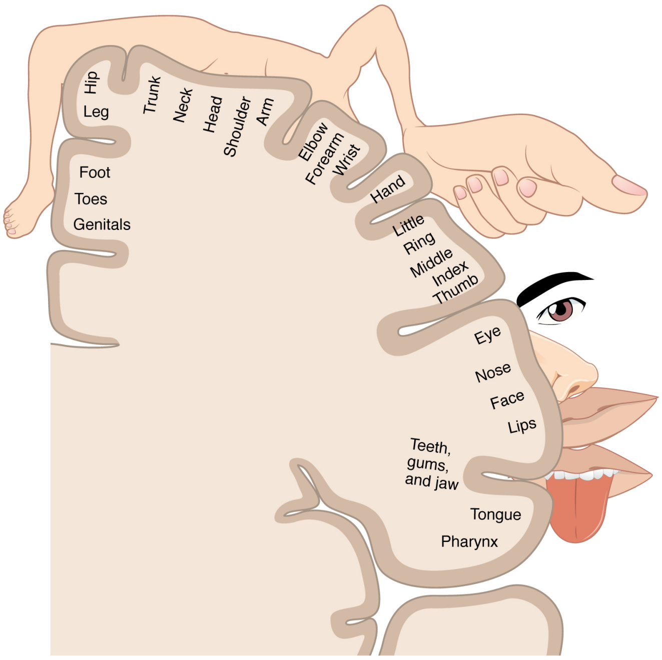

FIGURE 2.12: The cortical homunculus map.

Prior to the 1960's there was general consensus among neuroscientists that the structure of the brain after childhood was relatively immutable. This belief partially stemmed from the fact that there was relative homogeneity found in the cortical maps of different people. However, in the late 60's indisputable evidence of the contrary was proposed. Merzenich et al. [287, 288] found that the observed cortical maps of a monkey who had a large portion of its hand's peripheral nerves cut and allowed to regenerate, did not match expectations. Aware that the peripheral nervous system was capable of regeneration, it was assumed that some neurons would inevitably "rewire" themselves incorrectly to the wrong axons and would therefore stimulate the wrong nerve. However, after remapping the monkeys hand it was found that the resulting map was normal, with no evidence of cross wiring as expected. They concluded from these results that the brain must be capable of "normalizing" itself when stimulated with an irregular input and therefore that the adult brain must be plastic.

In addition to being re-organisable, Merzenich et al. went on to show that cortical maps are highly dynamic and that body parts are in constant competition for mapping real estate. They highlighted this property through an experiment in which they severed the median nerve of a monkey's hand to investigate what the resulting cortical map would look like when all input was removed. After two months, the hand was remapped. It was found that when the middle of the hand was touched no activity occurred at the median nerve location, however surprisingly when the sides of the monkey's hand were touched, activity was found in the median nerves location. They concluded that cortical remapping must have occurred and that the maps for the radial nerve and the ulnar nerve had remapped themselves, spreading out and infringing on the dormant median map, which no longer received any input [241].

2.7.2.3 Enhancement of Post-injury Plasticity

In the acute rehabilitation stage, after a patient has been stabilised, emphasis is put on maximising the natural recovery process of the brain. During this stage, specific deficits are identified and treatment is formulated to improve weakened function within these areas. As the rehabilitation process progresses focus is shifted towards replacing skills and functions that have been lost.

Plasticity is involved not only for the formation of new neural connections but also in the strengthening of existing ones. The goal of research rehabilitation is to maximize the functional benefits of post stroke motor rehabilitation through the development of interventions which promote motor learning related neuro-plasticity. While there are many factors which can promote plasticity, studies suggest that motor recovery rehabilitation programs should focus on the practise of **meaningful**, **intense**, **repetitive exercises** in an **enriched environment**.

Meaningful/task specific rehabilitation
There is strong evidence to support the notion that exercise therapies which focus on the practise of meaningful activities taken from everyday life improve recovery in stroke survivors [312, 361].

Intensity of rehabilitation
There are numerous studies which promote the importance of exercise intensity, suggesting that higher rehabilitation intensity is associated with better functional improvement at discharge for stroke patients [169, 196].

Repetitiveness of rehabilitation
There is strong evidence to suggest that there is a dosage dependency required to promote optimum plasticity and therefore re-learning after stroke. Studies designed to investigate neural-plasticity in animal models of stroke often require hundreds of daily repetitions of functionally-important task practice [183, 271, 272]. Similarly, studies in humans designed to investigate motor learning also employ large amounts of practice, although usually for fewer sessions. The number varies across studies but typical ranges are between 300 and 800 repetitions per session [48, 106]. A study by Huang et al

[154] on the impact of timing and dose of rehabilitation delivery on functional recovery of stroke patients showed that there is a dose-dependent effect of rehabilitation on functional improvement of stroke patients for the first 6 months post-stroke.

Enriched environment

Hebb (1947) first described the concept of enriched environments after noticing qualitative differences in the behaviour of rats which were kept in cages in his laboratory, to those that he brought home for his children to play with. In the early 1960s studies by Nithianantharajah et al. [265] and Rosenzweig et al. [308] provided some context to Hebbs observation by providing evidence that changes in the complexity of an environment and interaction in that environment can cause biochemical and structural changes in the brain. Since then there have been numerous studies employing enriched environments to study the mechanisms of experience-dependent plasticity in the central nervous systems of animals, a through review of which was conducted by Nithianantharajah and Hannan [265]. Studies with stroke patients also highlight the significance of the richness of the environment for promoting activity. Studies with stroke patient which assessed improvement in physical, cognitive and social activity relating to environment was conducted by Janssen et al. [166]. The results of these preliminary trials suggest that patients who were exposed to an enriched environment were more likely to be engaged in any activity compared with those in a non-enriched environment.

2.8 Summary

Stroke is a complicated and devastating disease, the result of which causes severe disability and suffering. Stroke is also a prevalent disease due to its age related risks and dependencies. Currently, the best intervention for stroke is taking precautions as to its prevention. While this approach will no doubt help stem the incident of stroke, preventive measures are not a cure for stroke, without which future strokes are inevitable, nor does it alleviate the suffering of those misfortunate enough to succumb to stroke. The perspective taken in this thesis is to treat stroke as a problem to be fixed, the effects of which are to be reversed, in an attempt to return the stroke sufferer back to their healthy normal self. As such, it is important to understand the effects of stroke on the brain and the innate mechanisms, primarily neuroplasticity, through which the brain can recover. The next chapter describes modern technology derived solutions for evoking, promoting and enhancing such effects for the recovery of healthy brain function after stroke.

Chapter 3

Literature Review

3.1 Introduction

One of the most exciting changes occurring today is the proliferation of embedded devices (i.e. special-purpose computing systems), their rapid diffusion into everyday life and the congruent development of large-scale distributed systems. Embedded systems have extensive applications in a wide variety of markets including consumer, commercial, industrial, automotive and healthcare. As a result, today powerful computers exist all around us and in the most unexpected places; smart watches, smart phones and now even glasses are packed with tiny advanced sensors that can tell us everything from our global geographical position to where the nearest bus stop is. In addition, innovations like the Arduino[1], an open-source electronic prototyping platform based on easy-to-use hardware and software, have bought such technology to the mainstream, allowing anybody to develop powerful digital devices and interactive objects that can sense and control the physical world around them. There is also an abundance of low cost sensors available to the enthusiast, which in combination with a micro-controller can be used to detect location, orientation, movement, light, humidity, temperature and proximity, among various other things. Advances in telecommunications technology have made the world a much smaller place. The Internet has evolved from its humble beginning as ARPANET (Advanced Research Projects Agency Network) [159], to a highly sophisticated, global collective network of billions of machines. Millions of kilometres of cables now connect even the most remote parts of the globe, creating a super information highway, teeming with electrons carrying information close to the speed of light to remote corners of the world. That is not to mention the unfathomable amount of wireless signals constantly pulsating into space, with the purpose of being redirected to the other side of the world

[1] Arduino: https://www.arduino.cc/

by a network of satellites in low earth orbit. Currently we are on the verge of yet another computing revolution, that is the convergence of embedded systems and the internet, commonly referred to as the Internet of Things (IoT). The IoT refers to the network of physical objects or "things" embedded with electronics, software, sensors, and network connectivity, which enables these objects to collect and exchange data [120]. It is estimated there is approximately 25 billion embedded devices currently connected to the Internet and reports by Cisco predicts that by the year 2020 this number will have risen to 50 billion devices [100]. Innovations such as these have the capacity to revolutionise the way in which we perceive and ultimately utilise technology.

From the perspective of healthcare, this emerging technology allows for the development of cost effective solutions and tools which can augment the efforts of conventional rehabilitation programs, reducing the burden on healthcare specialists and helping to diffuse expert knowledge into semi-automated rehabilitation programs. Wearable sensors can help monitor and access patient progress in a non-invasive and cost effective way. Ubiquitous embedded systems can assist in developing ambient intelligent environments, that is, electronic environments that are sensitive and responsive to the presence of people. Low cost micro-controllers and electronic prototyping platforms allow for the rapid, cost effective development of prototype rehabilitation tools and systems. The IoT grants these systems the ability to seemingly tap into an enormous library of knowledge, to better make decisions, to interact with another system autonomously, and to confer with human specialists. However, despite the recent advancement in rehabilitation technology and the importance of reducing the burden on healthcare services, traditional low-tech approaches for stroke rehabilitation still remain dominant. The slow uptake of technology in the rehabilitation field is due to many factors. The need to often physically interact with the patient for assessment and treatment purposes, and the need to objectively measure physical performance both present significant technical challenges for the developers of rehabilitation technologies [1]. In addition to, and arguably more importantly than replicating the physical touch of the therapist, is maintaining the psychological aspect of therapy. The therapist plays an extremely important yet often under appreciated psychological role in the rehabilitation process. During rehabilitation therapy they constantly monitor and assess the patient's physical and mental state and when required they stimulate and motivate the patient through feedback coaxing methods, designed to elicit additional effort or engagement. Developing technology which can deliver comparable feedback during therapeutic training is an immensely difficult challenge. Additionally, there is a need to stimulate industrial developments in the field of technology for healthcare, in an attempt to strengthen interest from small and medium enterprises [362]. To achieve this goal there is a need to demonstrate the potential and usefulness of assistance technology (AT) towards improving the quality of life of disabled people and towards developing new approaches to delivering healthcare. This process starts here, through the action of research which creates the necessary studies that can build evidence as to the effectiveness and utility of such technology for healthcare applications.

This chapter briefly discusses current innovative efforts already under-way to tackle such problems and towards gaining acceptance in the use of such technology for rehabilitative purposes. This chapter also discusses current challenges facing the advent of such technology for use in the home setting and highlights key areas where improvement needs to be made. The following literature review is subdivided into 4 key areas of interest which are prevalent throughout this thesis. The development of **wearable sensors**, specifically the design and application of sensor gloves, for the augmentation of functional hand recovery after stroke, see Section 3.2. The role of **extrinsic feedback** on implicit motor learning and its capacity for enhancing participant motivation and self-efficacy after stroke, see Section 3.4. An investigation of **robotic movement devices** and their **control systems** for use post stroke, see Section 3.3. Finally, a review of the most prominent **neurofeedback** solutions currently being employed for use in chronic stroke rehabilitation, see Section 3.5.2.

3.2 Sensor Gloves

A sensor glove, also known as a data glove, cyber glove, or historically as a wired glove, is an interactive device resembling a glove worn on the hand which facilitates tactile sensing and recording of motion pertaining to the hand and fingers. A considerable amount of research effort has been devoted to developing sensor glove technologies for studying interaction and manipulation. Sensor glove systems for hand movement acquisition have been in development since the late 1970's and to this day continue to engage a growing number of researchers. In fact, recently there has been renewed interest in devices for hand motion capture with many developers recognising their potential to compliment the re-emergence of virtual reality headsets, spearheaded by devices such as the Oculus Rift(Oculus VR, California, USD)[2]. As a result, there has been a vast range of devices developed over the last 3 decades, more than could possibly be described here concisely. Instead, the following section consists of a review of the most prominent data gloves studies, including some of the pioneering data gloves systems (Sayre and MIT-LED) which brought the development of such devices into the mainstream. After this, focus is directed toward describing more recent sensor glove systems which focus on functional hand recovery after stroke. For a more general and thorough survey of

[2]Oculus Rift: https://www.oculus.com

glove-based systems the reader is directed to the work of Sturman and D. Zeltzer [351], Zhou and Hu [416] and Dipietro et al. [86].

3.2.1 Methods for Position Tracking

Accurate assessment of motor abilities is important in selecting the best therapies for stroke survivors. Sensor glove-based systems represent one of the most important efforts aimed at acquiring hand movement data. The process of tracking a hand generally involves calculating some of the properties of the hand (i.e. position, orientation and pose). There are several documented methods for position tracking when using glove-based input [351], the most common being; optical tracking [75, 115, 337, 389], magnetic and inertial sensing [87, 103, 189, 190, 293], mechanical sensing [46, 280, 358, 369] and acoustic tracking [274, 275]. In practise, a combination of these methods are often used for hand/finger tracking as each solution has its own advantages and disadvantages.

3.2.1.1 Mechanical Sensing

Conceptually, mechanical sensing is perhaps the simplest approach to position tracking and typically involves using some form of direct physical linkage between the target and its environment. For finger tracking this typically involves using electromechanical transducers such as potentiometers or shaft encoders, positioned at the fulcrum point between two articulated segments of the finger (i.e. adjacent phalanges of the finger). As the finger bends, the articulated segments change shape and the transducers move accordingly. The subsequent electrical output of the transducer can then be sampled and used to estimate the joint position of each segment of the finger.

Finger tracking of this kind is typically quite robust and cheap to design. However, it is difficult to develop a sensor glove based on these principles which is adjustable for multiple users with various sized hands, as the measurement is derived from mechanical components which need to be carefully positioned at the intersection of each joint. Adjustable devices have been developed of this kind, however the added mechanisms required to achieve this often clutter the device, making it cumbersome and difficult to use. Furthermore, such devices are often aesthetically disconcerting, which can have a negative impact psychologically on patient compliance with therapy.

3.2.1.2 Optical Tracking

Optical tracking typically refers to one of two methods used for real-time spatial tracking of an object, either by tracking visual markers, typically coloured patterns, see Figure 3.1[3], or alternatively using the silhouette method, see Figure 3.2[4], which detects objects by their outline using an edge detection approach.

Marker based optical tracking relies on the ability to triangulate the three dimensional position of a marker in real-time with respect to a camera's frame of reference. This type of tracking system is robust and useful when the interaction space of an object is known or fixed and when there is sufficient computation power available to process large numbers of images quickly. To be useful for real-time hand tracking, an optical tracking solution needs to be able to process camera frames and track the hand, at a minimum of 30 frames per second.

FIGURE 3.1: Example of a colour glove used for optical marker based tracking.

A great deal of work has also been done on natural gesture tracking, i.e. tracking the naked hand without a glove. This is typically achieved by detecting the silhouette of a hand through edge detection [206] or template matching [346]. While this form of hand tracking allows for the most natural user experience, tracking the hand without any invariant tracking features is a complicated task. Camera systems are extremely sensitive to environmental changes such as variation in natural light, the casting of shadows by other objects, the reflection of light off surfaces, all which can have a dramatic affect on the observed color of objects in view. The observed shape (silhouette) of the hand also changes dramatically as its ordination is changed, making it difficult to identify. Hence, a robust model is required to track the hand as it moves around the work space.

[3]Image:Color glove, source: MIT's Computer Science and Artificial Intelligence Lab (CSAIL), [389]
[4]Image:Silhouette of hand, source:[337]

FIGURE 3.2: Example of silhouette method used for hand detection.

The major drawback of camera based systems is that they are restricted to the space in which the cameras are placed. Additionally, optical tracking systems suffer from visual occlusion of the fingers or markers, that is the obscuring of an object as it moves behind another object, due to the cameras fixed reference position [99, 190]. To solve this problem, additional cameras, each with a unique perspective of the workstation can be used [147, 376]. However, adding additional cameras increases the amount of processing required to detect objects and given constrains, might not be a feasible solution.

3.2.1.3 Inertial & Magnetic Sensing

An alternative sensing method used in sensor gloves is based on local magnetic actuation. The availability of Micro Electrical Mechanical Systems (MEMS) technology has resulted in the development of tiny, low-cost Inertial and Magnetic Measurement Systems (IMMS) devices that can be easily attached to textile clothing without impairing or restricting movement. An IMMS is an electronic device that consists of a combination of different inertial sensors which measures orientation and gravitational forces. An IMMS typically consists of a combination of accelerometers, which measure changes in acceleration, gyroscopes, which detect changes in rotational attributes including pitch, roll and yaw and magnetometers, which assist calibration against orientation drift. IMMS are ideal for measuring motion in compact environments where space and weight are of concern, they are self-contained, they do not require line-of-sight for measurement and are not sensitive to interference from electromagnetic fields or ambient noise. They also have extremely low latency (typically a couple of μs) and can be measured at relatively high rates (thousands of samples per second). For this reason they are an excellent means for measuring the position and rotation offset of the hand.

However, to measure finger movement using this technique would require three separate IMMS for each finger and another 2 for the thumb, totalling 14. Suitable devices for this task, that is IMMS which are small and light enough are expensive. Designing a nimble sensor glove suitable for use with a patient suffering from movement weakness, housing 14 IMMSs, not to mention the additional peripherals and supporting electronics required for their function, as well as a micro-controller, power supply and communication device, would be a difficult task. In addition, although each IMMS can be sampled at relatively high rates, the computational speed required to sample 14 IMMS at a sufficient sample rate to attain fluid motion capture is high. Another disadvantage of IMMS for tracking is that they typically suffer from accumulated error. This is because the current estimation of position is based on previous estimation of position, therefore, any errors in measurement regardless of how small are accumulated. This leads to a drift in position measurement (i.e. an increasing difference between where the system thinks it is located and its actual location) [266].

3.2.1.4 Acoustic Tracking

Acoustic sensors use the transmission and sensing of high frequency audio signals to track motion. Acoustic ranging systems typically operate by timing the flight duration of a brief ultrasonic pulse. In practise, this is accomplished through a series of transmitters and receivers, where the transmitters (speakers) are usually positioned on the object to be tracked, in this case the glove itself, while the receivers (microphones) are positioned around the tracking environment, in this case a display device such as a TV or monitor. The transmitters take turns transmitting a short radio burst, which are subsequently detected at different times by the receivers, depending on their distance away from the signal source. Then using a triangulation algorithm, the relative position of the glove with respect to the display device can be determined.

Acoustic tracking may be appealing in situations were both optical and inertia/-magnet sensing are not practical. For example, magnetic tracking is easily disturbed by metal objects, which might be common in the application domain. Likewise, optical tracking is sensitive to background lighting and suffers from occlusion [80]. While this technique has be used to estimate the location and orientation of the hand, and in theory could also be used to estimate the position of each of the segments of the finger, in practise the latter is not feasible due to physical properties of ultrasound.

In general, acoustic tracking faces a number of problems for hand tracking. Acoustic sensing is sensitive to environmental dynamics as it is subject to reflection and occlusions

[335]. Acoustic sensing also suffers from high latency due to fly time delay and as a results can only be sampled at a limited rate [274].

3.2.2 Early Sensor Glove Technology

3.2.2.1 Sayre Glove

The Sayre glove was designed in 1977 by Daniel J. Sandin and Thomas Defanti and is often cited as the first sensor glove [351]. The Sayre glove was designed to be an inexpensive, lightweight glove to monitor hand movements and provided to be an effective method for multidimensional control, such as controlling a set of virtual sliders on a computer screen. The device used light-based sensors with flexible tubes with a light source at one end and a photocell at the other, an idea credited to Rich Sayre, hence the name of the glove. As the fingers were bent, the amount of light that hit the photocells varied, thus providing a varying voltage proportional to the bend. This voltage could then be sampled and digitalised and used as an input for controlling a user interface.

FIGURE 3.3: Photograph of the Sayre Glove.

3.2.2.2 MIT LED Glove

The MIT-LED glove, developed in the early 1980s by the architecture machine group of the MIT Media Laboratory, as part of a camera system for motion tracking of the body and limb position for real-time computer graphics animation. The glove used a series of LEDs mounted on a cloth glove for position tracking. This glove is one of the very first designed for motion capture, however the device was not sufficiently developed to gain acceptance as a practical technology and the glove was only used briefly [351].

Although no longer using an LEDs based glove for motion capture, the MIT group have more recently developed an inexpensive vision based motion capture glove system that facilitates 3-D articulated user-input using the hands [389], see Figure 3.1. The system uses a single camera to track a hand wearing a fabric glove that is imprinted with a custom coloured pattern. The pattern is designed to simplify the pose estimation problem. Using computer vision techniques such as a nearest neighbour approach, the hands are tracked at interactive rates. The intention of this glove is to be a foundation for new interactions in modelling, animation control and augmented reality.

3.2.2.3 Digital Entry Data Glove

The digital entry data glove [124], a novel sensor glove developed by Gary Grimes et al. in 1983, was the first glove to integrate multiple different sensor modules. It consisted of touch or proximity sensors for determining whether the user's thumb was touching another part of the hand or fingers and four knuckle-bend sensors for measuring flexion of the joints in the thumb, index, and little finger. The glove also has two tilt sensors for measuring the tilt of the hand in the horizontal plane and two inertial sensors for measuring the twisting of the forearm and the flexing of the wrist. This glove was intended for creating alphanumeric characters from hand positions defined in the single hand American sign-language alphabet manual[5]. Hand gestures were recognized using hard-wired circuitry, which mapped 80 unique combinations of sensor readings to a subset of the 96 printable ASCII characters.

3.2.3 Commercialised Sensor Gloves

3.2.3.1 VPL DataGlove

The first commercially available data glove appeared in 1987 and was sold by VPL Research Inc. (VPL Research, Inc., Redwood City, CA), referred to as the VPL DataGlove. The DataGlove was an improved version of a data glove developed by Zimmerman [417], albeit with major improvements. The DataGlove was based on the 6502 microcontroller (MOS Technology, Inc., Pennsylvania, USA.), used fibre optics instead of light tubes as its predecessor had and carried multiple sensors. For the first time it allowed real time tracking of the hand, including 10 individual finger joints measurements (2 per finger

[5] Signal Hand American Manual Alphabet: https://en.wikipedia.org/wiki/American_manual_alphabet

and the thumb), and 6 degrees of freedom of the hands position and orientation, about the wrist. The DataGlove also did not rely on line of sight observation, was much lighter than its predecessors, was comfortable to wear and unobtrusive to the user. Commercialisation of the DataGlove by VPL Research [351], its low cost and multiple sensors options, lead to its widespread use by research institutions around the world. Inspired by the success of the DataGlove a number of similar devices were developed, including the ill-fated Nintendo (Nintendo Co., Ltd., Kyoto, Japan) Power Glove, see Section 3.2.3.2.

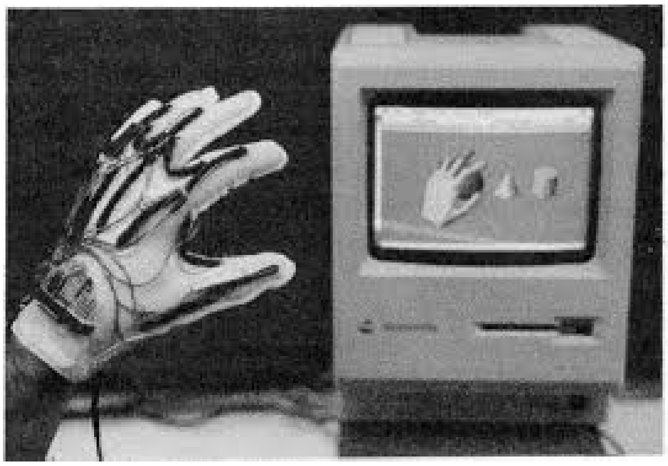

FIGURE 3.4: Photograph of the VPL DataGlove.

3.2.3.2 Power Glove

The Power Glove was developed as a control input for the Nintendo entertainment system (NES) and was commercialized by Mattel Intellivision (Mattel, Inc., El Segundo, CA) in 1989. It was one of the first attempts to bring sensor gloves technology into the mainstream and had it been successful, sensor gloves might today be more common. Unfortunately, the Power Glove was criticized for its imprecise and difficult-to-use controls and was a commercial failure.

The Power Glove system worked using two ultrasonic speakers (transmitters), which were positioned on the glove body and three ultrasonic microphones (receivers) which were placed around the TV monitor. The transmitters take turns transmitting short bursts of inaudible sound (40 Khz), which the receivers pick up at various different times as a result of the difference in path length between each of the sources relative to each of the receivers. Triangulation is then used to determine a rough location of the sensor glove in relation to the TV.

Figure 3.5: Photograph of the Nintendo PowerGlove.

A research paper by Williams and Green illustrated how with slight modification the Power Glove could be interfaced with a Macintosh computer, allowing the Power Glove to be used instead of the Macintosh mouse [397]. This paper also referenced a supplementary software demo which was demonstrated using the Power Glove to manipulate a virtual three dimensional cube. The aspirations of this work was to increase the accessibility of the device to the academic community in the hopes of enabling further research, potentially for healthcare applications. However, to the authors regret, no further publications regarding the use of the Power Glove were found during this literature review.

3.2.3.3 CyberGlove

The CyberGlove was developed by James Kramer at Stanford University as a tool for translating American Sign Language into spoken English. The glove was commercialised by a Stanford research lab spin-off company, Virtual Technologies (Virtual Technologies Inc., Palo Alto, CA) in 1992. The original CyberGlove consists of a custom-made cloth glove with up to 22 thin foil strain gauges sewn into the fabric to sense finger and wrist bending. Since then the CyberGlove has gone through two major revisions, (i.e. CyberGlove II and CyberGlove III). Both CyberGlove models utilise a proprietary resistive bend-sensing technology to accurately transform hand and finger motions into real-time digital joint-angle data. The sensors are accurate to less than 1 degree bend resolution, and are sampled at 90Hz.

The CyberGlove II comes in two versions, an 18 sensor or 22 sensor variation. The 18-sensor version features two bend sensors on each finger, four abduction sensors, plus sensors measuring thumb crossover, palm arch, wrist flexion, and wrist abduction. The 18-sensor system includes open fingertips, which allow the user to easily type, write, and grasp objects. The 22-sensor version contains the same array of sensors as the 18-sensor glove, as well as an additional flexion sensor per finger, increasing the total to three per finger.

FIGURE 3.6: Photograph of the CyberGlove II[6].

The CyberGlove III is the latest addition to the CyberGlove range. It is essentially an upgraded version of its predecessor, with significant improvements having been made to motion capture accuracy, reliability and filtering. The glove also now carries an upgraded Wi-Fi communication module providing for improved connectivity and an increased operating range of more than 100 feet. In addition, the CyberGlove III also boasts on board portable data storage, 12-bit A-D conversion unit, extended battery life and recording time and camera markers on glove for additional tracking capabilities.

FIGURE 3.7: Photograph of the CyberGlove III[7].

Currently, the CyberGlove III is one of the most impressive and accurate sensor glove devices commercially available [199]. The 18 sensor glove version costs $12,295, while the 22 sensor glove is $17,795.

[6]Image:cyberglove-ii.png, Source: http://www.cyberglovesystems.com/cyberglove-ii/
[7]Image:cyberGlove-iii.png, Source: http://www.cyberglovesystems.com/cyberglove-iii/

3.2.3.4 MIT AcceleGlove

The AcceleGlove glove [141], is a programmable glove that records hand and finger movements, developed under MIT spin-off company AnthroTronix and was released in 2009. The AcceleGlove uses a series of accelerometers to measure finger positions and hand orientation. A single accelerometer is positioned just below each fingertip, with another placed on the back of the hand. When the user's hand moves, the accelerometers can detect the three-dimensional orientation of the fingers and palm with respect to Earth's gravity. The accelerometers feed the position information to a central processing board positioned on the back of the hand. This board also acts as a gateway between the host PC and the glove, facilitated by a USB cable, for data transfer and power.

FIGURE 3.8: Photograph of MIT's AcceleGlove.

AnthroTronix initially developed data gloves for US Defence for controlling robots. However, after going commercial, the AcceleGlove has found application in video games, sports training, and physical rehabilitation. The glove costs approximately $499.

3.2.3.5 5DT Data Glove

The 5DT Data Glove is developed by Fifth Dimension Technologies (Fifth Dimension Technologies, Pretoria, South Africa). The 5DT Data Glove uses propriety optical-fibre flexor sensors technology. 5DT offer multiple variations of their data glove, differing in the amount of sensors depending on the accuracy required. The base model, the 5DT Data Glove 5 Ultra, features 1 sensor per finger with 10-bit flexure resolution and an integrated pitch and roll sensor position on the wrist. The sensors can be sampled at a rate of 200 Hz per finger. The 5DT Data Glove 14 Ultra model has an additional sensors per finger, as well as 4 additional abduction sensors between the fingers.

The gloves are made of a stretchable material (Lycra™) with open finger tips and is marketed as one size fits many. They use a standard tethered USB based interface with a host computer. In addition to a customisable number of sensors, 5DT also offer different variations of their glove suitable for different environments, including a wireless (Bluetooth) version and a version suitable for use in Magnetic Resonance Imaging (MRI) environments.

FIGURE 3.9: Photograph of the 5DT Data Glove[8].

The 5DT gloves range in cost depending on the glove version and sensor configuration, however they start at approximately $1,000 for the standard 5 sensor 5DT glove (i.e. 5DT Data Glove 5 Ultra) and go as high as $7000 for the 14 sensor MRI glove (i.e. 5DT Data Glove 14 Ultra MRI).

3.2.4 Haptic Feedback Gloves

3.2.4.1 Dexterous Hand Master

The Dexterous Hand Master is not really a glove but rather a lightweight aluminium exoskeleton, consisting of an arrangement of sensors, held over each finger joint by lightweight pads and Velcro™ straps [155]. Each sensor houses both a Hall-effect magnetic pickup and a small magnet to measure the bending angle of each joint. As the finger bends the magnet is brought closer or further away from the Hall sensor, generating a varying voltage proportional to the strength of the magnet's magnetic field. The Dexterous Hand Master measures bending of the three joints of each finger as well as

[8]Image:hw_data_glove_wireless_01.jpg, Source: http://www.5dt.com

abduction of the fingers and complex motion of the thumb. Hence, in total the Dexterous Hand Master measures 20 degrees of freedom of the hand, 4 for each finger and 4 for the thumb. The analog signals acquired from the joint sensors are collected by a custom A/D board at up to 200 samples per second and are transmitted to a PC through a serial port connection.

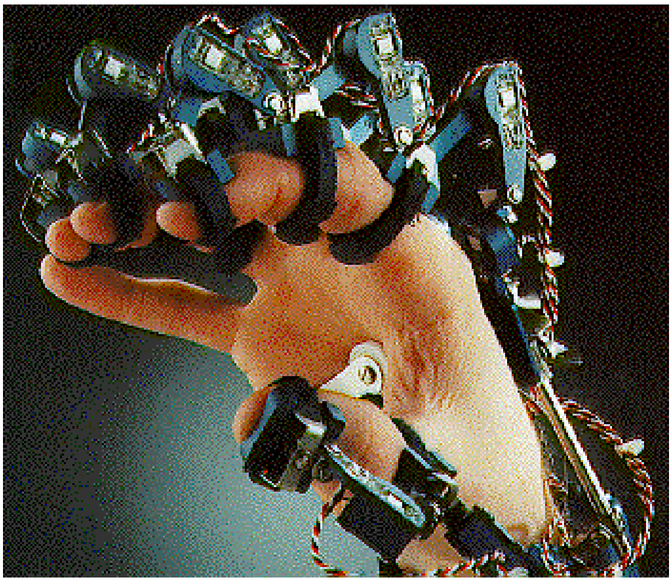

FIGURE 3.10: Photograph of the Dexterous HandMaster.

Originally the Dexterous HandMaster was developed as a controller for the MIT Dexterous Hand robotic hand [165], however it was then commercialised and sold by EXOS (EXOS, Inc., Burlington, MA, United States). The device is no longer for sale, however it was priced around $15,000.

3.2.4.2 Rutgers Master II-ND

The Rutgers Master II-ND glove is a haptic feedback glove designed to enable dexterous interactions within virtual environments [35]. The glove provides force feedback up to 16 N each to the thumb, index, middle, and ring fingertips. It uses custom pneumatic actuators arranged in a direct-drive configuration. The glove uses two Hall-effect sensors to measure the flexion and adduction/abduction angles of the pneumatic actuators. An infrared sensor measures the translation of the piston inside an air cylinder. In addition to force feedback the glove can also measure position of the hand and fingers, using integrating non-contact Hall-effect and infrared sensors. The glove has a haptic-control interface, consisting of pneumatic servo valves, signal conditioning electronics, a power supply and an embedded Pentium PC. Communication with a host PC, i.e. streaming of sensor data and for the actuation of the pneumatic actuators is accomplished using a serial port connection.

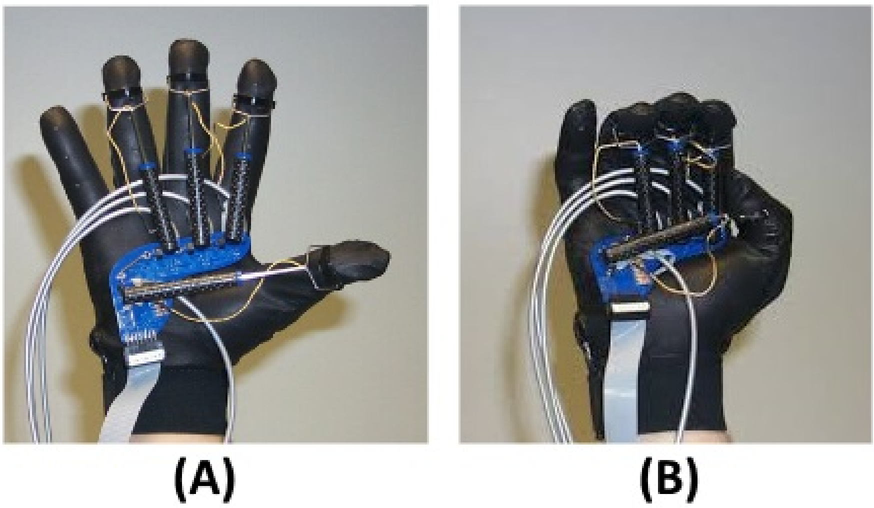

Figure 3.11: Photograph of the Rutgers Master II-ND. A) Hand open, B) Hand closed.

3.2.5 Stroke Studies with Commercial Gloves

Despite the fact that sensor gloves are an ideal means of capturing hand motion data and although their is ample commercially available gloves for this purpose, there is a surprising deficit of studies as to the efficacy of sensor gloves for use in stroke rehabilitation. Albeit, some studies have been conducted which signify the potential of such devices.

Boian et al. investigated the potential use of a glove based VR-based training system for reducing finger impairments in chronic stroke patients. Two commercial gloves, a CyberGlove and a Rutgers Master II-ND haptic glove were used in this investigation. 4 chronic patients participated in the study. Each patient had to perform a variety of VR exercises to reduce impairments in their finger range of motion, speed, fractionation and strength. Patients exercised 2 hours per day, 5 days a week for 3 weeks. Results showed that three of the patients had substantial gains in thumb range (50-140%) and moderate improvements in finger speed (10-15%) over the three weeks trial. All four patients had significant improvement in finger fractionation (40-118%) [33].

An additional study of the effectiveness of both the CyberGlove and the Rutgers Master II-ND, for delivering force feedback during motor function rehabilitation, was conducted by Adamovich et al. 8 chronic stroke patients participated in VR training consisting of 4 training sessions, including; range of motion, speed of movement, fractionation of individual finger motion and strengthening of the fingers. The subjects trained for 2 to 2.5 hours each day, 5 days a week for 3 weeks. The results of the study reported that 6 out of the 8 subjects increased their finger and thumb range of motion significantly. Similarly, 4 subjects improved finger speed and 2 in thumb speed, 7 in fractionation and 3 in strength exercises. Patients also showed good retention when measured one-week post intervention [2].

Camerirao et al. developed and tested a rehabilitation gaming system (RGS) based on the 5DT data glove, which recorded hand position, arm joint angles and finger flexure. 14 acute and sub-acute stroke patients participated in the study, which consisted of completing three 20 minute training sessions a week for 3 months. The patients were randomised into three groups; an RGS group and two control groups (Control A and Control B). The RGS group performed tasks with the addition of virtual reality (VR) feedback using the 5DT data glove for input. Control group A preformed motor tasks similar to the RGS group but without visual VR feedback. Control group B performed non-specific games with the Nintendo Wii console. The outcomes of this preliminary trial suggest that the RGS may induce a sustained improvement in motor outcome based on the Chedoke Arm and Hand Activity Inventory (CAHAI) scores and Motricity Index scores [45].

Martin and Vargas performed two investigations using the AcceleGlove for the quantification of functional hand grip using electromyography and inertial sensor-derived accelerations [230, 231]. The evaluation explored the potential use of the AcceleGlove for the measurement of 6 functional hand movements including; terminal pinch, terminolateral pinch, tripod pinch, power grip, extension grip and ball grip. The primary objective of these studies was to investigate the feasibility of using a combined measurement of electrical muscle activity, recorded through EMG and hand motion, recorded by the AcceleGlove, as a means for analysing hand function.

3.2.6 Custom Sensor Gloves and Stroke Studies

Given the high cost of commercial sensor gloves many researchers interested in hand rehabilitation have opted to instead develop their own sensor glove systems. Subsequently, many sensor gloves have been developed for a variety of different applications [97, 129, 163, 205, 245, 314, 340]. A sub-collection of sensor gloves which have been used in clinical trials, as well a collection of the most notable glove designs, are described below.

Friedman et al. proposed a novel sensor glove, the MusicGlove, which was developed to facilitate and motivate at home practise of hand movements [113]. This low cost device uses music as an interactive and motivating medium to guide hand exercise and to quantitatively assess hand movement recovery. A proof of concept study was conducted using MusicGlove with 10 chronic stroke patients, with disabilities ranging from severe to moderate hand impairment. During training, the patients first learned to perform functional movements, including pincer grips, key-pinch grip and finger-thumb opposition. During practise, the patients used these movements to play different musical notes and to play along to songs displayed by an interactive video game. The study found that the glove was well suited to patients with a Box and Blocks score of 7 or above and that the glove was capable of obtaining a measure of hand dexterity that correlates strong with a Box and Blocks score. The study suggests that the use of music for training significantly improved both objective measures of hand motor performance and self-ratings of motivation, in addition, music assisted the ability to hit the right note with the right grip, but did not have any affect on timing.

A pneumatic glove, the PneuGlove, and an accompanying immersive virtual reality environment for hand rehabilitative training after stroke was proposed by Connelly et al. The PneuGlove provides independent extension assistance for each finger without limiting hand movement. A proof of concept study for this device was conducted with 14 stroke patients. The patients were divided into two groups, each containing 7 patients. Both groups completed a six-week rehabilitation training protocol, consisting of three 1 hour training sessions, performed once a week. One group wore the PneuGlove during training, performed both within a novel virtual reality environment and outside of it with physical objects, while the other group, a control group, completed the same training without the device. A Fugl-Meyer assessment, a Box and Blocks Test and palmar pinch strength assessment was conducted with each patient after the completion of the training. Significant improvements in upper extremity, the hand/wrist portion of the Fugl-Meyer assessment, the Box and Blocks test, and palmar pinch strength were observed in both groups. Whereas there was statistically little difference between groups, the group training with the PneuGlove showed greater mean improvement on each of these measures [64].

Flynn et al. developed a novel smart glove to facilitate the rehabilitative process of rheumatoid arthritis, through the integration of sensors, processors and wireless technology to empirically measure range of motion (ROM) [273]. The glove uses a combination of 20 bend sensors, 16 tri-axial accelerometers and 11 force sensors to detect joint motion. The sensors are housed on a flexible printed circuit board (PCB) to provide high levels of flexibility.

Nathan et al. proposed the design of a low cost functional electrical stimulation grasp-assistive glove for use with task-orientated robotic stroke therapy. The glove measures grasp aperture while a user completes real-life activities, and when combined with an integrated functional electrical stimulator (FES) it assists in hand opening and closing. Results from 5 subjects with stroke validate the FES system, showing that the glove can deliver qualitative FES to subjects and that this does indeed help with hand opening [259].

Simone et al. developed a low cost instrumented glove for extended monitoring and functional hand assessment was proposed. The glove was evaluated for feasibility, measurement repeatability and reliability, fidelity of wireless transmission, and user acceptance. Five healthy individuals participated in the study of repeatability, while 10 healthy individuals and 10 individuals with acquired brain injury participated in trials to assess feasibility and user comfort. Results demonstrate that the glove has a strong potential to be used as a tool for objective hand function evaluation in the home and community for both short- and long-term monitoring [340].

3.2.7 Discussion

Sensor glove technology represents great potential for use in hand rehabilitation therapy post stroke. While there are a range of high quality sensor glove systems commercial available for this purpose, such systems are prohibitively expensive, costing anywhere from $500 to $20,000, making them inaccessible both for the aspiring researcher and for patients who might use them as part of their home-based rehabilitation program. As a result, their has been a proliferation of custom designed sensor gloves developed, as researchers opt to develop their own sensor gloves solutions. However, in the authors opinion most of the custom gloves reviewed are either over designed for a specific purpose, or are simply not suitable for use in patients with movement weakness. Most of the gloves reviewed sacrifice moveability for motion capture accuracy, boasting an excessive number of sensors for acquiring redundant degrees of motion capture, at least for the purpose of hand impairment assessment. Furthermore, most reviewed gloves were either designed to use a tethered interface, or forced to do so because of the amount of data they acquire. In addition, the author did not come across any self-contained, autonomous sensor glove designs. Instead, researchers opted to design their gloves to rely on external computers to process data, or to make use of the captured data. These design considerations place restrictions on the users moveability, and in the case of a wired interface, effectively restrict the user to the proximity of the computer, thereby limiting its interactive space and potential usability.

As new smart technology continues to invade our homes there is great opportunity to take advantage of wearable technology and ubiquitous computing to develop ambient intelligent environments, that is environments which are sensitive and responsive to human presence. There is thus a need for a simple sensor glove design which is self-contained, that can function autonomously, having the ability to communicate sensor data wirelessly while remaining cheap and easy to reproduce.

3.3 Robotic Devices for Upper Limb Rehabilitation

The history of robotics is fascinating. The fundamental components of automation have their roots in the industrial revolution, a period now almost two centuries old. Robots are the epitome of autonomous automation, they work continuously and systematically, never deviating from their objective, repetitively churning out complex products in a fraction of the time and cost of their human counterpart. As a result, robots have replaced humans in performing repetitive and dangerous tasks, or tasks which take place in extreme inhospitable environments, such as outer space or the bottom of the ocean. However, more recently robotics are also starting to play an active role in more normal working environments, to supplement the efforts of highly skilled human workers, mostly in relieving the burden on manual labour. From the perspective of recovery after neurological injury such as stroke, robot devices can assist patients in a number of circumstances. They can aid with passive range of motion to help maintain range and flexibility, to help reduce hypertonia or resistance to passive movement. A robot can also help with active movement, where a patient is too weak to move of their own accord.

There has been a proliferation in the application of robotic devices for healthcare over the last few decades and subsequently many literature reviews on robotic devices for upper extremity rehabilitation have been conducted. As such, many comprehensive literature reviews have been performed on the use of robotics for motor rehabilitation [37, 52, 221, 226, 298]. Combined, there are 140 plus unique clinical robots reviewed in the aforementioned systematic reviews, far to many to go into detail in this literature review. Instead, an overview of the different robotic control strategies and mechanisms for use in motor rehabilitation is given here, as well as a brief discussion including a small subset of the most prominent robotic systems for rehabilitation of the upper extremity which are current at the stage of clinical trials.

3.3.1 Control Signals

A variety of different signals have been used as control input for robotic movement devices. The more simple systems tend to rely on kinematic measures of forces (position, torque, acceleration etc.) typically provided by an actuator encoder. More advanced control inputs, such as biometric measurements of muscle activity have also been more recently used, for example, surface electromyography (sEMG), which provides information about the intention of the person to perform particular movements.

3.3.2 Control Strategies

A comprehensive review of control strategies for robotic movement training was conducted by Marchal-Crespo and Reinkensmeyer [226], in which they proposed that control strategies for movement rehabilitation devices can be separated into two categories, low-level and high-level control strategies. Low-level control strategies refers to strategies which control the force, position, impedance or admittance factors of the robotic device. In contrast, high-level control strategies refers to strategies designed explicitly to provoke motor plasticity.

Additional systematic review of control strategies for robotic movement training after neurologic injury have been conducted by Maciejasz et al. [221] and Winstein et al. [399].

3.3.3 High-level Control Strategies

There are a number of different ways in which robot devices can assist with movement. The most common high-level control strategies are; active, passive, haptic and coaching.

3.3.3.1 Active Devices

Active assistance involves helping an individual to complete a motion by producing force feedback. In terms of robotic therapy, this is typically achieved using an actuator which applies a force in the direction of the desired motion. Active assistance is often used when a patient is too weak to perform specific exercises alone. The majority of robot devices for motor rehabilitation are active movement devices. A review of active systems with 3-DoF or more, containing 30 different exoskeleton prototypes for neurorehabilitation of the upper limbs was conducted by Jarrasse et al. [167].

All active assist control strategy follows the basic principle that; when the participant moves along a desired trajectory, the robot controller should not intervene, however if the participant deviates from that path, then an appropriate restoration force should be applied which encourages the participant back onto the desired trajectory. The resulting controller is termed an assistance-as-needed (AAN) controller. The first and most basic form of assistance controllers used were based on the proportional feedback position control which enforce a form of virtual channel that guides limb movement [249, 367, 368]. One concern about such controllers is that they enforce strict adherence to a fixed trajectory, which might be suboptimal for rehabilitative training because they abolish variability, an intrinsic property of neuromuscular control [42, 170]. To advert this effect, dead-bands are often included into the control scheme which allow for variation outside some threshold to occur without intervention from the robotic controller. Another variation on the standard feedback controller is to include some form of triggered mechanism. Here, a trigger variable, which could be a measure of elapsed time, a measure of force, spatial tracking error, limb velocity or muscle activity, triggers assistance only after some performance threshold is reached.

3.3.3.2 Passive Devices

In contrast to active devices, a passive device is a device which resists movement, for this reason they are also commonly called challenge-based control strategies. This imposed challenge is often achieved using an actuator which provides resistive force, for example a break. Passive devices are commonly used for strength or resistive training and are often used in motor adaptation experiments [368]. Passive devices are also used for physical therapy where suppression is required, for example in the case of tremor suppression [305] and to manage muscle spasticity [55].

3.3.3.3 Haptic Devices

Haptic devices supply tactile sensation to the user by applying forces, vibrations, or motions. Haptic robotics have the potential to address sensory impairments. Haptic feedback devices may be useful for partial sensory impairment as a means of sensory augmentation facilitating motor control and rehabilitation in patients post stroke [338]. For example, damage to the vestibular system after stroke often affects postural control, which can lead to issues with balance and can cause difficulties in standing or walking [90]. Haptic feedback may help improve standing stability in such cases by substituting or reinforcing damaged feedback pathways in the brain [5]. Haptic feedback devices may also help close the sensorimotor loop for stroke patients with severe disability who cannot actively move without assistance [121].

3.3.3.4 Coaching Devices

A robotic coaching device is a device which does not physically contact the participant but instead serve as a coach, helping to direct the therapy program, motivate the participant, and promoting motor learning through non-tactile feedback. This concept is better known as socially assistive robotics (SAR). SAR devices focus on helping human users through social rather than physical interaction, through the application of robotics for the provision and administration of motivation, encouragement, and rehabilitation for those suffering from cognitive, motor, and social deficits [385]. These devices often use some form of sensor based monitoring to tracking motion, however they do not actively or passively interact with an individual during movement practise. SAR is an innovative, interdisciplinary and increasingly popular research area that brings together a broad spectrum of research including robotics, social and cognitive sciences, and neuroscience [357].

3.3.4 Low-level Control Strategies

The majority of low-level control approaches for robotic rehabilitation of the upper limb are either impedance or admittance based.

3.3.4.1 Impedance Control

Impedance control is an approach in which the dynamic interaction between a robotic manipulator and its environment are altered to apply assistance. Impedance control doesn't regulate force or position directly but rather regulates the relationship (input/output) between force (e.g. pull, push) and reactions (i.e. position, velocity and acceleration). An impedance controller takes a position, velocity or acceleration, as an input and produces a resulting force as output. The MIT Manus [146] and the L-Exos exoskeleton [114] are two classic examples of robots which utilise an impedance based control strategy.

Impedance control is efficient for lightweight backdrivable exoskeletons, in which cable-driven systems are often used for torque transmission. The problems relating to impedance control are the compensation of gravity and friction, particularly in tendon-like systems [167].

3.3.4.2 Admittance Control

Admittance is the inverse of impedance. An admittance controller measures force exerted by the user and then generates the corresponding displacement accordingly. The admittance control strategy has been implemented in [244] and [73]. For exoskeletons that lack backdrivability, admittance control may be more appropriate, because there must be measurements of the force at the interfaces with the human limb to move the robot, considering its inertia and dynamic effects [167].

3.3.5 Clinical Robotics Trials

While there has been significant effort over the last two decades to improve the design and control strategy of robotic rehabilitation devices, there has been little development to prove the efficacy of such systems in clinical rehabilitation settings. The majority of clinical trials reported are small, and lack the use of a control group for comparison treatment. Prange et al conducted a systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke, including 8 studies [298]. Kwakkel et al., performed a systematic review on the use of robotics for rehabilitation of the upper extremity following stroke, containing 10 studies [195]. A more recent review by Mehrholz et al. included 19 trials (328 subjects) in the evaluation of electromechanical and robot-assisted arm training devices [239]. An even more recent review [221] consisting of 132 robotic devices for upper limb rehabilitation was conduced by Maciejasz et al.

The following section describes a subset of the most prominent robotic devices which have been used in clinical trials to date.

3.3.5.1 MIT-Manus

The first robotic system to receive extensive clinical testing for movement rehabilitation was the MIT-Manus [146]. It features a 2 degree of freedom robot actuator that assists in shoulder and elbow movement. It also provides visual, auditory and tactile feedback during goal-directed movements.

Figure 3.12: Photograph of the MIT Manus

An overview of the clinical trials undertaken with the MIT-Manus was conducted by Krebs et al. [191]. The outcome of this work shows that the group of stroke patients treated daily with additional robot-aided therapy during acute rehabilitation had improved outcome in motor activity at hospital discharge, compared to a control group that received only standard treatment. Further, the groups still statistically differed in motor impairment at a 3-year follow-up [382]. There has been an additional 10 clinical studies conducted with the MIT-Manus, the most recent [207] and [66] both contained large groups (127, 62 patients respectively). The results of these studies continue to be promising, showing modest improvements in recovery outcomes compared to standard rehabilitation, indicating that supplemental robotic therapy can improve recovery in acute and chronic stroke patients.

3.3.5.2 MIME

The Mirror Image Motion Enabler Robot (MIME) [214] is a 6 degree of freedom robot developed to assist with bi-manual movements with both assisted and resistive movements of the hemiparetic upper extremity. Clinical trials conducted by Burger et al. comparing robot-assisted therapy using MIME to traditional therapy in 21 chronic stroke subjects showed significant improvement in the Fugl-Meyer (FM) measure of motor recovery in the robot group, which exceeded improvements in the control group [38].

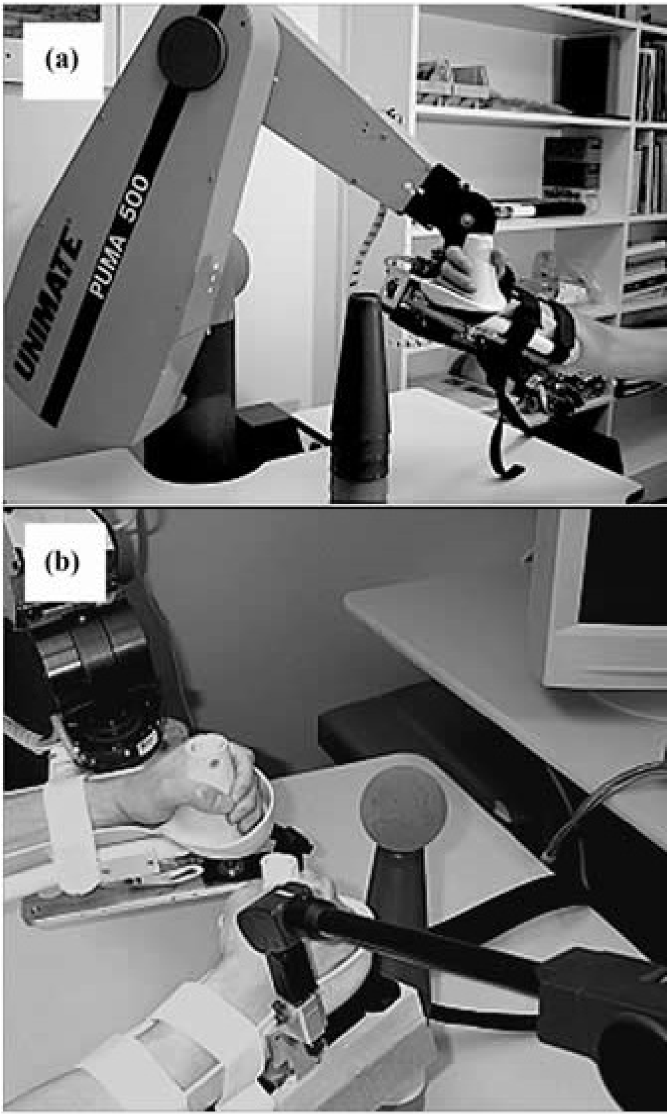

Figure 3.13: Photograph of the MIME Robot

Lum et al. conducted a study comparing the effectiveness of robot-assisted movement training to conventional therapy for the rehabilitation of the upper-limb motor function after stroke. 27 stroke patients with chronic hemiparesis participated in the study. Subjects were randomly assigned to either a robot group or control group. Each subject received twenty four 1 hour training sessions over 2 months. Subjects in the robot group practised shoulder and elbow movement with the assistance of MIME. Subjects in the control group received neuro-developmental therapy which targeted upper limb function. Patients were assessed using a Fugl-Meyer assessment, FIM™instrument, and through bio-mechanical measures of strength and reaching kinematics. The results show that the robot group had larger gains in strength and increased reach extent after 2 months when compared to the control group. At 6 months no significant differences were seen between groups in the Fugl-Meyer test, however the robot group had larger improvements in the FIM™instrument [214].

An additional study by Lum et al. assessed the use of MIME for upper limb neuro-rehabilitation in sub-acute stroke patients. The goal of this study was to confirm the previous results and to identify the therapeutic features of MIME robot therapy. 30 subjects participated in the study which consisted of fifteen 1 hour treatment sessions, over 4 weeks. Subjects were randomly assisted to one of 4 treatment groups (one control and three robot). Subjects in the three robot groups received 50 minutes of MIME assisted movement training, while subjects in the control treatment group received 50 minutes of conventional treatment. Motor impairment was assessed with the upper limb portion of the Fugl-Meyer (FM) and Motor Status Score (MSS). The results showed that greater gains were attained by robot groups in proximal FM and MSS synergy scale compared to the control group [213].

Burgar et al. conducted a clinical assessment of MIME for delivering robotic assistance for the upper limb in an acute rehabilitation setting. 54 hemiparetic subjects participated in the study. Subjects were randomly separated into four groups, a (control) group who received usual care, and three other groups which received additional training on top of usual care, including, low dosage robotic assisted (RA) training (15 hours), high dosage RA training (30 hours) or 15 hours of additional conventional therapy. The primary outcome measure was the Fugl-Meyer Assessment (FMA). A secondary outcome measure was the Functional Independence Measure (FIM). Results of the study show that significant correlations were found at discharge between FMA gains and the dose and intensity of RA training groups. The high dose group also had great FIM gains than controls at discharge and great tone but no difference in FIM changes compared with low-dose RA training at 6 months [37].

3.3.5.3 ARM Guide Robot

The Assisted Rehabilitation and Measurement (ARM) Guide robot uses a linear rail to move the user's hand in a straight line trajectory [175]. ARM measures and applies assistive or resistive forces to linear reaching movements across a wide workspace.

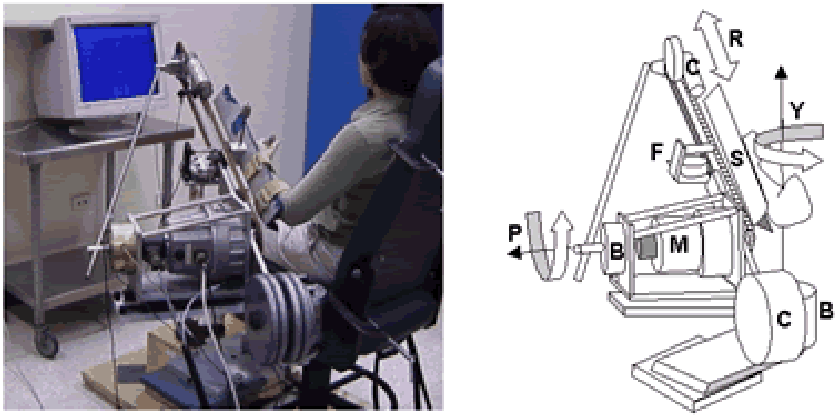

FIGURE 3.14: Photograph of the ARM Robot

Kahn et al. conducted a pilot study with 10 chronic stroke patients to assess the use of the ARM Guide robot. Subjects were randomly assigned to either a robot group or control group. Subjects in the robot group performed self-initiated reaching movements under their own power with active assistance from the device. Control subjects practised reaching without ARM Guide assistance. Both training groups participated in 45 minute training sessions, 3 times a week, for 8 weeks. Each training session involved performing 50 reaching movements while feedback was given visual performance feedback during training, however only the robot group received mechanical assistance. Results of this study showed that significant improvements were made by both groups in functional ability movement, velocity and range of motion of supported reaching and straightness of unsupported reaching. However, there was no significant difference noted between groups [174].

3.3.5.4 Bi-Manu-Track

The Bi-Manu-Track [142] is a computerized motor-driven arm trainer that allows bilateral training of two distinct movement patterns; forearm pro- and supination and wrist flexion and extension. The Bi-Manu-Track supports three computer-controlled modes of practice. In the passive-passive mode the robot controls both arms. In the active-passive mode the less impaired upper limb actively moves the control handle while the robot guides the most impaired upper limb. In the active-active mode both arms perform actively by overcoming an initial isometric resistance. Movements can be either mirror-symmetric (in-phase) or parallel (anti-phase). Amplitude, speed, and resistances can be set individually.

FIGURE 3.15: Photograph of the Bi-Manu-Track robot

Hesse et al. performed a pilot trial of the Bi-Manu-Track arm trainer for the passive and active practice of bilateral forearm and wrist movements with hemiparetic subjects. 12 chronic stroke patients participated in the study. Participants received in addition to an ongoing comprehensive rehabilitation program, daily upper limb training of 15 minutes in all three modes of the Bi-Manu-Track, for 3 weeks. Outcome was measured after the 3-week interval and at 3 months follow up, using the Modified Ashworth Scale (MAS) to measure spasticity and the Rivermead Motor Assessment (RMA) to assess motor control ability. After treatment MAS scores revealed significant muscle tone reduction in wrist and fingers. However, scores returned to pretreatment values at 3-month follow up. The RMA score did not change significantly at either 3-weeks or 3 months [142].

Hesse et al. also conducted a randomized controlled trial (RCT) to compare a computerised arm trainer (AT), the Bi-Manu-Track for repetitive practise of passive and active bilateral forearm and wrist movement training, and electromyography-initiated electrical stimulation (ES) of the wrist extensor in severely sub-acute stroke patients. A total 44 subacute patients with severe arm paresis after stroke were randomly assigned to either the AT or ES group. AT patients performed 800 repetitions per session with the Bi-Manu-Track. ES patients performed 60 to 80 wrist extensions per sessions. The primary outcome measurement was a FMA, the secondary measures were upper limb muscle power and tone, measured using the Medical Research Council (MRC) scale, and the Ashworth scale, respectively. At the end of the training program, upper limb muscle power and FMA scores increased significantly more in the Bi-Manu-Track group than in the electrical stimulation group post-treatment and at 3-month follow-up. The AT group also had a significantly greater MRC score than the ES group, both post-treatment and at 3-month follow-up [143].

Liao et al. performed a randomized controlled trial (RCT) to study the effects of robot-assisted upper limb rehabilitation on daily function and real-world arm activity in patients with chronic stroke. 20 post stroke patients participated in the study. Participants were randomised into two groups, Robot-assisted therapy (AT) or dose-matched active control therapy (ACT). All patients received therapy for 90–105 minutes each day, 5 days per week, for four weeks. Outcome measures included arm activity ratio and scores on the Fugl-Meyer Assessment Scale, Functional Independence Measure, Motor Activity Log and ABILHAND questionnaire. The robot-assisted therapy group significantly increased motor function, hemiplegic arm activity and bilateral arm coordination compared with the dose matched active control group [204].

3.3.5.5 RUPERT

A robotic upper extremity repetitive therapy device dubbed "RUPERT" is currently being developed by the Arizona State University in partnership with Kinetic Muscles, Inc. (Arizona, USD). RUPERT is developed to provide a low cost, safe and easy-to-use, robotic-device to assist the patient and therapist to achieve more systematic therapy at home or in the clinic [353]. RUPERT I and II are powered by four pneumatic muscles to assist movement at the shoulder, elbow and wrist. The design was based on a kinematics model of the arm, which showed where to locate the pneumatic muscles and how much force was needed for normal reaching and feeding movements. The mechanical arm is adjustable to accommodate different arm lengths and body sizes.

Figure 3.16: Photograph of the RUPERT robot

Zhang et al. performed two feasibility studies of robot-assisted stroke rehabilitation with RUPERT. The first study involved 6 patients who received therapeutic training three times weekly, for 4 weeks, at a clinic setting [135]. The second study involved 2 patients who received therapeutic training daily, for 4-5 weeks, in the home setting [411]. In both studies, patients' performances were assessed using both the Wolf Motor Function Test and Fugl Meyer Assessment (FMA), both before and after the training. Half of the clinic-visiting patients demonstrated a significant increase in the proportion of successfully reaching targets, and no significant function deterioration to other targets. Similar results were noted in the home-application group, with both patients demonstrating functional improvement after the training, including significant increase in the proportion of successfully target hitting and movement smoothness.

3.3.6 Discussion

The field of robotics is slowly moving from the realm of science fiction to the leading edge of healthcare advancement. Rehabilitation robots represent the potential to mitigate healthcare burdens by taking over aspects of rehabilitation which can more readily be automated. Robots also represent a means of administering intensive, controlled, task oriented and interactive therapies without the need for continual supervision by a professional. Over the past couple of decades great advancement has been made towards achieving these goals and as a consequence there has been an assortment of robotic devices developed by research initiatives around the world. However, to date much of this effort has been focused on developing more advanced hardware, in a bid to increase the degrees of freedom, dexterity and functionality of the robot end effector, in order to support movement training of more complicated movements. In contrast, little progress has been made towards the progression of high-level control strategies, which specify how these devices interact with participants in an attempt to provoke motor plasticity, and therefore improve motor recovery. The present evidence supports the use of robot-assisted therapy for improving motor function in stroke patients as an additional therapeutic intervention in combination with the conventional rehabilitation therapies [52]. Nevertheless, robotic devices are currently struggling to produce results which improve upon conventional means and there is ample opportunities for improvement in the near future. Currently, robot control strategies have been designed on an ad hoc basis, usually drawing on some concepts from the rehabilitation, neuroscience and motor learning literature. There is thus a need for innovative thinking which can help foster more sophisticated control systems suitable for delivering optimal assistance during rehabilitation training.

Furthermore, owing to the complexity of such devices, current available commercial robotics systems are prohibitively expensive for researchers and physicians who would otherwise study and use such devices. Efforts need to be made towards developing low cost robotic devices which are affordable enough to enable research, which in turn can help to generate the necessary studies as to the efficacy of such devices for rehabilitative purposes, and which will encourage interest from small and medium companies who would ultimately commercially develop such devices.

3.4 Extrinsic Feedback

Feedback is an essential component in the successful acquisition and development of skills. Feedback provides information about the performance that allows the learner to adjust and improve or continue efficient performance. Feedback can be classified as either *intrinsic*, resulting from a direct result of producing a movement through the kinaesthetic senses (i.e. vision, proprioception, touch, pressure and audition) or *extrinsic*, received from external sources (outside the body) for example, from a coach, watching taped performances, through performance scores, or through measurements derived from sensors.

Extrinsic feedback typically offers information which is not naturally available to an individual or which substitutes or supplements damaged inherent feedback mechanisms. Extrinsic feedback is categorised as either “knowledge of performance” (KP) or “knowledge of results” (KR). KR refers to information, obtained from an outside source, regarding the outcome of performing a skill or about achieving a goal [225]. For example, when a dart player sees their dart hit the target. In contrast, KP refers to information about the movement characteristics that led to a performance outcome. For example, when a trainer gives the dart player feedback about the form of their throw. Although it is clearly possible to learn motor tasks without the provision of extrinsic feedback, studies have shown that learners given KP or KR feedback show improved retention compared to those who receive no feedback at all [77, 149, 243, 324, 379, 395]. In addition, studies have shown that feedback is also important for sustaining the learners motivation during training [377]. As a result, there has been extensive research conducted on the effectiveness of extrinsic feedback for improving motor learning, both in healthy individuals and in patients with neurological injury. A meta-analysis review examining the effects of extrinsic feedback was conducted by Deci et al. [83]. A comprehensive review synthesising the research findings and evidence as to the effectiveness of extrinsic feedback was presented by Vliet [379]. The definitive book on extrinsic feedback was written by Schmidt [324].

This section attempts to highlight the role of extrinsic feedback on implicit motor learning and to explore its capacity for enhancing participant motivation and self-efficacy after stroke. Towards this goal, a brief overview of feedback is given here, highlighting different feedback modalities and their applications. For a more intensive overview, the reader is referred to the aforementioned works.

3.4.1 Instruction Type

Extrinsic feedback can be delivered by many different means, the most common forms are; visual feedback, verbal feedback, haptic (i.e. tactile or kinesthetic) feedback, virtual feedback or bio-feedback. The latter feedback modality, bio-feedback, is not discussed here but instead is discussed in a later section devoted to physiological feedback, see Section 3.5 for a detailed discussion.

3.4.1.1 Verbal Feedback

Verbal feedback is the most common form of extrinsic feedback used routinely during training, and is traditional used by trainers and therapists to elicit performance boosts from learners. A study of the effectiveness of different types of verbal feedback on learning complex movement tasks was conducted by Vallerand et al. [377]. The outcome of this study suggests that verbal feedback produced increased feelings of competence and intrinsic motivation in subjects. Verbal feedback has been applied to numerous training scenarios with positive results. Zaton et al. showed that immediate verbal feedback had a positive effect on performance on modifications of stroke length during swimming training [410]. Argus et al. found that verbal feedback on upper-body performance in elite athletes lead to improvements in upper-body power output of well-trained athletes [19]. Cirstea et al. found that verbal feedback was effective in improving motor skill reacquisition outcomes in patients with stroke [59]. Kannappan et al. investigated the effects of verbal feedback on surgical skills performance and motivation, finding moderate improvements in accuracy and significant improvement in time, when feedback was presented during a peg transfer task [177].

3.4.1.2 Visual Feedback

Visual feedback is another commonly used means of providing feedback on performance. For less experienced learners, visual feedback is often given by demonstration by a trainer or more experienced practiser. For more experienced learner, self-education is often used, for example by watching recordings of experts performing a task. Visual feedback has been shown to be useful in learning during a diversity of complicated tasks. Wierinck et al. found visual feedback improved performance during manual dexterity training [394]. Zheng et al. found that video watching improved learning of a tennis swing [415]. Hoppe et al. reviewed the effects of visual feedback on the acoustic quality and physiological aspect of singing performance [148]. Hopper et al. found that visual feedback has a significant positive influence on power during leg press exercises, in elite women field hockey players [149].

3.4.1.3 Haptic Feedback

Haptic feedback typically refers to two distinct types of feedback, either tactile or kinesthetic. Tactile perception is usually conveyed through the skin, such as by vibrations or pressure. Whereas, kinesthetic feedback refers to knowledge about the position and movement of the body and its parts [30]. Haptic feedback is often used either to replicate real-world interaction forces, or to provide cues that are not available in the physical world. Haptic feedback or haptic guidance has been shown to be extremely useful for presenting motor patterns to an individual that a user is expected to internalize and later recall [253]. Feygin et al found that haptic feedback contributes to learning spatiotemporal trajectories [105]. Williams et al employed haptic feedback in a medical simulator and also found that it contributed to learning position trajectories [398]. Patton and Mussa-Ivaldi found haptic feedback useful for teaching movement patterns during robot-assisted movement training [286]. Huang et al found visuohaptic feedback to be superior to the other feedback modalities in exciting a virtual oscillator [153]. O'Malley et al found that using haptic constraints provides significant benefit for both performing and learning movement patterns during training [277]. Afzal et al. demonstrated the use of kinesthetic haptic feedback for improving standing stability of healthy subjects and stroke patients [5].

3.4.1.4 Virtual Feedback

Virtual reality (VR) is a technology which allows an individual to interact with a digital environment. VR has emerged as a new treatment approach in stroke rehabilitation. Virtual reality may be an advantageous approach to deliver novel feedback, because it provides the opportunity to practise activities that are not, or cannot be practised within the clinical environment [198]. Moreover, VR programs are often designed to be more interesting and enjoyable than traditional therapy tasks, thereby encouraging higher numbers of repetition of otherwise tedious and monotonous movement tasks. Henderson et al. conducted a systematic review of VR systems for rehabilitation of the upper extremity that included 6 studies evaluating VR technology [140]. The consensus of the report was that VR feedback might be more effective compared to no therapy. Another systematic review was conducted by Saposnik et al., including 12 studies, 5 of which were randomised clinical trials (RCTs) [317]. In the 5 RCTs, VR was shown to significantly improve FMA scores (speed of arm movements, range of motion and force) compared to moderate improvements in a control group. In the other 7 studies (non RCTs), there was moderate improvements in motor function measurements. A more recent review [198] included 19 VR RCTs, of which 8 examined upper extremity intervention. Of these, 7 studies showed a statistically significant effect on arm function. However, in summary, the report found that there was limited evidence that the use of VR may be benifical in improving arm function and activities of daily living when compared to conventional therapy. Furthermore, the report suggests that although VR appears to be a promising intervention, at present studies are too few and too small to draw conclusions. Another interesting finding was that recruitment rates were low (approximately 34% of participants screened we recruited). Such findings perhaps reflect either a lack of interest in video game based VR therapy by patients or their unsuitability to the trails.

3.4.2 Comparison of Feedback Modalities

The choice of feedback delivery mechanism often comes down to practicality and ease of implementation, for example verbal feedback is often given during sport training by a trainer positioned on the side lines. In such a situation, other feedback modalities are impractical, either burdening the learner or risk distracting them during training. Similarly, visual feedback is often the preferred feedback modality for tasks involving aiming accuracy, for example showing a driver the result of their parking is a more effective means of feedback than telling them. However, in some situations there is no obvious feedback mechanism which is most suitable. Subsequently, some studies have been conducted on comparing the effectiveness of different feedback techniques.

Jung and Hallbeck studied the influence of instruction type, verbal encouragement, and visual feedback on static and peak handgrip strength. 31 male students participated in the study that employed an isokinetic wrist dynamometer to measure handgrip strength. The results revealed that both verbal and visual feedback had significant positive effects on static grip strength, peak grip strength and time to reach the maximal strength [172].

Kirazci investigated the effects of verbal and visual feedback on anticipation timing task during a series of acquisition and retention trials. 48 participants were recruited and randomly assigned to one of four groups, visual-visual, visual-verbal, verbal-visual, and verbal-verbal conditions. Results indicated that there was no statistically significant difference among the groups in their performance of the task [181].

Akamatsu conducted a comparison of tactile, auditory, and visual feedback in a pointing task using a modified computer mouse. No differences were found in overall response times, error rates, or bandwidths; however, significant differences were found in the final positioning times. For the latter, tactile feedback was the quickest, visual and auditory feedback was the slowest [6].

Pollard and Ashton compared different feedback modalities for teaching individuals to control their heart rate. 60 subjects were divided into six separate groups; (1) visual feedback, (2) auditory biofeedback (tone generated from ECG signal), (3) combined visual and auditory biofeedback, (4) no feedback but instructed to attempt to reduce their heart rate, (5) sitting quietly (i.e. no attempted heart rate control) and (6) abbreviated relaxation training. The results indicated that all groups showed evidence of heart rate reduction over the course of the experiment, however no differential advantage was observed for any of the feedback groups [210].

3.4.3 Feedback Scheduling

The scheduling of feedback during practice involves the timing and frequency with which extrinsic feedback is provided. Feedback timing has been shown to have a profound affect on the acquisition and retention of skills and thus should be adjusted during the learning process in order to optimise the outcome of training [220]. However, care must be taken when developing feedback systems as some studies have shown that feedback can have undesirable affects and can even diminish the learning process. Beukers et al. showed how when given erroneous verbal feedback during an anticipation timing task, it had the effect of overriding subjects own intrinsic feedback mechanisms, such that subjects adjusted their response to the incorrect verbal feedback [36]. Furthermore, studies by Schmidt have shown that feedback can have negative effects if provided too frequently, such that the learner become dependent on it [324, 325]. The guidance hypothesis, proposed by Schmidt, sums up these effects stating that extrinsic feedback can have negative effects on motor skill learning if it is provided too frequently or in a form that is too easy to use [325].

As a result, the literature suggests that for effective learning, extrinsic feedback should be provided sparingly and in a manner that does not enforce learned dependency [355]. Subsequently, many different modes of delivering scheduled extrinsic feedback have been developed, which are discussed next.

3.4.3.1 Concurrent Feedback

Concurrent feedback refers to feedback given instantaneously and continuously during execution of an action. A classic example of concurrent feedback is a speedometer in a car, which relays the current speed of the car to the driver in real-time. While concurrent feedback can be a useful means for controlling aspects of a task and has been shown to have significant affects on task performance when present during training, studies have shown that once withdrawn, such benefits quickly subside. As a result, the general consensus is that concurrent feedback is in fact detrimental for learning [329]. Schmidt et al. suggests that concurrent feedback can degrade motor skill learning, fosters learned dependency and the development of movement instability [329]. There are three competing views which attempt to explain the observed negative effects of guidance on motor learning. The prevailing view is that the learner becomes dependent on KR when it is presented too frequently. A second explanation is that frequent KR encourages the learner to make too many corrections during practise which leads to instability. A third explanation is that frequent and useful KR can encourage learners to ignore important sources of sensor feedback (e.g kinaesthetic) intrinsic to the task [12].

However, there is still much debate on the proposed effects of concurrent feedback, with some studies suggesting that the detrimental effects are evident in simple motor task learning. However, for complex motor tasks in early learning stages, concurrent feedback can be supportive.

3.4.3.2 Terminal Feedback

Terminal feedback, also known simply as delayed feedback, is information provided to an individual after the performance is complete, often a couple of seconds later. A systematic review on the effectiveness of terminal feedback delivery was conducted by Stanhope [345]. Terminal feedback has been found to be more effective than concurrent feedback, performing better in retention tests and transfer tests. It is believed that delaying feedback in such a manner helps an individual to internalise the required task dynamics, promotes error estimation and as a result, leads to more effective learning [356],[315].

Walsh et al. investigated the optimal timing of feedback for technical skills learning in novices. 30 novice endoscopists were tested on a colonoscopy simulator task, in 12 practise trials. Participants received feedback either during (concurrent) or after (terminal) each of the trials. Effectiveness of training was assessed (i.e. measures of execution time and blinded expert assessments) using an immediate post-test and one week later on retention and transfer tests. While both groups performed equally well on the pre-, post-, and retention tests. At transfer, the terminal feedback group performed significantly better [386].

Sigrist et al. found that terminal feedback outperformed concurrent visual, auditory, and haptic feedback in learning a complex rowing-type task. Sigrist concludes that terminal visual feedback was most effective because it emphasized the internalization of task-relevant aspects. In contrast, concurrent feedback fostered the correction of task-irrelevant errors, which hindered learning [338].

3.4.3.3 Bandwidth Feedback

Bandwidth feedback is an alternative form of scheduled feedback, which obfuscates direct performance to provide feedback only if the learners errors are outside of some predefined band of correctness, i.e. if the measured error is within some error band, no feedback information is provided, indicating to the learner that there performance is acceptable. Bandwidth feedback tends to produce more stable learning behaviour and better retention performance when feedback is withdrawn, in comparison to every-trial feedback [334]. Bandwidth feedback was first proposed by Thorndike as early as 1927, who experimented with delivering verbal right-wrong feedback after estimating the lengths of paper strips or drawing lines of particular lengths [366]. Since then, bandwidth feedback has been used in many studies involving learning tasks. The following selected studies investigate the application of bandwidth feedback for enhancing learning and provide support for the generalization of bandwidth feedback principles to complex tasks.

Goodwin and Meeuwsen investigated the predictions of the guidance and specificity hypotheses by manipulating different distributions of relative frequency of knowledge of results (KR) using bandwidth (BW) conditions. 120 subjects participated in an experiment and were randomly assigned to one of four groups, either a BW0%, BW10%, Shrinking-BW, or Expanding-BW condition. After 100 trials were completed, a double transfer design was employed in which the subjects were divided in half and randomly assigned to a no-KR or KR retention condition. Results of the retention test under the no-KR retention condition suggested that receiving high relative frequencies of KR at the end of the acquisition phase was as detrimental to motor skill learning as receiving high relative frequencies of KR throughout acquisition [123].

Sadowski et al. studied the benefits of bandwidth feedback in learning a complex gymnastic skill. 30 male acrobats participated in the study. The subjects were randomly assigned to one of two groups: B - bandwidth feedback or C - 100% feedback. Group B was provided with bandwidth feedback only, i.e. error information regarding the key elements of movement techniques. Participants performed 4 practise sessions per week, for 16 weeks, consisting of basic gymnastic routines, including a handstand, cartwheel, and somersault. Both groups performed ten trials during each training session for a total of 640 trials. Analysis of the results suggest that while group B made more errors in pre-test (one day before the experiment), results from the retention test (one day after the experiment) suggest that scores improved significantly in group B and insignificantly in group C [313].

Lee et al. studied the effects of bandwidth knowledge of results on motor skill learning, during observation of a model's performance. 28 participants were randomised into two groups, a bandwidth group and a yoked group. The bandwidth group received KR about the model's performance only when their performance fell outside the criteria for a correct response. The yoked group received KR on the same trials as the bandwidth group did but were not told that the KR was only about incorrect performances. Following the observation phase, both groups of participants performed 10-min and 24-hr retention tests. The study concludes that Bandwidth KR enabled that group to reduce its performance variability and, to a lesser extent, to enhance its performance accuracy [203].

Smith et al. studied the application of bandwidth feedback scheduling to a golf shot. Participants practised a golf chipping task with either KR or error correcting transitional information, under 0%, 5%, or 10% bandwidth conditions. Participants in the 10% bandwidth condition who had received transitional information performed more consistently in retention than all other participants [342].

3.4.3.4 Faded Feedback

Another form of feedback often used is termed faded feedback or "fading scheduling". Faded feedback is feedback in which more KR or KP is given early in practise and gradually reduced over time, as the learner becomes more competent at performing the task. Studies suggest that faded feedback generates similar effects to those observed in both terminal and bandwidth feedback, that being the improvement in performance retention. A comprehensive assessment of the literature on fading feedback was conducted by Goodman et al. [122], which outlines the key studies investigating the merit of faded feedback for motor learning. Feedback fading was extensively studied by both Winstein and Schmidt [400] and Wulf and Schmidt [406]. Both studies advocate the use of feedback fading for improving retention and skill acquisition during learning and are often cited as the two fundamental studies on the merits of fading feedback. However, more recent studies, some conducted by the aforementioned authors, have found either mixed results or no support for the benefits of faded feedback over fixed frequency feedback.

Dunham and Mueller studied the effects of fading KR on the acquisition, retention and transfer of a simple motor task. 45 subjects were recruited for this study and were randomly assisted to one of three feedback groups, continuous, intermittent or faded KR. The results of this study suggest that no significant difference was observed in acquisition, retention and transfer between groups [93].

Jarus investigated the effect of reduced relative frequency of KR of faded feedback on a kinesthetic awareness task. 90 healthy young and older subjects participated in this study, consisting of three task versions of kinesthetic acuity. Practice conditions of 100% KR were compared with 33% equally spread and 33% faded practice conditions. The results of this study suggest that reduced relative KR frequency depressed the performance of the older subjects but raised the performance of the younger subjects in the acquisition phase. In retention, reduced relative KR frequency produced more effective performance than 100% KR, with no difference between the two age groups or the two 33% KR frequency conditions [168].

3.4.3.5 Trial Delayed Feedback

Trial delayed feedback is essentially elongated terminal feedback, where feedback on performance is delayed by more than a single trial. For example, feedback on performance would not be provided to the performer until after a set of intervening trials have been completed. Initial investigation into trial delayed feedback speculated that it might be distributive to the learning process as the learner might have difficulty linking the feedback with their past performance. However, more recent studies have shown that feedback about a group of trials, after which all trials in that set were completed, resulted in greater retention performance [330].

3.4.4 Evidence for Feedback After Stroke

An important question for stroke is whether the benefits cited in literature for healthy subjects transfer to patient's recovering from brain injury.

A randomized controlled clinical trial was conducted by Cirstea et. al, consisting of 37 patients with chronic hemiparesis. The study assessed physical (motor impairment, function) and kinematic (movement time, precision, segmentation, variability) variables before and after practice. The study reported that use of KP during repetitive movement practice resulted in better motor outcomes than KR [59]. A follow up study, containing 28 chronic stroke patients suggested that when the learners' attention was directed to the movements themselves (KP), motor improvements reflect recovery compared to when attention was directed toward movement outcomes (KR) [60].

Regardless of the approach KP or KR, feedback appears to have a positive effect on motor recovery, and has been shown to be more effective than no feedback at all. Systematic reviews of extrinsic feedback [352],[379], [409] found strong evidence supporting the provision of explicit feedback for implicit motor learning in both the upper and lower extremity post stroke.

3.4.5 Discussion

Extrinsic feedback is clearly a powerful means for augmenting learning of both simple and complex tasks, as is evident from the literature reviewed. Tremendous work has been conducted on the application of such feedback for enhancing training in healthy individuals, and in particular for improving peak performance in professional athletics. In addition, ample studies have also proven such feedback can also be of great utility for augmenting the benefits of motor relearning after neurological injury, such as is common after stroke. With recent advancements in information and communications technology, as well as the pervasiveness of computer systems, there is great opportunity to develop therapeutic training systems which incorporate mechanisms for delivering extrinsic feedback on performance during exercise training. Such systems may help increase the amount of rehabilitation a stroke survivor carries out, as well as providing a platform, suitable for use in the home setting, which can facilitate long term self-managed rehabilitation in the comfort of a patient's own home.

3.5 Physiological Sensed Feedback

This section deals with the subject of physiological feedback for rehabilitation. What is meant here by physiological feedback is simply feedback which is acquired by the use of electronic sensing technology, such as EEG and EMG, for the measurement of secluded physiological signals, e.g. electrical activity of the brain and body. This section deals with two particular types of physiological feedback, bio-feedback and neuro-feedback. In essence, neurofeedback is fundamentally a form of biofeedback, often referred to as EEG-biofeedback, however, here a distinction is made between the physiological source of the feedback in question. This distinction is made primarily to better segregate the growing field of neurofeedback from other non-brain based biofeedback methodologies. Henceforth, the term biofeedback refers here to signals measured from the PNS, for example, EMG and ECG. In contrast, neurofeedback refers here to signals measured from the CNS, more specifically the brain itself, for example, EEG or hemoencephalography (HEG). It is also important to differentiate physiological sensed feedback from that described previously in section Section 3.4, termed extrinsic feedback. Physiological sensed feedback refers to feedback which reveals or gives direct access to otherwise hidden information about the autonomic functioning of the body. In contrast, extrinsic feedback refers to information gained that is not naturally derived from intrinsic mechanisms of the body but rather from an external source. Extrinsic feedback often substitutes for the lack of, or loss of intrinsic feedback, whereas physiological sensed feedback alludes to the presence of an otherwise obscured form of intrinsic information.

3.5.1 Biofeedback

Biofeedback is a technique which helps individuals to learn to control physiological functions, such as blood pressure, heart rate, muscle tension and balance, by giving the individual access to information pertaining to these systems. This process is typically mediated by sensors, often from surface mounted electrodes attached to the skin. For example, an ECG can relay feedback about the electrical and muscular activity of the heart, which in conjunction with manipulation of breathing can be used to decisively control heart rate.

Biofeedback has been extensively applied to treat a wide variety of illnesses and disorders, including but not limited to; speech disorders and to improve speech performance (i.e. phonatory disorders) [232], urinary incontinence [119], gastrointestinal disorders [233], Bruxism (a condition in which you grind, gnash or clench your teeth) [158], Dysgraphia (deficiency in the ability to write) [160], primary Raynaud's phenomenon (excessively reduced blood flow in response to cold or emotional stress) [178], peak performance training in sport [297] and for stroke rehabilitation [262]. From the latter perspective, that of stroke rehabilitation, biofeedback has been applied to numerous aspects of the rehabilitation process. Many extensive literature reviews of the use of biofeedback in stroke rehabilitation have been conducted, for a comprehensive in-depth discussion the reader is referred to [118, 262, 404]. The following section gives a brief overview of the relevant literature, giving context to the utility of biofeedback for stroke.

3.5.1.1 EMG Biofeedback

EMG biofeedback for neuromuscular re-education was one of the initial biofeedback technologies applied to stroke rehabilitation for individuals with hemiparesis. EMG uses surface electrodes to detect a change in skeletal muscle activity, which is then fed back to the user usually by a visual or auditory signal. Following a stroke, normal regulation of muscle tone is disrupted, as is the ability to in-act direct specific control over target muscles, as a result of neuronal damage to the motor circuits. However, typically some of the motor circuits survive and are partially left intact. The theory behind EMG biofeedback is that through feedback, individuals may be able to learn how to use these preserved pathways, which over time might help to strengthen and rebuild the damaged pathways and hence the recovery of motor function. EMG feedback is particularly suitable in the earlier stages of stroke recovery or when paresis is more severe, when the individual's ability to generate movement is small and less easily observable kinesthetically. There has been a series of independent meta-analyses conducted to investigate the effectiveness of EMG biofeedback for stroke.

An analysis by Schleenbaker et al. including 8 studies, with a total of 192 patients, found that EMG biofeedback improves functional outcomes in patients with hemiplegic stroke [323].

A meta-analysis was conducted by Moreland and Thomson, containing 6 studies and examined the efficacy of electromyographic biofeedback compared with conventional physical therapy for upper-extremity [251]. This study found small effect size increases with biofeedback therapy compared to conventional physical therapy [251].

A later meta-analysis by Moreland, including 8 studies on the effects of EMG biofeedback for improving lower extremity function after stroke indicates that EMG biofeedback is superior to conventional therapy for improving ankle dorsiflexion muscle strength [252].

A more recent Cochrane review by Woodford and Price was conducted on the use of EMG biofeedback for the recovery of motor function after stroke. 13 trials, involving 269 individuals with stroke were included. All trials compared EMG biofeedback plus standard physiotherapy to standard physiotherapy either alone or with sham EMG biofeedback. The review suggests that there was a small amount of evidence to suggest that EMG biofeedback had a beneficial effect when used with standard physiotherapy techniques [404].

3.5.1.2 Force Platform Biofeedback

The body maintains a sense of balance through a complex set of sensory-motor control systems, primarily using input from the vestibular system (motion, equilibrium, spatial orientation) but also sensory input from vision (sight) and proprioception (touch). Damaged caused by stroke to any of the subsequent control areas of the brain can result in a reduced sense of stability and balance. Difficulty with balance is therefore very common after stroke and as a result approximately 40% of stroke survivors have serious falls within a year of their stroke [391]. Much effort has thus been allocated to improving balance during stroke rehabilitation. One method for improving balance is to provide additional information to an individual during training that can help reinforce information coming from the bodies correctly functioning intrinsic balance apparatus. Force platform biofeedback is one such method for providing an individual with information about the location of their center of gravity with reference to the location of their feet.

A Cochrane review, containing seven trials and 246 participants, which assessed the use of force platform biofeedback, found that biofeedback significantly improved stance symmetry [24].

3.5.1.3 Mirror Biofeedback

Although technically a form of visual feedback, mirror feedback is more aptly categorised as a form of bio-feedback. Mirror box therapy was first described by [299] for the relief of phantom limb pain, a phenomenon common in individuals who have had a limb abruptly amputated. It occurs because the nerve endings at the amputation site still send messages to the brain which preserves a sense of that limb within the CNS. The principal behind mirror feedback is that vivid kinaesthetic sensations of movement can be evoked by observing movement of the healthy hand or arm in a mirror. It is suggested that observing such movement causes additional neural activity in motor areas located in the affected hemisphere, which should eventually result in cortical reorganization and improved function [319]. In practise, during mirror box therapy the amputated limb is obscured by a mirror box, which projects a virtual inverted copy of their healthy limb back to the patient. The patient then attempts to move both limbs while watching the reflection in the mirror. The mirror essentially leads the brain to perceive the missing limb is intact and responding correctly to their motor command and subsequently relays this sensorimotor information to the contralateral portion of the brain and closes the motor feedback loop. This motor-sensory information stimulates the otherwise dormant cortex region and in turn elevates the phantom pain.

Since its initial discovery, application of the mirror box therapy technique has also been successfully reported in patients with other pain syndromes and in sensory re-education of severe hyperaesthesia after hand injury [307]. For motor recovery after stroke, mirror therapy might provide patients with sensorimotor feedback which substitutes for the lack of, or decreased proprioceptive input from a paretic limb.

Altschuler et al. performed an initial proof of concept study of mirror therapy for recovery of hempiparesis in chronic stroke patients. The patient were randomly assigned to one of two groups, a mirror group or transparent plastic group (control). Patients practised using either a mirror or transparent plastic sheet, for 15 min, twice a day, 6 days a week, moving both hands or arms symmetrically (moving the affected arm as best they could) while watching the good arm in the mirror. During practise patient performance was assessed by two graders. After competition of the trials, both graders found that substantially more patients improved from the mirror group compared to the control group [8].

Sathian et al. describe the successful application of mirror therapy to the post-stroke rehabilitation of a patient with poor functional use of an upper extremity. Although small and not sufficiently controlled, the results of this study are promising, reporting improved range of motion (ROM), speed and accuracy of arm movement after mirror therapy [320].

Michielsen et al. showed that in patients with chronic stroke, unsupervised home-based practise with a mirror resulted in statistically significant improvements in upper extremity motor function and that mirror therapy caused a shift in activation balance M1 toward the lesioned hemisphere, suggesting neural reorganisation [246].

More recent studies, [408] and [88] conducted high-quality, randomized control trials which both reported mirror therapy-improved motor function in patient with acute and sub-acute stroke.

3.5.2 Neurofeedback

Neurofeedback, also referred to as neuro-biofeedback or neurotherapy, is a biofeedback technique that uses real-time displays of brain activity to teach self-regulation of brain function. Neurofeedback has its origins as far back as the 1960's and was popularised by the work of two independent researchers, Dr. Kamiya and Dr. Sterman.

Kamiya is often cited as the first to describe the use of neuro-feedback for conditioning of brain activity. In an enduring series of innovative experiments Kamiya investigated the use of feedback to condition subjects to elicit alpha brain waves. Initially, conditioning was achieved by verbally prompting subjects when they achieved the desired alpha state. Later, improvements were made to the experiment and with the addition of electronic circuity a tone was generated automatically whenever alpha waves were achieved. Kamiya showed that through feedback and with training, subjects were able to learn to alter their brain activity to elicit increased levels of alpha [176, 267]. Around the same time, Sterman et al. conducted a series of studies investigating learned suppression of a previously rewarded response for food in cats through the use of EEG monitoring [309, 347, 349]. The experiment consisted of first training cats to press a lever when they wanted food. Once the cats were conditioned to this task a tone was introduced and the cats learned that they would only receive food if they press the lever after the tone subsided. Sterman observed that while the cat was waiting for the tone to stop, it remained absolutely still, though extremely alert. Sterman discovered that this state was characterised by a specific rhythmic brain frequency of 12Hz to 15Hz over the sensorimotor cortex which he called the sensorimotor rhythm (SMR). After discovering the SMR, Sherman changed the experiment by removing the lever and instead rewarded the cat whenever it produced a half second of the SMR frequency. Over time the cats learned how to produce the frequency at will. Although at the time the use of neurofeedback training and the ability to elicit SMR was not well understood and had no practical applications.

Since these initial studies great interest has been shown in the potential application of neurofeedback for treating a variety of different physiological illnesses and neurological diseases including; seizures suppression [348], hyperactivity and attention issues [211], anxiety [250], posttraumatic stress disorder [132], addictions [291] and more recently as a means of enhancing learning after neurological injury after stroke.

A thorough literature review on the use of Neurofeedback and traumatic brain injury was conducted by May et al. [235]. The following is a brief review of the evidence for and application of neurofeedback after stroke.

3.5.2.1 Evidence for Neurofeedback After Stroke

Recently neurofeedback is gaining much attention as a potential treatment for traumatic brain injury, with some clinical studies highlighting the effectiveness of neurofeedback therapy in patient with stroke. During practise, some form of extrinsic feedback, typically visual or auditory feedback is used in conjunction with neurofeedback, to provide cues as to guide the patient toward a healthy brain response, as defined by a sample of healthy subjects. A series of studies investigating the effectiveness of neurofeedback for use in stroke rehabilitation have demonstrated potential, albeit most of these studies are small and not sufficiently controlled.

Rozelle and Budzynski demonstrated that neurofeedback therapy in combination with audio/visual feedback (over 6-month) with a 55-year-old male chronic stroke patient, lead to an inhibition of 4-7Hz activity and simultaneous increase of 15-21 Hz activity in the sensory-motor and speech areas. The outcome of which resulted in significant clinical improvement including; speech fluency, concentration and visual-motor coordination [311].

Cannon et al. found that neurofeedback training was efficacious in the treatment of a 43-year-old female stroke patient with a series of physical and mental deficits. EEG data was collected for both pretreatment and post-treatment evaluation. Prior to beginning neurofeedback a self-developed symptom checklist was provided to the participant and was repeated every 10 sessions. The participant then received 52 neurofeedback sessions. Following treatment, comparative EEG and eLoreta analyses [284], illustrated significant decreases in the absolute and relative theta power measures and significant elevations of absolute and relative beta power in the occipital areas. These suppressions corresponded to self-reported improvements in patient cognitive functioning (sleep quality, emotional regulation, and energy) and depressed mood.

Kubik et al. conducted a series of neurofeedback studies in patients with acute and chronic pain syndromes. They observed that while their studies indicate neurofeedback is an effective treatment methodology, that a high dosage of training (typically performance of 40+) are required before positive therapy results are observed. One such study including 9 stroke patients with long term paresthesias, reported that first positive results were observed only after 20 trainings. A further 40 to 60 trainings 3 times a week, were required before permanent pain relief was noted. In addition, a further 15 patients with troublesome headaches after craniocerebral trauma were also treated. 40-60 neurofeedback training sessions, 3 times a week, were conducted by this group, after which positive results were achieved.

However, more recently researchers are starting to realise the potential application of brain computer interface (BCI) controlled haptic devices for delivering neurofeedback. A BCI can help achieve enhanced self-initiated motor rehabilitation through a neurofeedback process in which measures of motor program engagement can be detected with appropriate feature extraction and machine learning, to produce a control signal which is then used to close the feedback loop through triggering of appropriate feedback. Such an approach may have tremendous utility in providing closed loop neurorehabilitation to stroke patients, especially those with severe motor deficits.

3.5.3 Brain Computer Interfaces for Neuro-rehabilitation

One of the most substantial recent innovations in stroke rehabilitation is the application of BCI for neuro-rehabilitation. A BCI uses brain-activity signals to directly interface with an external device. While this technology may have numerous potential applications, from the perspective of healthcare, the obvious application of such technology is its potential use in patients with severe motor impairment. Result of preliminary case studies suggests that BCI-mediated feedback therapy may be viable for stroke rehabilitation.

Shindo et al. conducted a preliminary case study investigating the effects of neurofeedback training with an EEG-based brain-computer interface for hand paralysis. 8 chronic stroke patients with moderate to severe hemiparesis participated in the study. Participants practised imagine movement with a BCI driven mechanical orthosis system, once or twice a week for a period of 4-7 months, after which clinical and neurophysiological examinations pre- and post-intervention were compared. New voluntary EMG activity was measured in the affected finger extensors in 4 cases who had little or no muscle activity before the training, and the other participants exhibited improvement in finger function [336].

Murguialday et al. evaluated the efficacy of daily brain–machine interface driven robotic arm orthoses training in chronic stroke patients with severe hand weakness. 32 chronic stroke patients were randomly assigned to 2 groups, one received BCI controlled movement of an arm orthoses and another, the control group received sham movements of the orthoses, which occurred randomly. Training lasted for approximately 18 days. Upper limb motor function scores, electromyography from arm and hand muscles, placebo–expectancy effects, and functional magnetic resonance imaging (fMRI) blood oxygenation level–dependent activity were assessed before and after intervention. Fugl–Meyer assessment (FMA) scores improved more in the experimental than in the control group, presenting a significant improvement of FMA scores reflecting a clinically meaningful change from no activity to some in paretic muscles [300].

Ang et al. investigated the effectiveness of BCI controlled Haptic Knob (HK) orthosis biofeedback. The study consisted of 21 chronic hemiplegic stroke patients which were randomly allocated to one of three groups, BCI-HK, HK-only, or Standard Arm Therapy (SAT) group. All groups received 18 sessions of intervention over 6 weeks, 3 sessions per week, 90 min per session. Significantly larger motor gains were observed in the BCI-HK group compared to the SAT group at intermediate points during training, motor gains in the HK-only group did not differ from the SAT group at any time point [13].

3.5.4 Discussion

Recent research demonstrates that neurofeedback and biofeedback are effective interventions for many neurological and physiological disorders. As a result there has been much academic interest in such techniques and their potential application to stroke rehabilitation. Such feedback is particularly useful for delivering feedback during training in patients with severe motor impairment, where normal intrinsic feedback pathways, or conventional extrinsic feedback are little or no use. For example, in the case of movement therapy in patients with severe weakness, EMG based biofeedback may provide information about movement attempts which are too faint to be detected kinetically. In such a case, biofeedback can help positively reinforce desired behaviour and help the patient to isolate and improve mental function. In the case of total arm paralysis, hemiplegia, where little or no movement can be detected, EEG based neurofeedback may provide feedback on attempted or imagined movement. Taking this idea one step further, neurofeedback systems can be used in a brain computer interface configuration to drive a haptic feedback device, to close the motor-sensory feedback loop.

However, neurofeedback research is currently sparse and neurofeedback has not gained popularity in clinical practice, primarily because of a lack of empirical evidence as to its effectiveness. This is partially due to the requirement of sophisticated equipment and the high costs associated (i.e. EMG or EEG acquisition systems, and a haptic feedback device). In addition, such systems are often unsuitable for home deployment given their size, costs, complexity and technical operation requirements. The major disadvantage of home-based rehabilitation programs is the current lack of specialized equipment and insufficient data as to their efficacy. Unfortunately this lack of data makes it difficult for companies which might provide BCI-driven haptic feedback systems to justify the investment required to make this technology widely available. This, in turn, makes collection of the required evidential data even less likely to happen. Hence, their is a need for more studies to add evidence as to the effectiveness and utility of home-based BCI rehabilitation systems.

3.6 Summary

This chapter describes current technological solutions for augmenting motor rehabilitation of the upper extremity post stroke, in particular, the use of wearable sensor solutions, robotic devices - their control systems, and brain computer interfaces. In addition, this chapter attempts to highlight the role of feedback on implicit motor learning and subsequently its capacity to improve the benefits of training and increase the outcome of recovery. Using the knowledge described in this chapter, and through the development of custom low-cost experimental platforms, the following chapters investigate applications of this work for improving the efficacy of rehabilitation, with emphasis on developing solutions suitable for the home setting.

Chapter 4

A Sensor Glove System for Rehabilitation in Instrumental Activities of Daily Living

4.1 Introduction

Upper extremity dysfunction is common after stroke, effecting approximately 60% of stroke survivors [384]. Chronic deficits in the hand are particularly prevalent in people with hemiparesis and are a major contributor to disability post stroke. In particular, the ability to extend and flex the digits of the hand is the motor function most likely to be impaired [107]. The loss of hand function is a significant impairment for an individual, severely limiting their ability to engage in activities of everyday living such as feeding and dressing one's self. Ideomotor apraxia (IMA), a neurological disorder characterized by the inability to correctly imitate hand gestures and voluntarily mime tool use, is often associated with stroke patients. Persons with IMA exhibit a loss of ability to carry out simple, common motor movements and patterns such as, waving goodbye or brushing one's hair, and may show errors in how they hold and use tools [219]. There is strong evidence that gesture training is associated with improvement in IMA, and may subsequently extend to improvements in activities of daily living [361]. However, as with all motor learning tasks, functional improvements are made according to the intensity of practise. Hand function can be recovered under certain circumstances when the patient engages in prolonged movement practice [51], however for many the inability to move significantly means that the patients find such activities difficult and unrewarding. As a consequence, impairment of hand function is often exacerbated by learned non-use which in turn leads to a loss of cortical representation of the limb. Therefore, it is imperative that efforts are made to encourage use of the hand and fingers, in an attempt to maintain intact cortical representations and to facilitate recovery through reorganisation and repair, by stimulating the damaged brain region with novel neuronal activity, derived from repetitive, active movement exercises.

Body language (kinesics) and in particular hand gestures play a significant role in the efficacy of human communication, providing reinforcing visual imagery of what we are trying to convey verbally. Naturally then the use of hand gestures could also provide an attractive alternative for interacting with computer systems [257]. With the evolution of pervasive computing systems and as more and more devices fill up our homes, there is an opportunity to develop wearable devices which can help inaugurate the concept of ambient intelligent environments, that being digital environments that are sensitive and responsive to the presence of people. Towards this objective, there is already an assortment of digital entertainment devices in the home which rely on common interfaces (i.e Infrared, Bluetooth, Wifi etc.) which could easily be controlled through gestures derived from such wearable sensors. From the perspective of stroke rehabilitation, there is also an opportunity to use such technology in an attempt to diffuse functional therapeutic rehabilitation into the activity of daily living. Such a design places the rehabilitation process at the heart of relevant activities of daily living which are both personalized to the specific user and which should elicit motivational engagement. In addition, approaches such as this might help enhance self-care and independent living, empowering the user through regained control of their environment.

Sensor gloves exemplify the aspiration of developing low cost, immersive human-computer input devices and subsequently many novel sensor gloves have been developed with a wide range of applications. Sensor gloves have been designed as interfaces for virtual reality [129] and gaming [205], as a tool for learning sign language [97] and even as an experimental tool for developing music through motion capture [314]. Researchers has also expressed a keen interest in sensor gloves from a healthcare perspective, with many realising their potential for non-invasive hand impairment assessment [245], remote monitoring of the usage of a paretic hand [340] and the ability to add context to otherwise tedious and repetitive physical exercise programs [163]. While there has been an assortment of sensor gloves designed for healthcare application, see Literature review for detailed synopsis, typically such systems are designed as novel peripheral input devices for a PC, and thus do not functioning autonomously but instead are tethered to a host, limiting the freedom of the user, the range of possible motions performable and restricting the potential application of the device. Further, a large portion of those sensor gloves described are simply not suitable for people with movement disability due to their cumbersome designs which utilise non-docile material, heavy bulky parts, expensive components and restrictive wired interfaces. In addition, there is a tendency by designers to integrate an excessive amount of sensors, paradoxically impinging on the practical usability of the device, (i.e. limiting a devices battery life, increasing it's weight and restricting the users dexterity). This also increases the cost and required set-up procedure, as most sensors require some form of calibration before use, making them less appealing for unsupervised home use.

As healthcare services inevitably move towards home-based rehabilitation, it is important to develop support systems which can more efficiently integrate professional knowledge, afforded by healthcare experts, into the training process and to maintain the presence of the therapist in the rehabilitation process. Another application ideal then for sensor gloves is the non-invasive recording of movement activity and operational context over time, such that numbers of repetitions and performance scores can be reviewed remotely by an occupational or physical therapist at a later stage.

Towards these objectives, the following Chapter describes the development of a novel sensor glove system, designed using open source technology, as an innovative, wireless, autonomous wearable solution for use in the home setting. The content of this chapter is divided into four parts. In the first section details are given regarding the core design of the aforementioned sensor glove system, describing in detail the hardware used and its configuration. After which an additional three sections illustrate unique applications of this system. First, we describe the use of the sensor glove system for gesture based control of personal electronic appliances (TV, radio, etc.), demonstrating the sensor gloves potential for integrating repetitive, therapeutic practise of functional hand skills into the activities of daily living. Second, a complementary visualisation and playback system is presented, providing a means for quantisation and analysis of the captured motion data with emphasis on the use of such technology for remote monitoring by a therapist. This system utilises open source promiscuously licensed technology (i.e. an open source graphics rendering engine and 3D Model) to articulate a realistic 3D model hand using the captured sensor data. And third, a hybrid sensor solution which integrates the sensor glove with a depth sensing camera, for full spatial hand and finger tracking is described. This step expands the capabilities of the glove system as a human-computer interaction (HCI) device. A detailed discussion follows expanding on the use of such a tool for developing more advanced therapeutic applications, such as the development of interactive games or the virtualization of testing procedures, such as the nine-peg hole test.

4.1.1 Motivation

As already discussed in Chapter 2, the cortex contains a topological map of the body. The amount of cortex devoted to any given body region is proportional to how richly innervated that region is and how skilled the brain is at manipulating that body part. For example, functional magnetic resonance imaging (fMRI) scans of professional string players show larger representations of the fingers of the dominant hand, than that of control groups [96]. The cortical map of Braille readers show significant larger representation of the reading hand than the non-reading hand [283]. The cortical maps of professional badminton players show more pronounced representation of the dominant playing hand compared to their supporting hand, and compared to that of amateur players [289].

After injury to the cortex, as often occurs with stroke, it is common for there to be considerable damage to the fore-brain, i.e. the sensory and motor apparatus. An infarction of the motor cortex can damage or disrupt motor representations, resulting in the impairment of motor functions. Fortunately as already discussed, the brain can repair itself after such neurological injury, through the process of reorganisation and restructuring. Motor learning or perhaps more aptly, motor re-learning, plays an important role in the reacquisition of functional movement skills after stroke. Motor skill learning can be described as the modification of the temporal and spatial organization of muscle synergies, which result in smooth, accurate, and consistent movement sequences [133]. It is suggested that motor learning occurs in two stages [375], an initial stage which is characterised by a fast learning period in which rapid gains are made in relatively short periods of time. Followed by a secondary phase of learning in which incremental performance gains are made but at a much slower pace. The hypothesis being that fast learning involves processes that select and establish an optimal routine or plan for the performance of the given task. While slow learning may reflect the ongoing structural alterations of the basic motor modules, which with practise over time cause strengthening of links between motor neurons and their recruitment into the task specific representation of the practised movement [179].

Studies on animals have shed light on the relationship between motor skill learning and changes in motor map representations. Nudo et al. [272] trained three monkeys to retrieve food pellets using digit and wrist movements, while a fourth control monkey was instead trained to retrieve food pellets using its forearm and wrist. Training lasted a total of 10 days during which a high number of task repetitions were performed. Post training cortical mapping showed cortical changes that directly reflected the demands of the particular task. The monkeys in the first group showed increased representation of the digits and wrist compared to pre-training maps, while the latter control group showed an increase in wrist and forearm representation. Additional studies on monkeys have showed that after a limb is deafferentation, cortical territories which used to represent that limb start to diminish over time [241]. Another study in monkeys showed that 2-8 months after a digit is amputated, its cortical representation is completely occupied by new and expanded representations from adjacent digits or the palm [242]. These fundamental studies highlight the importance of frequent use of the impaired limb in strengthening cortical representation after neurological damage and imply that intense, repetitive rehabilitation may significantly improve motor function. In addition, these studies also highlight that failure to increase cortical representation of the impaired limb might result in infringement of this motor area by other neighbouring representations.

Although research suggests that increasing motor representation improves motor function, the optimal level of exercise dosage required to promote the underlying neural-plastic change is unknown [184, 212]. Studies of recovery in animals after neurological injury suggest that daily repetition of the order of hundreds are required in order to provoke lasting cortical change. For example, a study of cortical reorganisation in healthy rats required 400 repetitions of a skilled reaching task to be performed daily, for 10 days [183]. Similar numbers, 500-600 repetitions daily, for 10-11 days, were required in a study which examined the affects of motor learning on cortical map representations with healthy monkeys [270]. In contrast, the current level of activity encouraged in practise during rehabilitation training with humans is low. A comprehensive study including 312 physical therapy sessions from 7 sites around the United States and Canada investigated the amount of practice, in numbers of repetitions, currently occurring in stroke rehabilitation [197]. Practice of upper extremity movements were observed in 162 of these sessions, while functional upper extremity movements were only observed in half of these sessions. The average number of functional upper extremity repetitions in those sessions was 32. These findings indicate that doses of movement practice currently provided during stroke rehabilitation are substantially smaller than those deemed necessary for cortical reorganisation in animal models investigating the plasticity of motor circuits. Perhaps these results shed some light on why as many as 50% of patients leave primary care with some degree of physical impairment [49].

After returning home, stroke patients are encouraged to engage in daily physical rehabilitation which focuses on the use of their weakened limb. In the case of weakness in the upper extremity, functional hand movements involved in activities of daily living are often practised, including; reaching, grasping, pinching, as well as movements which involve manipulation of the wrist, for example, turn a door handle and opening a sealed jar. However, for a recovering patient these tasks are extremely difficult and the inability to perform them can be frustrating and discouraging. For this reason, it is common that stroke survivors learn to compensate for their weakness and quite often stop using their affected limb altogether, a condition known as learned non-use [360]. Learned non-use has serious consequences for neural reorganisation as it is a self reinforcing behaviour. The less the limb is used the smaller the cortical representation of that limb becomes and the less control the patient has over it, leading to further disuse.

Subsequently, a movement therapy paradigm called constraint induced movement therapy (CIMT) in which a patient's healthy arm is restrained, typically using a sling, a splint, a half glove, or a mitt [53], has been suggested to encourage the use of the weakened limb. CIMT has been shown to produce significant improvements in the amount of use of the paretic limb in patients with chronic stroke [247]. Unfortunately, few rehabilitation centers offer CIMT because insurance companies will not support it and because it is impractical in terms of time requirements and available resource [248]. From the perspective of home based rehabilitation, CIMT can also be hazardous especially if a patient is attempting CIMT independently, as restricting the use of the healthy arm can displace balance and in the case of a fall, will impair the ability to cushion an impact.

Thus, we are interested in developing an affordable wearable sensor glove for stroke rehabilitation, suitable for use in the home, which places emphasis on the use of the weakened hand without constrained or restricting the use of the healthy arm. Instead, it is hoped that the novelty of the device and the extended abilities it offers will help foster increased use of the weakened hand.

4.2 Sensor Glove Design

Most sensor gloves are designed as novel peripheral input devices only doing the most minimal, if any, on-board computation themselves and instead rely entirely on a host machine (PC) to make use of the acquired sensor data. The design novelty of the sensor glove described here is that it functions autonomously, acquiring sensor data, classifying hand gestures and wirelessly transmitting control signals and or sensor data using on board hardware, independent of a host machine. To accomplish this feat the glove incorporates a powerful micro-processor, five independent sensors, a high density light weight battery power supply and two independent wireless communication systems (IR and Bluetooth). Such design considerations allow the sensor glove to be used as an agile unconstrained controller, freeing the user from the typical confined and tethered user interaction space of a desktop. The sensor glove system was designed around a standard, knitted fabric cotton glove. Cotton was chosen as it is comfortable, cheap and pliable, being easy to attach sensors and other electronic components. The glove was also designed with adjustability in mind, the chosen cotton fabric is inherently elastic allowing it to stretch to accommodate different size hands. The flex sensors are fixed to the glove only at the tip of the finger, with the remaining body of the sensor guided by elastic through holes at each of the finger's phalanges. This mechanism allows the rigid flex sensors to tightly following the curvature of the fingers as they bend without compressing and opposing movement, see Figure 4.1.

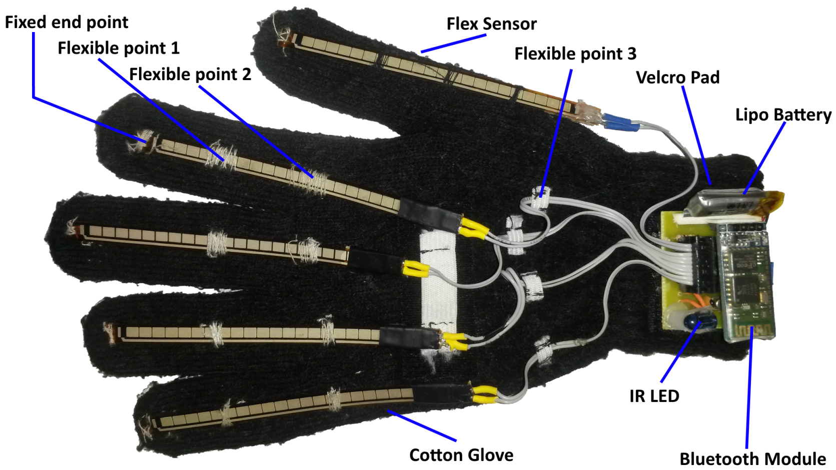

FIGURE 4.1: Sensor glove: highlighting main components and joints.

4.2.1 Bend Sensor

The sensor used for acquiring finger position is a bi-directional flexible bend sensor (Flex Sensor – Spectra symbol Corp, Salt Lake City, USA), see Figure 4.2.

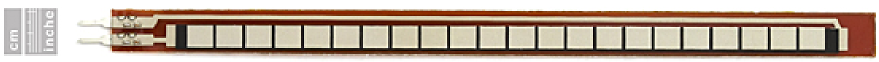

FIGURE 4.2: Sensor glove

The flex sensor exhibits a varying resistance that is proportional to its bend, with a nominal $25k\Omega$ at rest and an intermediate resistance which is proportional to the applied bend radius. In order to sample and subsequently quantify this physical changing property of the sensor we need to convert the resistance into a varying voltage. This is accomplished by incorporating the sensor into a standard voltage divider configuration, with the output going to an analog-to-digital converter (ADC), see Figure 4.3. An impedance buffer is also incorporated into the sensor acquisition circuit to reduce error caused by the source impedance. A voltage divider circuit and ADC channel are required for each flex sensor, totalling 5 for our design.

4.2.2 Micro-controller

In order to remove the dependency on an external PC, we based our system around a powerful embedded microprocessor, the PIC16f688 (PIC16f series, 8 bit micro-controller, Microchip corps, USA). We selected this microprocessor as it has the necessary functionality and additional internal hardware required for our sensor glove design requirements. That is, five dedicated (ADC) channels, three digital I/O pins, one of which has pulse width modulation (PWM) support required by the IR LED and the remaining two having universal asynchronous receiver/transmitter (UART) support as required for the embedded Bluetooth module. The chosen PIC16f688 is a suitable micro-controller meeting all the above requirements; however an alternative equivalent micro-controller would suffice.

4.2.3 Communication Modules

The sensor glove incorporates two separate communication modalities, Infrared (IR) and Bluetooth (BT). IR is used for transmitting control signals to environmental devices such as home entertainment systems, including (TV's, DVD players and radio/CD players). Most consumer electronics work on one of two wavelength: 870nm or (930-950)nm. To accommodate both, an IR LED of each wavelength was integrated into the gloves design. The IR LEDs are driven by Pulse Width Modulate (PWM) using a dedicated peripheral pin of the micro-controller.

Bluetooth is used for live streaming of sensor data from the glove to a host device at high speeds and can be used in conjunction with custom designed software for data capture and presentation, see Section 4.4. The Bluetooth module used is the (HC-05 Bluetooth Module - Guangzhou HC Information Technology Co., Ltd.). The BT module is connected over dedicated peripheral pins, a universal asynchronous receiver/transmitter (UART) module of the micro-controller.

4.2.4 Power

The entire system is powered by low voltage (i.e. 5V DC), using a 3.3V DC lithium polymer battery and a step-up DC to DC converter (NCP1402-5V, ON Semiconductor Components Industries, USA).

4.2.5 Electronic Schematics

The complete hardware schematics (electronic circuitry) are shown in Figure 4.3.

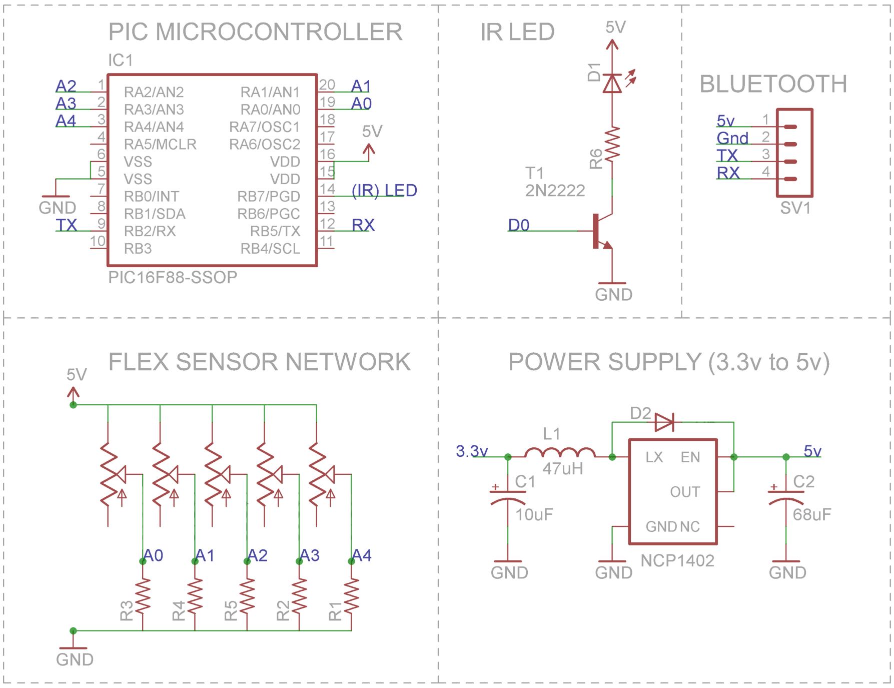

FIGURE 4.3: Electronic schematics for sensor glove system.

4.2.6 Safety

From a safety perspective, many considerations were made when designing the sensor glove. Cotton, which is an extremely good insulator was used for the main body of the sensor glove. Hence there is both good heat insulation, which protects the user from any heat dissipation from the electronic components, as well as good electrical insulation. In addition, the printed circuit board (PCB) which houses the electronic components rests on top of a thin layer of plastic, further isolating the user. Only very low voltages (i.e. 3.3 V and 5 V DC) are used to power the glove, which are of no danger to the user even if they came in direct contact with skin.

There are no moving mechanical parts used in the glove which is made from completely docile material. The bend sensors incorporated into the glove are flexible and offer little or no noticeable resistance to movement. The PCB is attached to the body of the glove using Velcro™, hence, from a hygiene perspective all the components can easily be removed from the base glove which is machine washable. The glove is also comfortable to wear and easy to don and doff.

4.3 Gesture Based Environmental Control in the Home

Current recommendations post stroke suggest that high levels of physical activity are important for promoting optimal recovery after stroke. Regardless, evidence gathered from systematic reviews repetitively finds that in spite of this evidence, hospitalised stroke patients consistently spend large proportions of their day inactive. Furthermore, through interviews with care workers and therapists it was found that patients treated at home spend a considerable proportion of their day stationary, sitting or lying down while interacting with entertainment systems. On average, patients were alone for more than half of the day. It is recommended that physical exercise programs should focus on the practise of functional movement which are important to activities of daily living (ADLs). In the home setting, patients receive on average one hour of guided physical therapy a day and are expected to practise such exercises on their own as often as they are capable. However, as the previous chapters have affirmed, unguided exercise programs are extremely difficult for patients struggling with weakness and such exercises are not naturally motivating. The result of which often leads to neglect of the impaired limb and subsequently poor recovery of function.

This section describes an application of the aforementioned sensor glove system which uses hand gesture recognition to control personal appliances, in an attempt to integrate functional movement into the activities of daily living. It is hoped that this approach will help promote increased use of the paretic limb through the intrinsic reward of controlling one's surrounding through interactive hand gestures.

4.3.1 Finger Position Estimation

The skeleton of the human hand is made up of 27 bones which are categorised into there groups, the carpals, metacarpals and phalanges. The **carpals** consist of eight small bones that make up the base of the hand, protruding from the wrist. Above these are the **metacarpals** which form the base of the fingers ending with the knuckles, from the ends of which stem the **phalanges**, the bones of the fingers. See Figure 4.4[1].

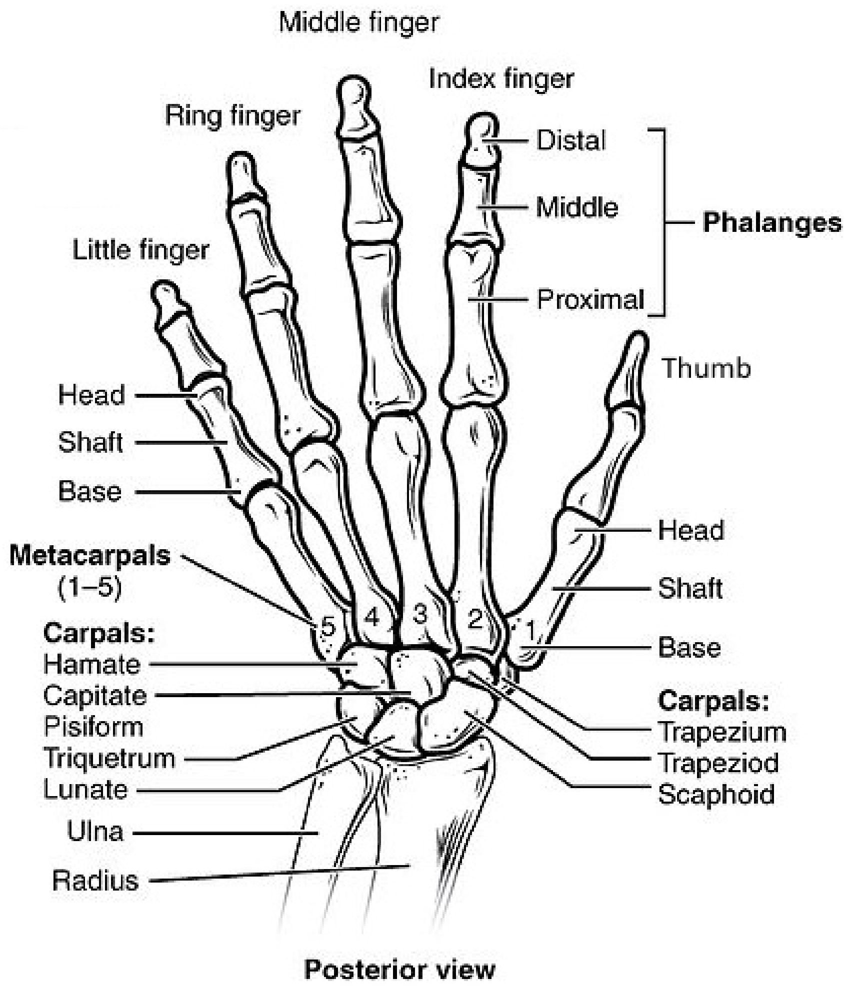

FIGURE 4.4: Skeleton structure of the human hand.

Each finger consists of three bones, the proximal, middle, and distal phalanges. The joints between, the distal and middle phalange, and the middle and distal phalange are hinged, each having a single degree of freedom. The base joint between the metacarpals and distal phalange has two degrees of freedom. However, natural gestures made with the fingers are for the most part simple and are well captured by only the flexion and extension of the phalanges. Hence, lateral abduction of the fingers can for the most part be ignored and the base joint (metacarpals - distal phalange) can be reduced to a single degree of freedom.

Although the human hand is extremely complex with many individual degrees of freedom, joint movements are correlated. Hand motion studies involving simple activities

[1]Source: 806-Hand-and-Wrist.jpg Creative Commons Attribution 3.0 Unported

such as reach-to-grasp [234, 316], and skilled activities such as typing [108, 343] reveal that a small dimensional space accounts for a large fraction of the postural variance observed during these tasks. Therefore, finger position can be estimated to a high degree of accuracy using only a single flex sensor, measuring the overall bend of the finger with respect to the metacarpals.

To estimate finger position using the chosen flex sensor, a two stage calibration method is used to determine the maximum and minimum sensor values (X_{max}, X_{min}), corresponding to the angles (θ_{max}, θ_{min}) of the open hand and closed fist, respectively. A linear mapping system is then used to map the intermediate flex sensor value $X_i(t)$, for each of the five flex sensors (X_1, X_2, X_3, X_4, X_5), to its corresponding finger's angle of flexion $\theta_i(t)$, for each of the five fingers (θ_{little}, θ_{ring}, θ_{middle}, θ_{index}, θ_{thumb}), see Equation 4.1.

$$\theta_i(t) = \theta_{i(min)} + \frac{\theta_{i(min)} - \theta_{i(max)}}{X_{i(min)} - X_{i(max)}} \times [X_i(t) - X_{i(min)}] \tag{4.1}$$

4.3.2 Gesture Recognition

Several hand gesture recognition techniques already exist, most of which are based on Hidden Markov Models [40, 54], Fuzzy Logic [27] or Neural Networks [17, 137]. These methods provide accurate real time recognition of hand gestures but the computational costs associated are high and are therefore not suitable for deployment on an embedded micro-controller. Hand gestures are instead recognised by a custom template matching technique that compares attempted gestures against a table of pre-defined gestures stored in memory on the micro-controller.

To ensure a detected gesture was actively attempted by the user and not just part of some natural movement (such as arm movement while walking) each gesture is encapsulated by a proceeding and succeeding static pose that initialises the gesture checking routine, see Figure 4.5 [2].

[2] Hand gesture 30690 sourced from www.freegreatpicture.com

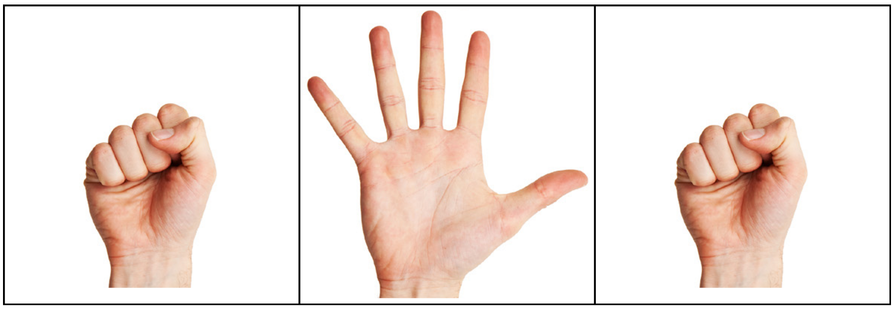

FIGURE 4.5: (a) proceeding pose, (b) attempted pose and (c) succeeding pose

A pose P is defined as,

$$p(t) = [X_1(t), X_2(t), X_3(t), X_4(t), X_5(t)] \tag{4.2}$$

Where, $X_i(t)$ is the value of the *i-th* flex sensor at time t.

The micro-controller continuously monitors incoming sensor values, creating pose candidates and searching for the framing pose which at the start of a gesture is considered the proceeding pose and at the end of a gesture is termed a succeeding pose. When it finds a match corresponding to the proceeding pose, it then starts buffering the next N consecutive poses until either a time-out occurs or the succeeding pose is captured. If a time-out is detected, the sensor glove dumps the captured poses and returns to its previous routine. If instead the succeeding pose is detected within the time limit, the micro-controller stops buffering poses and proceeds to check each of the buffered poses against a gesture lookup table. An intermediate pose p matches one of the pre-defined poses g if the sum of the Euclidean distance D between each element of those poses is less than or equal to some error threshold E, see Equation 4.3.

$$\begin{aligned} D &= \sum_{i=0}^{5} \sqrt{(g_i - p_i)^2} \\ f(D) &= \begin{cases} 1, & D \geq E \\ 0, & otherwise \end{cases} \end{aligned} \tag{4.3}$$

4.3.3 Transmitting (IR) Codes

In the case where a match is found between an attempted pose and a pre-defined pose, the index of that pose in the gesture lookup table will be used to retrieve its paired IR code from an additional table. IR codes are transmitted by an LED modulated with a carrier frequency of 38kHz, using pulse distance encoding following the NEC infrared transmission protocol (Semiconductors, 2013), see Figure 4.6.

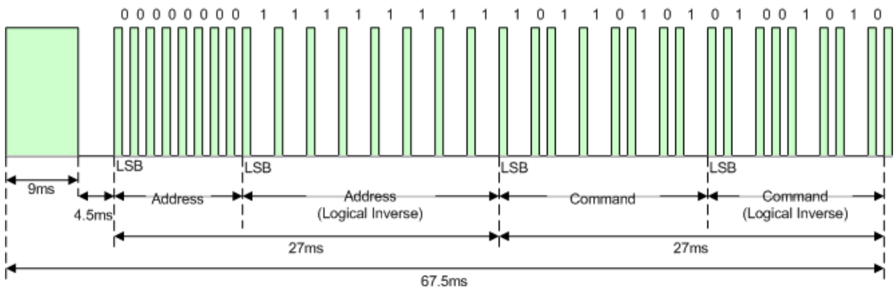

FIGURE 4.6: NEC transmission protocol: illustrating, leading pulse, 8-bit address, logical inverse of address, 8-bit command, logical inverse of command and end of transmission burst.

A logic "0" is encoded as a 562.5μs pulse burst followed by a 562.5μs space. A logic "1" is encoded as a 562.5μs pulse burst followed by a 1.6875μs space. See Figure 4.7.

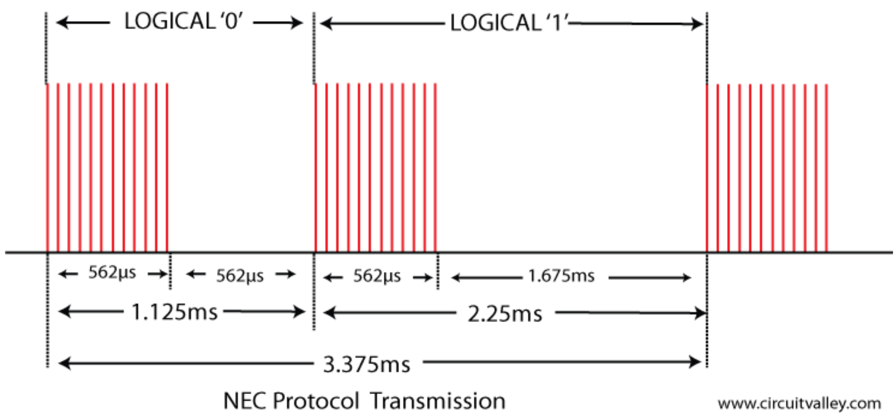

FIGURE 4.7: Illustation of NEC logic encoding

The NEC protocol was chosen as it is widely used by commercial IR products and for which command codes are freely available. This design consideration allows our device to interact with many commercial based home entertainment systems, including (TV's, DVD players and radio/CD players).

4.3.4 Dynamic Difficulty Adjustment

The inclusion of a dynamic task difficulty mechanism allows for the automatic increase or reduction in the precision of the gesture required, according to the user's continuous performance. The difficulty of a task can be increased or decreased by changing the error threshold E or adjusting the time limit T, see Equation 4.3. Dynamic difficulty adjustment (DDA) is a useful method often used in gaming to optimize engagement through matching player's ability with an appropriate challenge [156]. We currently use a DDA approach which adjusts E or T based on a running average of the relevant performance measures (D_A or T_A) for the previous M gesture attempts. When D_A (or T_A) is greater than E (or T) we gradually increase E by an increment each gesture iteration until an appropriate balance is obtained and similarly if the gesture is too easy the difference measure is used to increase the difficulty level. This feature is designed to provoke the necessary motor learning associated with effective therapy.

4.3.5 System Testing and Validation

4.3.5.1 Data Capture

Figure 4.8 shows the raw output from each of the five flex sensors during a series of rapid hand movements, designed to evaluate and demonstrate the gloves ability to capture variable movement.

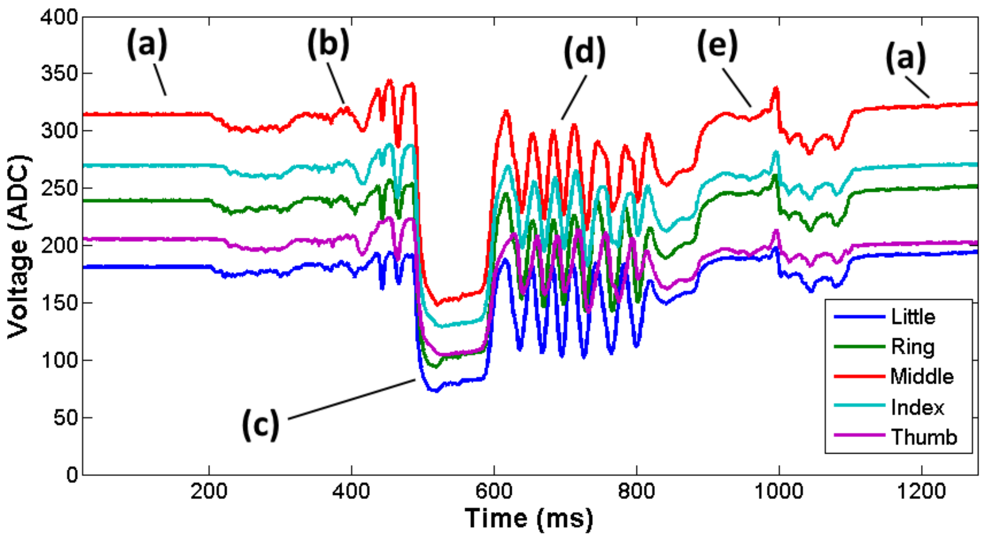

FIGURE 4.8: Raw data output from sensor glove: illustrating, (a) period of rest, (b) initial movement, (c) brief maximum clenching of the hand into a fist, (d) rapid opening and closing of the hand, (e) transient muscle spasm while returning to rest.

4.3.5.2 Gesture Recognition Accuracy

A preliminary test with 3 healthy users was conducted to validate the operation of the gesture recognition system. Subjects were thought five unique hand gestures and learned the association with these gestures and their commands signals, see Table 4.1. Subjects were then sat in front of a TV and asked to attempt to control different functionality during a 10 minute session. The time limit T chosen in which a gesture needed to be performed was $500ms$ and an error threshold E was chosen to be 8%, see Section 4.3.2.

TABLE 4.1: Hand Gestures and resulting command codes

Gesture ID	Command	Hand Gesture
1	Channel Up	
2	Channel Down	
3	TV On/Off	
4	Volume Up	
5	Volume Down	

The results of this test were averaged across the subjects and are presented in Table 4.2. The results illustrate the average number of times each gesture was performed, the number of successful and failed classifications, the average time taken to perform a gesture (measured as the difference between detection of framing poses), and the accuracy with which each gesture was performed (measured as the difference between the pose candidate and the nearest matching predefined pose).

Table 4.2: Average sensor glove testing results across subjects.

Gesture	Attempts	Successful	Failed	Time(ms)	Error	Command
1	15	14	1	443	5.3%	Channel Up
2	14	12	2	459	6.5%	Channel Down
3	6	6	0	462	6.1%	TV ON/OFF
4	20	19	1	426	5.5%	Volume Up
5	15	13	2	463	6.2%	Volume Down

4.3.5.3 Discussion and Conclusion

Evidence suggests that the level of exercise dosage undertaken by stroke patients in the chronic stage of rehabilitation are suboptimal for recovery. In fact, observed levels of exercise repetitions are far lower than those deemed necessary to promote neuroplastic response in stroke models. Through interviews with carers and therapists it was determined that patients spend a considerable proportion of their day interacting with entertainment systems and that the interfaces to such devices can be very challenging to operate. Consequently, we designed our sensor glove as an IR-based augmented controller for personal appliances (TV, DVD, radio etc.). Such a design places the rehabilitation process at the heart of relevant activities of daily living which are both personalized to the specific user and should elicit motivational engagement.

Subsequently, the sensor glove application described here was designed to encourage the user to perform gestures which are derived from therapist-specified motor exercises, the successful execution of which acts as a control input to an environmental control system. A preliminary test of the accuracy and usability of the glove was conducted with healthy subjects. Users found the glove system intuitive, responsive and fun to use, requiring little or no training other than learning the relationship between gestures and the corresponding triggered commands. These results are encouraging, as the devices usefulness as a healthcare apparatus is contingent on the practicality and gratification of use.

Future work will involve validating the device with chronic stroke patients to investigate the practically and usefulness of our system as a tool for promoting exercise.

4.4 Visualisation and Playback of Sensor Glove Data

According to statistics compiled by the National Stroke Association, 10% of people who have a stroke make a full recovery, 25% recovery with only minor complications, 40% make some recovery but end up with moderate to severe problems, and 10% require long term care in a nursing home or similar facility. While the rate of recovery after stroke is contingent on many factors, there is strong evidence that adherence to post-acute stroke rehabilitation guidelines is strongly associated with improved recovery outcomes [92, 164]. While exact figures are hard to come by, reports suggest that non-adherence to physical exercise could be as high as 70% [341]. Many studies have identified key factors which affect adherence, such as; misunderstanding instructions, low self-efficacy, depression, anxiety, poor social support/activity and pain [163].

From the perspective of physical therapy for stroke rehabilitation there are many strategies which can be employed to improve adherence. Providing explicit instructions for the required movement task, checking and analysing the patient's movement attempts and providing positive feedback on performance [26, 101, 331]. In this respect, support and encouragement from a therapist are very important elements which help shape the outcome of therapy. It is especially important that the patient believe that their hard work, elicited through countless hours of repetitive exercise, can and will help to promote recovery.

This section describes a therapeutic application of the previously introduced sensor glove system, for the visualisation, capture and playback of movement during exercise training. The aspirations of this tool are to increase the therapist's involvement in everyday exercise training by allowing the therapist to keep track of the patient progress and to analyse their exercise sessions remotely.

4.4.1 Sensor Data Acquisition

The sensor glove buffers data that has been processed (i.e. converted from Analog to Digital) until one sample is acquired from each sensor. After which the data is then organised into frames for transmission. Data framing ensures the correct transmission of data from the sensor glove to the receiving software. A frame typically includes a synchronization sequence which indicate the beginning and end of the payload and some delimiting characters to break up the data. If the receiver connects to the system in the middle of a frame transmission, it can then ignores the data until it detects a new frame synchronization bit. Given the limited processing power of the embedded micro-controller, a custom framing protocol was implemented to maximise the data transmission rate, see Figure 4.9.

# Byte	1	2	3	4	5	6	7	8	9	10	11	12
Data Type	Start Bit	Sensor 1		Sensor 2		Sensor 3		Sensor 4		Sensor 5		Checkbit

FIGURE 4.9: Illustration of custom data framing protocol.

As previously described in Section 4.2 the sensor data was acquired using a 10-bit ADC on an 8-bit micro-controller. Therefore, the resulting ADC conversion is stored in two separate 8 bit registers named, ADCH and ADCL. The upper 2 most significant bits of this conversion are stored in ADCH, while the lower 8 significant bits are stored in ADCL. Hence, each sensor is represented by two bytes of data in the framing protocol.

A packet checksum is also included in the frame to ensure the data's integrity. The checksum is computed on the glove side and transmitted along with the sensor data, this checksum is then recomputed on the receiving end and matched with the transmitted checksum. If the checksums fail to match, the receiver simply drops the packet, otherwise it proceeds to parse the data and process the sensor information. The checksum C is simply calculated as,

$$C = \left(\sum_{2}^{11} X(i) \right) \%255 \tag{4.4}$$

Where:

$X[i]$ is the *ith* byte of the framing protocol.

4.4.2 Sensor Data Transmission and Reception

Data is transmitted over Bluetooth using the Universal Asynchronous Receiver Transmission (UART) protocol, at a baud rate of 115200 bits per second (BPS). The received data is buffered, demultiplex and filtered to reduce sensor noise. Each sensor is filtered separately, the filtering is done by a moving average filter described by Equation 4.5..

$$y[i] = \frac{1}{M} \sum_{i=0}^{M-1} x[i] \tag{4.5}$$

Where:

y is the output signal.

x is the input signal.

ith sensor value.

M is the number of points used in the moving average.

4.4.3 Real-time Visualisation

A software platform named "Ditto" was developed for real time visualisation of the sensor glove data. The software platform integrates an open-source graphics rendering engine called Ogre3D[3] (Object-oriented Graphics Rendering Engine), in conjunction with an open-source library for rendering and recognizing articulations of the human hand, LibHand [227], see Figure 4.10.

[3]OGRE-3D - url: http://www.ogre3d.org/

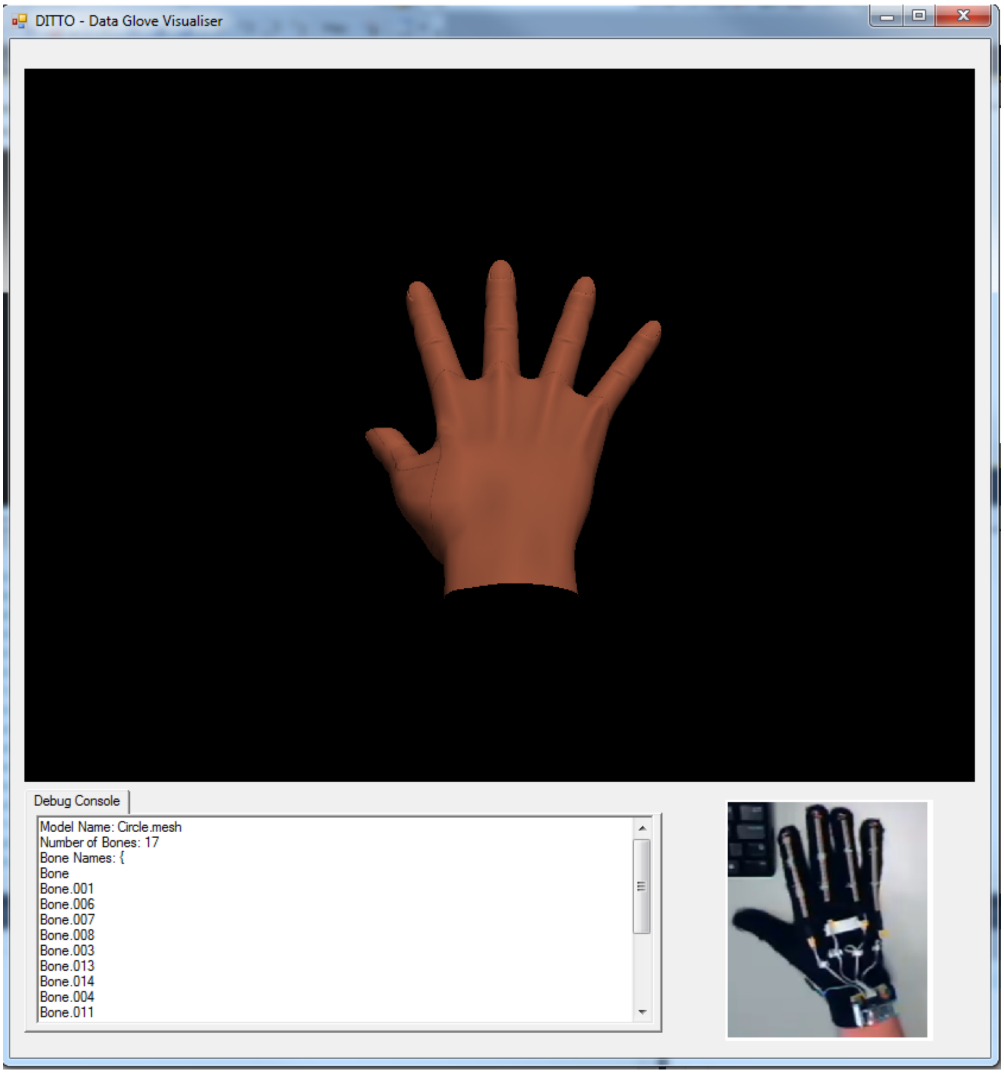

FIGURE 4.10: Screen capture of the Ditto software platform showing real time capture of sensor data articulating a 3D model hand.

Ogre 3D is released under the MIT License [4], a permissive open source license. Orge 3D is a full featured, self contained graphics engine designed to minimise the effort required to render 3D scenes and to be independent of 3D implementation (e.g. Direct3D, OpenGL, etc).

The **LibHand** library was created by Marin Saric and is released under the Creative Commons Attribution 3.0 Unported License [5]. LibHand contains a textured, rigged and skinned realistic model of a human hand, based on a 75k+ polygon mesh. The rig or skeleton is an important feature of LibHand as the Ogre 3D engine supports skeletal animation, a technique in which a model is represented in two parts: a surface representation (called skin or mesh) and a hierarchical set of interconnected bones (called the

[4] MIT License
[5] Creative Commons Attribution 3.0 Unported License

skeleton or rig) used to animate the mesh. Skeletal animation works by having a collection of 'bones' which are essentially joints, each with its own position and orientation, arranged in a tree structure.

For example, in the case of the hand skeleton, the distal phalanx is a child of the middle phalanx, which in turn is a child of the proximal phalanx, which is a child of the Metacarpals, see Figure 4.4 for reference.

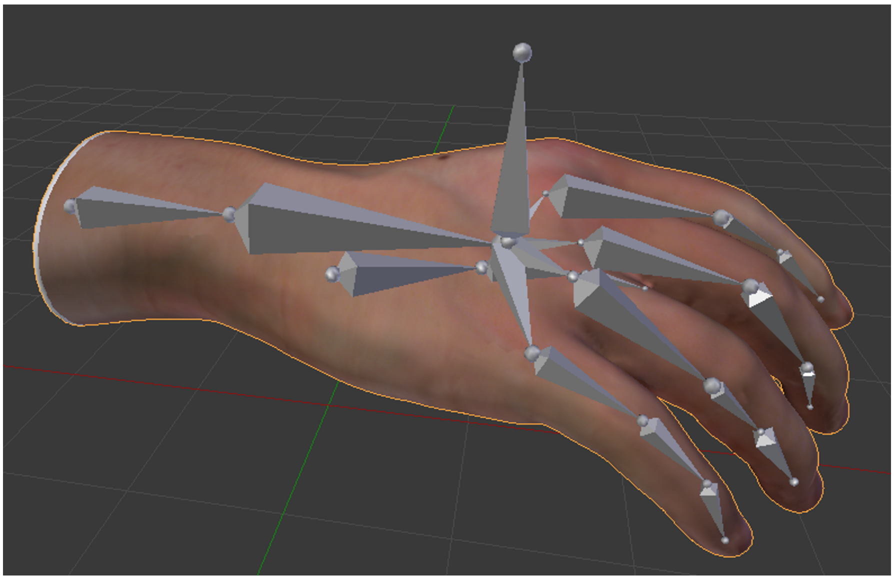

FIGURE 4.11: Skeleton structure of LibHand

4.4.3.1 Animation of LibHand

There are two main techniques which can be used to animate the underlying skeleton structure of LibHand. The first and most simple of the these is to manually manipulate the rotation and position of each of the bones separately. The second is to use inverse kinematics [256] to determine the joint parameters that provide a desired position of the end-effector. While the inverse kinematics approach is more sophisticated it requires a detailed model of the fingers kinematics and is not supported natively by the Ogre 3D engine. In contrast, the former approach can be achieved using a system of weights which determine the relative rotation of each of the fingers three joints, with respect to the overall bend of the finger, see Equation 4.6.

$$\begin{bmatrix} \alpha & \beta & \gamma \end{bmatrix} = X_i \begin{bmatrix} W_1 \\ W_2 \\ W_3 \end{bmatrix} \tag{4.6}$$

Where:

α: is the joint angle between the distal and middle phalanges.

β: is the joint angle between the middle and proximal phalanges.

γ: is the joint angle between the proximal phalange and metacarpal.

X_i: is the intermediate value of the *ith* sensor.

W_1: rotational weight applied to α

W_2: rotational weight applied to β

W_3: rotational weight applied to γ

The magnitude and direction of these operations is determined by the captured sensor glove data X_i, which approximates the *ith* finger position as described in Section 4.3.1.

4.4.4 Recording

Recording of captured motion was achieved using the Biovision Hierarchical (BVH) data format [240]. The BVH format is one of the most widely used motion data formats for representation of animation of humanoid structures. The BVH format was designed as a way to provide skeleton hierarchy information in addition to the motion data. A BVH file contains two sections, a header which describes the hierarchy and initial pose of the skeleton, and a body section which contains the motion data. The following description of the BVH format is derived from a lecture series by the UW Graphics Group[6].

The start of the header section begins with the keyword “HIERARCHY”. The following line starts with the keyword “ROOT” followed by the name of the root segment of the hierarchy to be defined. The BVH format now becomes a recursive definition. Each segment of the hierarchy contains some data relevant to just that segment then it recursively defines its children. The first piece of information of a segment is the offset of that segment from its parent, specified by the keyword “OFFSET”, followed by the X, Y and Z offset of the segment from its parent. The offset information also indicates the length and direction used for drawing the parent segment. The following line after an offset contains the channel header information, denoted by the “CHANNELS” keyword, followed by a number indicating the number of channels and then a list of labels

[6] http://research.cs.wisc.edu/graphics/Courses/cs-838-1999/Jeff/BVH.html

indicating the type of each channel. This information is required by the BVH reader and is used to parse each line of motion data. On the line of data following the channels specification there can be one of two keywords, either you will find the “JOINT” keyword or you will see the “End Site” keyword. A joint definition is identical to the root definition except for the number of channels. This is where the recursion takes place, the rest of the parsing of the joint information proceeds just like a root. The end site information ends the recursion and indicates that the current segment is an end effector (has no children). The end site definition provides one more bit of information, it gives the length of the preceding segment just like the offset of a child defines the length and direction of its parents segment.

In the body of the BVH file lies the motion section, which begins with the keyword “MOTION”. This line is followed by a line indicating the number of frames, this line uses the “Frames:” keyword and a number indicating the number of frames that are in the file. On the line after the frames definition is the “Frame Time:” definition, this indicates the sampling rate of the data. 30 frames a second is the usual rate of sampling in a BVH file. The rest of the file contains the actual motion data. Each line is one sample of motion data. The numbers appear in the order of the channel specifications as the skeleton hierarchy was parsed. See appendix for example BVH file.

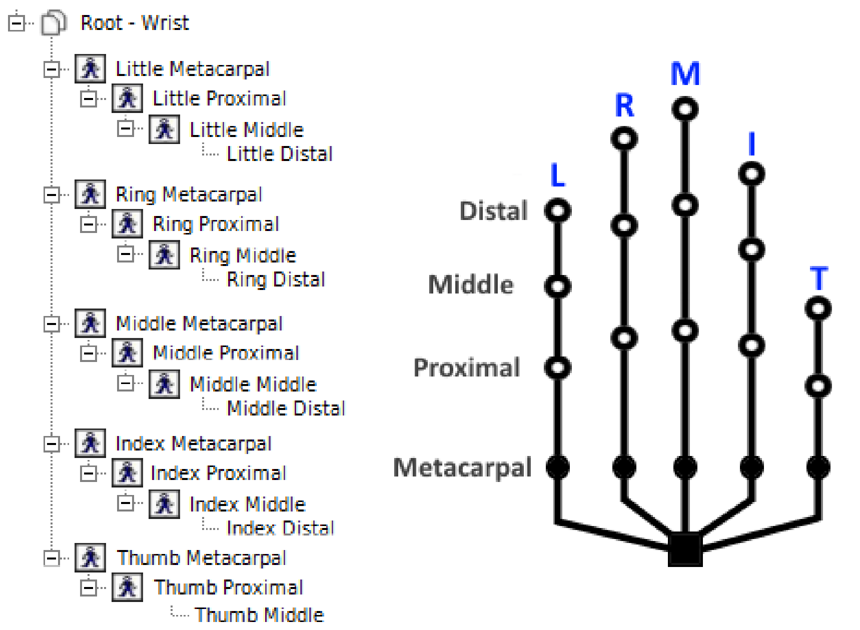

FIGURE 4.12: BVH Format

4.4.5 Playback

The BVH format stores the local position and rotation of each segment (i.e. bone), that is, its rotation and position relative to its parent. In order to animate a model correctly, the absolute, or global, position of each bone needs to be worked with respect to the root node, in this case the wrist. This can be achieved using matrix arithmetic. The nomenclature used for matrix notation is right to left.

To calculate the global position of a segment you first create a transformation matrix M from the local translation and rotation information for that segment, see Equation 4.7.

$$v' = vM \tag{4.7}$$

Where:

M: is the transform matrix

v: is the original vertex

For any joint segment the translation information will simply be the offset as defined in the hierarchy section and can be described by a translation matrix T. Similarly, the rotation information comes from the motion section of a BVH file.

The rotation matrix R can be constructed by multiplying together the rotation matrices for each of the separate axes of rotation (X,Y,Z), in the order they appeared in the BVH file, see Equation 4.8.

$$R = R_z R_x R_y \tag{4.8}$$

The resulting motion M of an individual segment is therefore calculated by applying a translation T and a rotation R to that segment. The resulting translation matrix M can be expressed as Equation 4.9.

$$M = \begin{bmatrix} R & R & R & T_x \\ R & R & R & T_y \\ R & R & R & T_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.9}$$

Since the BVH format uses a hierarchical structure, the local transformation of a bone only describes its orientation with respect to its local coordinate system, which in turn is subject to its parent's local orientations. To obtain a global matrix transform for a given bone, the local transform needs to be multiplied by its parent's global transform, which itself is derived from multiplying its local transform with its parent's global transform and so forth, see Equation 4.10.

$$M^n_{global} = \prod_{i=0}^{n} M^i_{local} \tag{4.10}$$

Using Equation 4.10 and the derivations of the local transforms, the global positions for each bone can be calculated. Then using this information, the bone can be drawn using the offset information in the hierarchy section of the file.

4.4.6 System Testing and Analysis

4.4.7 Sample Rate

The analog to digital (ADC) conversion rate is the fundamental limiting factor of the sensor glove sampling rate. The time required to complete one bit conversion on the PIC16f688 is defined by the ADC Clock Period, known as T_{AD}. One full 10-bit analog to digital conversion requires 11 T_{AD} periods. The source of the conversion clock is determined by the frequency of the oscillator (FOSC) driving the micro-controller and a clock divider factor. The fastest possible conversion time for the selected micro-controller is FOSC/2. Therefore, with the selected 20Mhz clock signal, the conversion time for each sensor is 1.1ms (909Hz). All five sensors can therefore be sampled in 5.5ms resulting in a refresh rate of (181.81Hz).

4.4.8 Capture and Playback

Data captured from the glove was converted into the BVH format as described in Subsection 4.4.4, at a rate of 60 frames per second (fps). Testing was done to evaluate the BVH conversion process in which data was captured using the sensor glove and subsequently converted it into the BVH format. This data was then loaded into an external BVH player and played back successfully.

4.4.9 Articulation of Sensor Data

Testing was done to evaluate the systems ability to render sensor data in real time, achieving a high frame rate (60 fps) resulting in smooth and clean looking hand motions.

4.4.10 Discussion

The ability to capture, record and visualise hand movement is a valuable asset allowing patients' progress to be monitored and assessed by both patient and therapist. From the perspective of healthcare there are numerous applications for this technology, which has been open sourced and made freely available by the author.

From the therapist perspective, the system described here could be used as a tool for remote analysis of patient exercise progression. The incorporated BVH capture functionality allows for session data to be recorded in a highly portable format, which for example could be emailed daily to the therapist. To review the data the therapist only requires either a copy of the original software platform or any freely available BVH player. Another advantage of this recording format is that unlike a video recording of the movement, the motion is captured independent of a frame of reference, allowing the therapist to change their viewing angle and to assess the motion from different perspectives.

From the patient perspective, feedback on the quality of movement might be beneficial in helping the patient to understand how they can improve functional skills. For example, an interactive model such as that employed here could be used to first demonstrate a hand gesture which the user then needs to mimic. After which, a gesture recognition program could analyse the movement attempt and offer feedback on performance. A dynamic difficulty adjustment variable could also be incorporated into the program to ensure the patient is constantly being challenged.

4.5 A Hybrid Sensor System for Full Hand Motion Capture

Over the last decade, studies in behavioural, cellular and molecular science have shown significant effects of enriched environments in animal models of neurological disease [265]. Van Dellen et al presented evidence that enriched environments helped to delay the onset of Huntington's disease in mice [378]. Arendash et al. showed that environmental enrichment improved cognition in Alzhemier's transgenic mice [18]. Studies in stroke patients have also shown that an enriched environment increases activity in patients undergoing physical rehabilitation [166]. These studies provide some insight into the mechanisms of experience dependent plasticity and suggest that enriched environments might have important implications for enhancing motor learning after stroke.

Virtual reality (VR) (i.e. computer-simulated environments) is set to play a huge role in the next generation of human computer interaction technology. We are currently awaiting the release of commercial VR headsets, including the much anticipated Oculus Rift [194]. Such devices enable advanced low-latency positional tracking allowing for the accurate mapping of your real world head movements into the virtual world, shifting and modifying your viewing experience as if you were really there. Body tracking and in particular hand tracking can further enhance a user's experience of immersive VR allowing them to not only move around in a virtual environment but also to interact with it in a natural manner. Subsequently, VR headsets are often coupled with other wearable sensors such as sensor gloves and motion capture suits.

However, capturing the full three dimensional motion of a hand in a cost effective and non-invasive manner is a complex problem. Sensor gloves are exceptional at capturing fine finger movement, cheaply and effectively. However, most sensor glove designs lack the veracity to make them useful for monitoring the full range of hand motions, principally; translations and rotations of the hand. Developing an autonomous, integrated solution to such a problem is challenging. That said, there have been commendable attempts at embedding additional sensors (accelerometers, gyroscopes, and altimeters) into the standard flex sensor based glove for this exact purpose. However, this class of sensors use a local inertial-frame for reference, which suffers badly from integration drift. To reduce this drift, existing algorithms make use of gravity and the earth's magnetic field measured by accelerometers and magnetometers respectively. These components themselves are sensitive to local magnetic interference and require further compensation mechanisms. Adding these to the lean sensor glove described earlier results in a design which is cumbersome, heavy and fragile, increasing the cost, power requirements and reducing the agility of the device. The software complexity also increases, requiring additional routines for acquiring and processing each of the newly added sensors and in some cases the implementation of computational expensive filtering algorithms, which have a severe impact on the responsiveness of the glove.

An alternative is to use a vision based approach for the motion tracking. The motion of an object from the camera perspective is used as a relative measure based on a static reference frame i.e. the camera's fixed position and field of view. One device that excels at this form of tracking is a depth camera. In this work we utilise the LEAP motion controller[7], an innovative, highly compact, affordable depth camera solution for hand motion tracking, Figure 4.13. The LEAP aims to make motion control ubiquitous, with a small device designed to be placed on a physical desktop, facing upward. It uses two monochromatic IR cameras and three IR LEDs. The LEDs generate a 3D pattern of dots of IR light and the cameras generate almost 200 frames per second of reflected data, which is sent to the host computer, where it is analysed by the LEAP Motion controller software. Using this approach the LEAP successfully tracks both translational and rotational hand motion, fluidly and at very high frame rates. However, it is not without its limitations. Visual forms of motion capture suffer from an alternative class of problems, mainly that of visual occlusion. While adept at hand tracking, the LEAP is poor at tracking finger positions, as the fingers become occluded from view when they are bent and flexed [128],[339], [16], [134].

This is problematic for healthcare applications, as accurate finger tracking is an important component of most exercise routines, such as pinching, or picking up an object. In this work we describe our attempts to develop a hybrid sensor system which combines our previously aforementioned sensor glove and the LEAP motion controller for high fidelity, full hand and finger tracking.

4.5.1 Hardware

The LEAP Motion controller uses two wide angle cameras as sensors which track an IR light source with a wavelength of 850 nanometres, emitted by three IR LEDs. The device has a large visual field of approximately eight cubic feet, which takes the shape of an inverted pyramid and can track movement at a rate of over 200FPS.

[7] LEAP motion controller

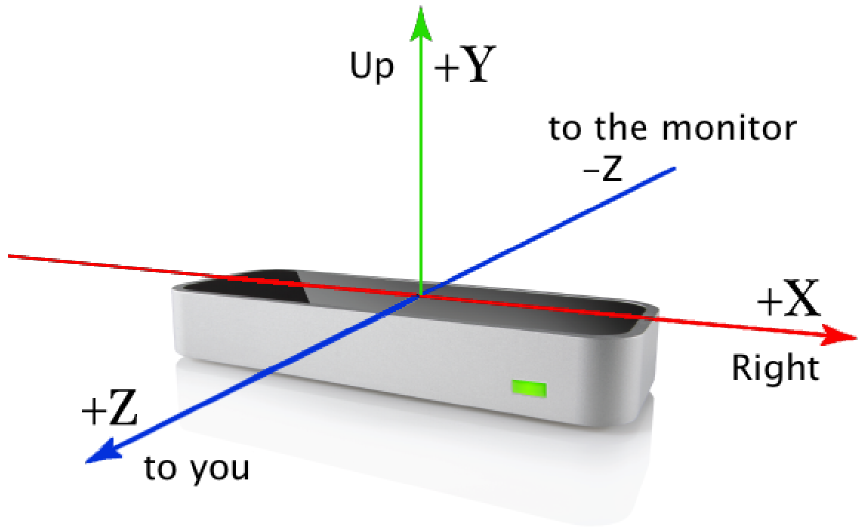

FIGURE 4.13: The LEAP Motion controller showing coordinate system.

The LEAP Motion system uses a right-handed Cartesian coordinate system, with its origin centred medially on the surface of the device, see Figure 4.13 [8]. The sensors are directed along the y-axis, facing upwards when the controller is in its standard operating position. The effective usable range of the LEAP extends from approximately $(25-600)mm$ above the device.

4.5.2 Motion Tracking

4.5.2.1 Frames

The LEAP Motion application program interface (API) encapsulates motion tracking data as a series of frames. Each frame may contain multiple tracked objects called entities, including fingers, hands and tools. The frame object contains spatial information about each entity in that frame, including their measured positions, rotation and velocity with respect to the LEAP's coordinate system. The Frame class defines several functions that provide access to the data in the frame. If a hand is present in the field of view, a hand object will be initiated in that frame, and will be subsequently updated with relative information about its location and orientation in consecutive frames. Simply polling the LEAP controller for frames is the simplest and often best strategy for retrieving motion data. However, when polling there is a chance that duplicate frames might occur if the application frame rate exceeds the LEAP frame rate. To solve this problem, each frame has a unique ID which can be used to mark processed frames.

[8]Leap_Axes.png sourced from the leapmotion developer API

4.5.2.2 Entities

The LEAP can label an entity as either, hand, finger or tool, depending on how the object is classified. For this application only the hand model is of interest. The hand model provides information about the identity, position, and other characteristics of a detected hand, the arm to which the hand is attached, and lists of the fingers associated with the hand.

The LEAP motion uses a model of the human hand to predict movement even when parts of a hand are not visible, see Figure 4.14[9]. The hand model always provides positions for five fingers, although tracking is optimal when the silhouette of a hand and all its fingers are clearly visible. The software uses the visible parts of the hand, its internal model, and past observations to calculate the most likely positions of the parts that are not currently visible.

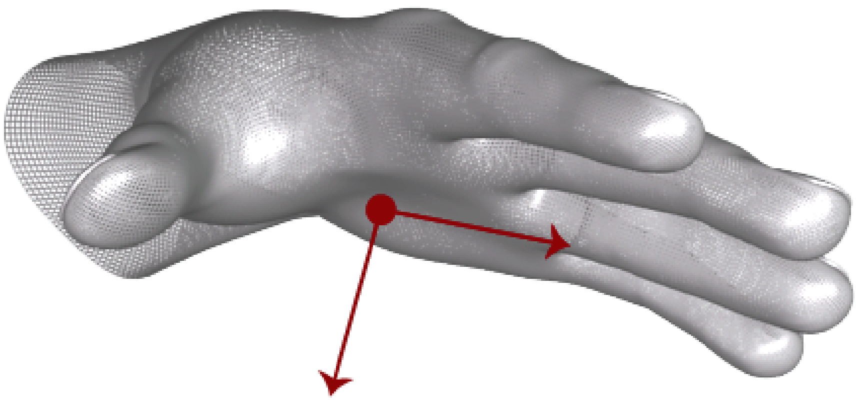

FIGURE 4.14: Hand tracking using the LEAP motion controller, showing coordinate system used.

The LEAP Motion controller provides information about each finger on a hand. If all or part of a finger is not visible, the finger characteristics are estimated based on recent observations and the anatomical model of the hand, see Section 4.5.2.2[10]. Fingers are identified by type name, i.e. thumb, index, middle, ring, and pinky. A Finger object provides a Bone object describing the position and orientation of each anatomical finger bone. All fingers contain four bones ordered from base to tip

[9]Leap_Palm_Vectors.png sourced from the leapmotion developer API.
[10]Leap_Finger_Model.png sourced from the leapmotion developer API

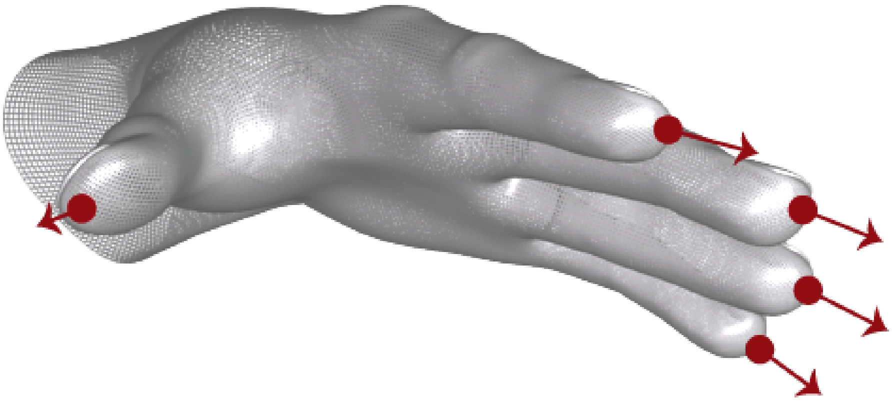

FIGURE 4.15: Finger tracking model using by the LEAP controller, showing vectors which provide position of a finger tip and the general direction in which a finger is pointing.

4.5.3 Integration

Interfacing the LEAP controller with the software system "ditto" was facilitated by an extensive well documented application programming interface (API), allowing the seamless detection and tracking of hands and fingers within the LEAP field of view. The LEAP controller is integrated with our system over USB, with data being communicated to a virtual serial port.

As previously described, the sensor glove communicates wirelessly with the software system through an embedded Bluetooth module, over a separate virtual serial port.

Once configured and connected, both the sensor glove and LEAP act as autonomous entities, grabbing new sensory data and piping it into the software platform, through their own independent pathways. See Figure 4.16 for system overview diagram.

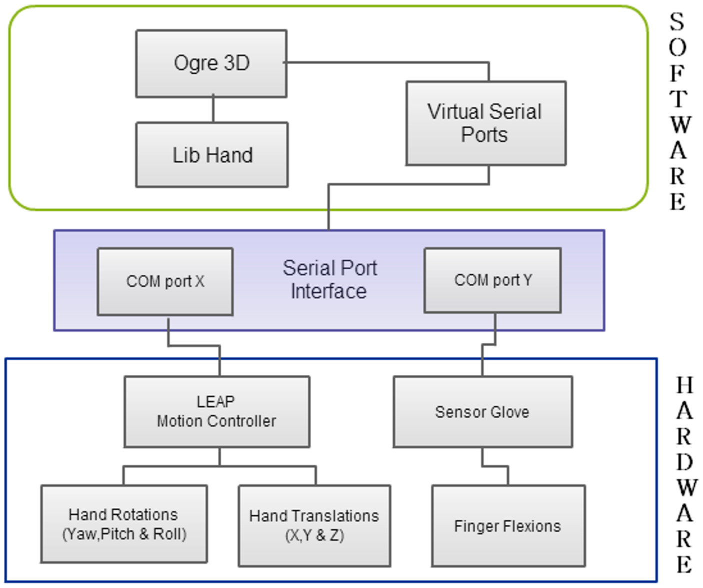

FIGURE 4.16: Hybrid system overview

4.5.4 Initial Investigation

It had been anticipated that the black matt fabric used in the sensor glove might pose issues with absorption and scattering of the IR light used by the LEAP sensor to detect objects. A preliminary test of the LEAP motion controller ability to detect a hand while wearing the sensor glove described in section 4.2 confirmed this problem. While wearing the glove, the LEAP was only able to partially detect and track the hand, reflected by a relatively high frame drop rate. Subsequently, testing was done with different coloured gloves to determine if a more suitable fabric would better reflect the IR light back towards the controllers cameras. It was found that the lowest frame drop rate was achieved using a high-visibility, reflective, fluorescent yellow glove. This material achieved a tracking rate similar to that of the naked hand. Subsequently, the original cotton glove was replaced with this new material.

4.5.5 Augmenting Finger and Hand Movement onto a 3D Model

Moving and rotating the model hand around the VR environment is trivial, and is facilitated by high level functions for applying rotation and translations of an objects orientation and position using the OGRE engine.

To accommodate any discrepancies between the LEAP motion controller's and sensor glove's sensor acquisition speeds, each of the devices were set up on their own processing threads. When new data arrives from either the LEAP or the sensor glove, it is processed separately and buffered. After a set amount of time (20ms) the buffers are then filtered using an averaging filter and the resulting data from both, the LEAP (hand position and rotation) and the sensor glove (finger flexion's) are applied to the model hand.

4.5.6 Discussion

The resulting hybrid system can track hand position and rotations as well as fine finger movement, resulting in accurate smooth manipulation of the 3D hand model. The Ogre3D graphics rendering system which we integrated into our system offers great flexibility for a developer, allowing importation of most well-known 3D model formats. Hence, interactive objects can easily be added to the virtual environment, facilitating the development of interactive environments. For example; a simple paper tossing game could be implemented in which the user has to reach for, pick up and throw a virtual piece of paper into a rubbish bin. Reaching, grasping and coordination are important functional movements that are integral to many activities of daily living, which most rehabilitation programs endeavour to incorporate. A simple scoring mechanism, adding competition to the game might encourage more replay-ability in which users try to beat their best scores or timing. Behind the screens, each movement made by the user can be tracked, recorded and quantified, allowing for a semi-automated assessment of recovery over time.

4.6 Summary

In this body of work, we present some of our recent efforts to leverage embedded technology to develop new and innovative approaches for promoting exercise training after stroke. Systems such as the sensor glove described here might offer new exciting ways for people to practise beneficial, therapeutic exercises as prescribed by their therapist. It is important to note that these devices are not intended to replace the need for conventional therapy but instead to be used as ancillary devices with the intention of supporting and enhancing recovery. Research shows that patient adherence to physical therapy reduces when they leave primary care (i.e. hospitals and clinics). This paradox can partially be attributed to the reduction in environmental stimulus and decline in positive reinforcing feedback, previously afforded by a team of trained professionals, without whom patients find their exercises difficult, unrewarding and frustrating.

The motivation for the work undertaken here was to engineer solutions which can help encourage the increased use of the paretic hand, in an attempt to promote the repetition deemed necessary for instigating neural plastic changes in the brain. Research suggests that exercises which are meaningful, such as movements which reflect activities taken from real life situations improve recovery in stroke survivors. Subsequently, our approach couples gesture-based environmental control with functional hand movements used in activities of daily living. It is hoped that there might be auxiliary benefits to using this technology, such that the newly acquired functional control over their environment might improve a person's sense of ability and independence. A virtual environment containing a realistic model of the human hand was also developed in an attempt to create an open source platform for the capture and playback of exercise training data. The intention of this platform is to reduce the gap between therapist and patient by helping to monitor and track patient progression and to make this data easily accessible to therapists. Finally a hybrid sensor solution for full hand and finger tracking was described, extending our visualization platform into a three dimensional virtual environment. This platform enables the development of enriched, stimulating environment through the addition of interactive 3D models and could be used as a foundation for the development of interactive therapy programs.

The author believes that such systems will play an active role in the future of healthcare, enhancing unsupervised forms of therapy through immersive interactive applications. Initial testing with healthy subjects was positive, finding the systems here easy to use, engaging and stimulating. However, much further work is required towards investigating the practical therapeutic benefits of such devices. Future work will involve conducting a pilot study with chronic stroke patients to investigate the potential of these approaches for healthcare applications.

Chapter 5

Developing Strategies for Automating Movement Therapy

Post stroke patients require continuous medical care and intensive rehabilitation often requiring one-on-one manual interaction with the physical therapist. Unfortunately, present demands and budget restrictions do not allow this intensive rehabilitation. Hence, there is an urge for new technologies improving the efficacy and effectiveness of post stroke rehabilitation. Thus robotic therapy might represent a successful and standard complement for post stroke multidisciplinary rehabilitation programs.

Robotic devices for rehabilitation are already starting to play a pivotal role in the evolution of healthcare practise for stroke. Robot assisted therapy presents the potential to deliver, highly structured, repetitive rehabilitation in a cost effective manner, reducing the burden on healthcare services and alleviating the dependency on healthcare specialists. However, the major drawback over manual rehabilitation is the loss of human insight and intuition which is used by the therapist to regulate how and when assistance is offered to a patient. For example, an experienced therapist will very quickly notice when a patient is making less effort to engage during periods of assistance. In such cases the therapist may reduce the amount of assistance they offer in order to coax more effort from the patient. This is an example of a strategy adopted by the therapist based on their experience of the patient's behaviour. In the same situation, a robotic controller lacking the therapist's insight might instead increase the level of assistance to such a patient in a naïve attempt to provide assistance. Subsequently, although there is great potential in the application of robotics for healthcare, such devices are currently struggling to deliver significantly functional improvement over conventional therapy in clinical trails [52, 195, 217] and in some cases have even been shown to reduce the effectiveness of training.

Designing suitable robotic controllers for automating movement-based rehabilitation therapy requires a better understanding of the interaction dynamics between patient and therapist. Current control approaches ignore the complexity which drives a patient's actions, their motivation and behaviour in response to their therapist's assistance and therefore are not sufficient for administering optimized therapy. We feel that a better understanding can be accomplished through framing the interaction as a problem in game theory.

Accordingly, the focus of this Chapter is to investigate the potential application of agent based modelling and game theory, for the design and analysis of patient/therapist interaction dynamics, with a view to designing more sophisticated control strategies. We demonstrate in a simplified implementation the effectiveness of this approach through simulating known behavioural patterns observed in real patient-therapist interactions.

5.1 Motivation

As expounded in previous Chapters, the efficacy of a motor intervention program post stroke depends heavily on its onset, duration, intensity and task-orientation. Treatment of motor defects after stroke is subsequently labour intensive, requiring extensive one-to-one training with a physical therapist. Such requirements put great stress on the physical therapist, consuming much of their time and limiting their ability to engage multiple patients. Consequently, these restrictions place limitations on the capacity of stroke care units, reducing the availability of rehabilitation services [236]. In addition and due to economic costs, the average duration of primary rehabilitation is getting shorter, as healthcare providers struggle to cope with the rising incident of stroke and subsequent need for rehabilitation services [49]. Subsequently healthcare providers are actively seeking means to alleviate the burden on hard-pressed physical therapist staff, in an attempt to cut costs and to improve the efficacy of treatment.

Given the repetitive nature of physiotherapy after stroke, there is both a need and an opportunity to deploy technologies such as robotics in an attempt to automate aspects of the rehabilitation process. While initially prohibitively expensive, over the past two decades there has been a revolution in technological innovation which has made the cost of developing such devices feasible. Subsequently, research into rehabilitation robotics has grown rapidly and many promising applications for automating movement rehabilitation having since emerged, see Chapter 3 for literature review of robotics devices for stroke.

The majority of this research has focused on developing more sophisticated, multi degrees of freedom robotic end effectors, in order to support more complicated movements, such as multi-joint arm and hand movements [67, 146, 209, 249, 294, 353, 367, 402]. In contrast, less effort has been focused on the development of more effective control strategies which specify how such devices interact with participants. This is partially because there is are concrete guidelines for how best to control such devices in such a way as to provoke plasticity and thereby maximise recovery outcomes. Therefore, current control approaches are designed on an ad hoc basis, usually drawing on concepts from rehabilitation, neuroscience and motor learning literature [226].

As a result, clinical trials with robotic devices have had mixed results and there is subsequently no significant evidence to suggest training with a robotic device in patients with chronic stroke is superior to conventional physiotherapy. A recent comprehensive survey comparing 120 robotic devices for upper limb rehabilitation sums up this consensus, remarking that there is still significant need to improve the effectiveness and reduce the cost of home-based devices for therapy and ADLs assistance [221]. These findings suggest that the current control strategies used to administer the level of assistance provided during robot movement therapy are sub-optimal. The issue of cost will be addressed in a later chapter in this thesis. The current chapter focuses on concepts related to the higher level control of the robotic assistance delivered in order to better understand how more effective therapy may be delivered.

5.2 Background

Therapeutic robots further the therapist's goal of facilitating recovery not only by delivering measured therapy but also by affording new ways to evaluate patients' progress. Robotic devices can help assist movement programs in a number of circumstances. They can assist in **active** movements, where a patient has some ability to move but not enough to complete a movement task independently. This scenario is very common during the acute and sub-acute phases of recovery after stroke, when a patient is just starting to regain some movement of their affected limb. Robotic devices can also assist with **passive** movement, such as movement which helps to increase range of motion and improve flexibility.

5.3 Conventional Control Strategies

The goal of any robotic control system, regardless of its control strategy is to augment the practise of therapeutic exercises in a way which provokes motor plasticity and therefore improves recovery. There have been a number of different active assistive control strategies developed over the last two decades, of which can be broadly group into four categories; assistive, challenge-based, haptic simulation and non-contact coaching [226]. An assistive controller can help participants to move their weakened limbs in desired patterns. For the upper extremity this involves assisting with motions involved in grasping and reaching, using an approach similar to the "active assist" strategy utilised by a rehabilitation therapist. An assistive controller effectively reduces the difficulty of a movement task. In contrast, the challenge-based controller can be thought of as the opposite to an assistive controller, in that it opposes motion, making them more difficult or challenging. The third controller paradigm, Haptic simulation, refers to the practise of functional movements in a virtual environment and is often used in patients with chronic stroke who have some movement control over their limb, to encourage practise of therapeutic exercise in the home setting. Finally, non-contact training is a paradigm in which there is no physical assistance provided to aid in completing a movement task. Instead the robot coaches the patient, helping to maintain motivation and to guide the execution of the therapy task. The most developed of these robotic control approaches is the assistive controller as it most closely resembles the strategy used by physical therapists during conventional movement rehabilitation and is therefore the focus of the work described here.

5.3.1 Assistive Controller

There are many reasons why the assistive controller has remained the dominant control strategy used in rehabilitation. The active assist strategy promotes both passive range of motion (PROM) and active assist range of motion (AAROM). PROM occurs when an external device or therapist moves the joints through the range of motion with no effort from the patient. Many people who lose the use of their arm and hand after a stroke experience spasticity, uncontrollable muscle tightness, and stiffness, which make movement difficult, stretching helps to reduce joint stiffness and to reduce spasticity [364]. AAROM occurs when the patient uses the muscles surrounding the joint to perform the exercise but requires some help from the therapist or robotic othesis to complete the movement. Another motivation is that moving the limb in a way which the participant cannot without assistance might provide novel somatosensory stimulation which helps provoke plasticity [296] and that providing an example of the desired movement pattern might help the participant to learn it.

Assistive control strategies typically follow a simple control paradigm. When a participants movement is along a desired trajectory the robot should not intervene, however, if the participant deviates from the desired trajectory then the robot should create a restoring force which guides the participant back onto the desired trajectory. For robotic assisted movement training this restoring force is typically generated using some appropriately designed mechanical impedance.

5.3.2 Impedance-based Assistance

Impedance control was first proposed by Hogan [144] and is an approach to control the dynamic interaction between a manipulator and its environment. Impedance assistance is achieved by changing the relationship between the input and output of a system, for example, between force and position, or velocity and acceleration. The MIT Manus (upper extremity) and Lokomat (lower extremity), two of the first therapeutic robotic assistive devices used in clinical trails post stroke both employed a combination of impedance and proportional feedback control to guide movement along a fixed trajectory [146, 191]. Since then many other robotic therapy devices have been built, a survey by [221] reviews 120 devices for the upper extremity alone, taking into account only those devices which support or retrain movement of disabled individuals. While much advancement has been made, the focus of which is mainly directed at improving the range of motion and degrees of freedom of the end manipulator, in addition to reducing the overall costs of such systems. In contrast, little effort has been made to improve upon the original control strategy utilised by their predecessors and subsequently most robotic therapy devices [9, 192, 209, 215, 216, 249, 401], rely on an impedance based proportional feedback controller or a variation of it for position feedback control.

5.3.3 Proportional Controller

The proportional or P-controller is the most basic form of the position feedback controller. The p-controller attempts to decrease the steady state error of a system by feeding back an error signal, which is the difference between the controllers current output and some desired value. This error signal is then used to adjust the next output state of the system, see Figure 5.1.

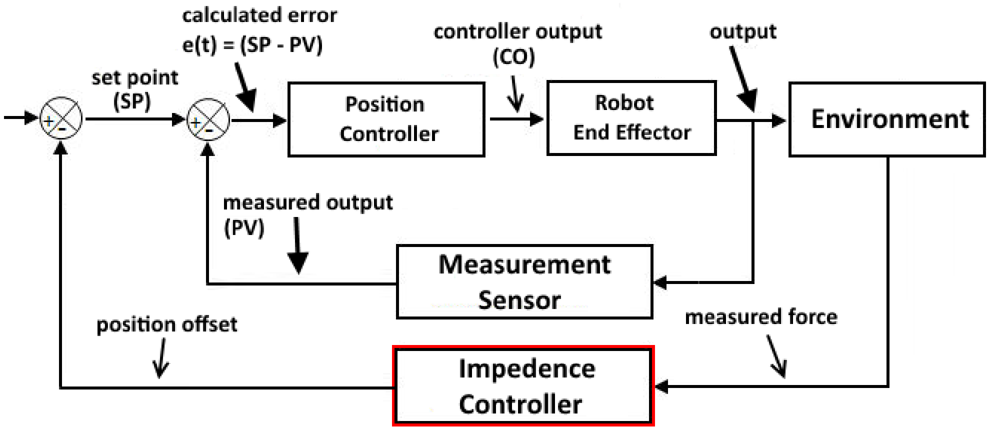

FIGURE 5.1: Proportional Position Controller.

The output of the controller P_{out} can be mathematically expressed as 5.1,

$$\begin{aligned} P_{out} &= K \times e(t) + c0 \\ e(t) &= SP - PV \end{aligned} \tag{5.1}$$

where:

K = proportional gain
e(t) = instantaneous process error at time t
c0 = controller output with zero error
SP = set point
PV = process variable

In practise more advanced variations of this controller are often used which increase the complexity of the underlying algorithm to better estimate the resulting error. Depending on the application and required control, two additional parameters are typically added to the standard proportional controller, the integral (I) and derivative (D) values, resulting in the well known and widely used PID controller.

Controllers based on this approach deliver a form of "assistance as needed" (AAN), since the restoration force generated is proportional to the intermediate error with respect to some desired trajectory. If the error is very large, the resulting restoring force will also be large, whereas if the error is small then the restoring force will also be small.

5.3.4 Assist as Needed Paradigm

The assist as needed hypothesis can be summed up as follows; contributing excessive assistance will cause the patient to decrease motor output, with negative consequence for use-dependent neuroplasticity. In contrast, not providing enough assistance might curtail the patient's range of motion, reduce the number of executed movement repetitions, and in some cases make the movement task impossible to accomplish, resulting in frustration and decreased motivation.

The basic principles of the AAN controller is to promote learning through constantly challenging the spinal cord and motor circuits by introducing uncertainty and variability into the training patterns. To achieve this, strong feedback or assistance is given when the subject's performance is far outside the nominal pattern, however as they get closer to the desired trajectory, gentler guidance is given, thereby allowing the subject to guide their own motions when doing well. In this way, a reasonable amount of variability is experienced during training as would be naturally experienced in normal movement.

Many approaches have thus been demonstrated which attempt to promote increased variability during movement practise. One such approach is to include a dead-band in the impedance control scheme which allows for some variations without evoking increased assistance from the robotic device [303]. Another variant on the basic impedance approach is to use some trigger to activate assistance. The intention here is to promote self-initiated movement, after which assistance is offered if some performance threshold is reached. Many different trigger variables have been proposed including; elapsed time [62, 209], force generated [9], trajectory error [175], velocity [192] and muscle activity [145, 294].

A comparison study of the efficacy of fixed trajectory algorithms against AAN algorithms on recovery of locomotion ability in completely spinalized adult mice by Cai et al. [42, 43] showed that mice who received AAN training showed higher levels of recovery than those which received a fixed training trajectory control strategy.

5.4 Persistence of Motor Adaptation

Motor adaptation is a form of motor learning, described as a process of acquiring and restoring movement skills. Motor adaptation can be thought of as the process by which the nervous system learns to anticipate novel environmental forces in an attempt to eliminate kinematic error. For example, motor adaptation plays an important role in learning to swing a new tennis racket or learning to walk in high heels. While an integral component of the motor system without which we could not possibly function in a dynamic world, motor adaptation poses complications for developing assistive robotic devices for movement rehabilitation. There are two key problems caused by components of the adaptation process which reduce the effectiveness of assistive robotics, referred to as the guidance hypothesis [326] and the slacking hypothesis [98].

5.4.1 The Guidance Hypothesis

Originally suggested by Annett [15], the guidance hypothesis states that; assisting movement changes the inherent dynamics of the underlying task and therefore what is learnt is not the intended task itself [326]. Schmidt et al. suggest that although guidance can be beneficial in reducing error during a movement, if relied upon heavily it may be detrimental for motor learning [325]. In order to promote neural plastic change which may facilitate repair and reorganisation of the motor circuit, the brain needs to actively plan, generate and execute motor commands. This process can be facilitated by assisting with the targeted movement, for example by supporting the arm and reducing its weight, or by gently guiding the movement trajectory. However, simply moving the paretic arm passively will have little or no therapeutic value as there is no associated neural drive with the movement. Therefore, robotic systems which passively guide movement along a fixed path might be suboptimal for therapeutic applications as they abolish variability which is an intrinsic property of neuromuscular control [170]. A significant concern is that too much guidance may force the central nervous system into a state of "learned helplessness" [405] since the neural systems are not being challenged to explore alternative motor patterns on their own accord. Cai et al. suggest that fixed trajectory training might cause an extensive level of habituation to sensory inputs such that there is eventually little or no response to the sensory inputs imposed by the robotic training device and therefore little or no motor output generated [44].

In support of the guidance hypothesis, recent studies have highlighted that passive guidance from a robot reduces the effectiveness of training [61, 193, 292].

5.4.2 The Slacking Hypothesis

Recent experimental evidence suggests that a fundamental property of the human motor system is that it "slacks"; that is, that it continuously attempts to decrease levels of muscle activation when movement error is small during repetitive motions [98, 302, 322]. For therapeutic applications of robotics, the implications of slacking are that it may reduce effort during movement training, with negative consequences for use-dependent motor recovery. For example, a study in people with incomplete spinal cord injury who walked with the assistance of a gait training robot consumed 60% less energy than in conventional manually-assisted therapy [161]. Similarly, chronic stroke patients who trained with an adaptively controlled assisitive robot gradually reduced their output, letting the robot take over a reaching task [402]. These actions are counter productive since the robot is taking more of the rehabilitation burden from the patient who can complete the task with less effort than they have the ability to offer. In such cases the patient is no longer contributing maximum effort and the resulting therapy will not be as efficacious.

5.4.3 Discussion

The major drawback to an automated rehabilitation approach is the loss of human insight and intuition afforded by the therapist to regulate how and when assistance is offered to the patient. Current control system approaches do not take into account the highly dynamic and interdependent nature of the relationship which exists between a patient and their therapist. For example, an experienced therapist will very quickly notice when a patient is making less effort to engage during periods of assistance. In such cases the therapist may reduce the amount of assistance they offer in order to coax more effort from the patient. This is an example of a strategy adopted by the therapist based on their experience of the patient's behaviour. In the same situation, a robotic controller lacking the therapist's experience might increase the level of assistance to such a patient in a naive attempt to provide assistance. This situation highlights one of the major concerns for using a triggered assistance approach, that is that after achieving the required threshold to activate assistance, a patient might then essentially "piggy back" on the robot who will complete the task for them.

Developing better models which describe both patient and therapist behaviour might help in designing more sophisticated controllers for automating therapist movement rehabilitation. Expanding on this idea, a novel approach to developing a dynamic control system for rehabilitation might be achieved through framing the interaction between patient and therapist as a problem in Game Theory.

5.5 Game Theory

Game theory was first proposed by John Von Neumann and Oskar Morgenstern [263, 383]. Game Theory is a branch of mathematical analysis developed to study social decision making in situations of competition and conflict. Typically a game consists of a set of rules which govern a situation in which two or more competitive participants (players) choose strategies designed to maximize their own winnings or to minimize their opponent's winnings. In such a game, the outcome of a players choice of action depends critically on the actions of others, see Figure 5.2 [1]

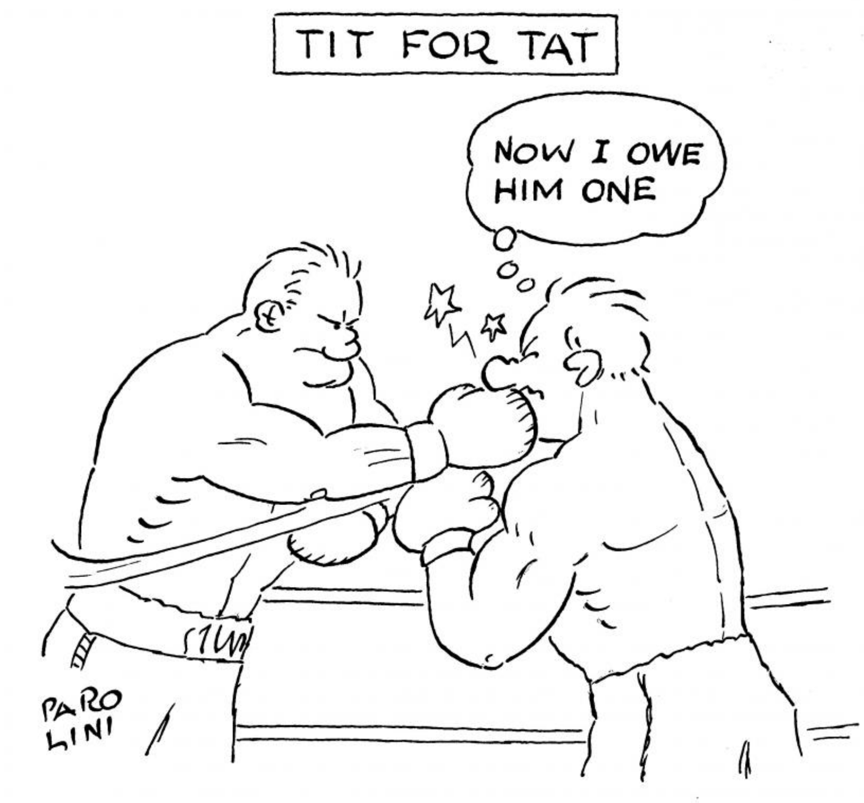

FIGURE 5.2: Boxing metaphor illustration of game theoretic principles of how a players choice of action depends critically on the action of others.

The payoff is the outcome of a move resulting from the actions or strategies taken by players. When played iteratively, participants can go through the adoption of strategies derived from the players model of their opponent to achieve improved pay-off over time [56],[306]. A strategy should not be confused with a player's move. A move is an action taken each round by a player, for example; playing a card, picking up a coin, or moving a chess piece. A pure strategy is therefore a complete set of rules or an algorithm which

[1] Source: tit-for-tat.jpg, id:20902799 licensed under Jantoo licence agreement.

dictates a players move for every possible situation throughout the game. A player's strategy set defines what strategies are available for them to play. In contrast to pure strategies, a player may also play a mixed strategy. A mixed strategy consists of possible moves and a probability distribution (collection of weights) which corresponds to how frequently each move is to be played. A mixed strategy approach can be useful when a player is faced with a situation in which there is no obvious benefit from playing any of their pure strategies, however they want to add uncertainty to their move so their opponent cannot predict it. In essence, a mixed strategy allows a player to randomly select a pure strategy to play, instead of playing deterministically.

Games analysed using a game theoretic approach can be divided into two main branches: cooperative and non-cooperative games.

5.5.1 Non-cooperative (zero-sum) Games

In their original work, Von Neumann and Morgenstern restricted their attention to zero-sum games, that is, games in which one player can only gain from another players loss. In such games, if the total gains and losses of all participants are summed up they will sum to zero. For this reason, a zero-sum game can be considered a strictly competitive game also known as a non-cooperative game, since players cannot work together in order to maximise both their pay-offs simultaneously. A simple game called "Matching Pennies" will be used to illustrate a zero-sum game.

The game involves two players, Player A and Player B. Each player starts off with an identical number of pennies. The rules of the game are that on each round players must simultaneously place a penny on the table. The payoff for each player depends on whether the pennies match or not. If the pennies do match, i.e. they are both heads or both tails then Player A wins. On the other hand, if the pennies do not match, Player B wins. The winner of each round gets to keep the other players penny and the game is over whenever one player has won all of the pennies. The payoffs for Players A and B are shown in Table 5.1.

Table 5.1: Payoff table for a game of Matching Pennies

(A,B)	Heads	Tails
Heads	(+1,-1)	(-1,+1)
Tails	(-1,+1)	(+1,-1)

The optimum solution to this game is not obvious as it appears that this game does not have a unique solution. The minimum and maximum pay-offs for each of the two strategies is the same, i.e. 1 and -1. There are two obvious pure strategies, either to play heads, or tails. However, doing so allows the opponent to simply play the counter strategy which maximises their pay-off. For example, if Player A always plays heads then Player B can maximise their pay-off by always playing tails. However, in the case of such a game, a more optimum solution exists by playing a mixed strategy, that is, a player can "randomize" their strategy by offering either a head or a tail, at random. Therefore, the game of matching pennies has a solution in mixed strategies, and it is to offer heads or tails at random with probabilities 0.5 each way.

5.5.2 Cooperative (non-zero-sum) Games

In contrast, a non-zero-sum game is a game in which players can gain without incurring a loss from their opponent. The distinction between cooperative and non-cooperative games was first clarified mathematically by John F. Nash [258]. Unlike cooperative games, in non-cooperative games there is no central authority which assures players conform to the predetermined rules, therefore while players can cooperate, any cooperation must be self-enforced. A classic example of cooperative game is illustrated in the "Prisoners dilemma" example [255].

Lets pretend two people, Mr. Blue and Mr. Red have been arrested for a minor crime. The authorities believe they may have committed a much larger offence, however they do not have any evidence to convict them. Instead they need a confession implicating the perpetrators in order to sentence them. The two detainees are put into separate holding cells so they can't talk and the police play a game. To try and force a confession they are given a choice. Admit your partner committed the crime and you will be pardoned but your partner will serve 3 years in prison. However, if you stay silent and your partner implicates you, you will serve the 3 years and your partner will be set free.

Now the detainees know that the police do not have any evidence and if they both stay silent that they will only go to prison for 1 year each, for the minor crime committed. However, if they both implicate each other then they will both have to serve a reduced sentence of 2 years each.

Given this information the players have two options, they can stay silent (cooperate) or betray (deflect). We can also develop a pay-off table for each player 5.2.

In terms of strategy, the players should co-operate since this is the best option for the group as a whole. By staying silent both players would therefore serve 1 year in prison. However, taking this game from Mr. Red's perspective, if he thinks Mr. Blue

Table 5.2: Pay-off table for a prisoners dilemma game

(Mr.Blue,Mr.Red)	Defect	Cooperate
Defect	(2,2)	(0,3)
Cooperate	(3,0)	(1,1)

might stay silent then he could maximise on the payoff by betraying him. On the other hand if Mr. Red thinks that Mr. Blue might attempt to betray him then he should also betray, since 2 years in prison is better than 3. Turning the tables on this perspective, Mr Blue is in the exact same situation.

It now becomes clear that they should both co-operate, however from an individual stand point they notice that if they betray, there is both a chance to minimise the potential damage that could be caused by the other player while also having a chance of getting off completely free. Since they have no control over each other actions, both players will defect to try better there own situation, hurting both themselves and the group. In this case this strategy is known as the dominant strategy, since it is the best strategy a player can play, no matter what other players might do. If each player has chosen a strategy and no player can benefit by changing strategies while the other players keep theirs unchanged, then the current set of strategy choices and the corresponding payoffs constitutes a Nash equilibrium.

Although this situation is contrived for the purpose of illustrating a non-zero-sum game, it does have practical applications in the real world [7, 41, 371].

5.5.3 Repeated Games

So far the games which have been explored have been games which are played once, known as stage games. However, things start to get more interesting when players play multiple iterations of a game, known as a repeated game, iterated game or super game. In an iterated game, players need to take into account the impact that their current action might have on future actions of other players. This characteristic of a player is often called the players reputation.

As opposed to one-shot games, repeated games introduce a new series of incentives: the possibility of cooperating means that we may decide to compromise in order to carry on receiving a payoff over time, knowing that if we do not uphold our end of the deal, our opponent may decide not to either. Our offer of cooperation or our threat to cease cooperation has to be credible in order for our opponent to uphold their end of the bargain. Working out whether credibility is merited simply involves working out what weighs more: the payoff we stand to gain if we break our pact at any given moment and gain an exceptional, one off payoff, or continued cooperation with lower payoffs which may or may not add up to more over a given time. Therefore, each player must consider their opponent's possible punishment strategies.

This means that the strategy space is greater than in any regular simultaneous or sequential game. Each player will determine their strategies or moves taking into account all previous moves up until that moment. Also, since each player will take into account this information, they will play the game based on the behaviour of the opponent, and therefore must consider also possible changes in the behaviour of the latter when making choices.

5.6 Agent Based Modelling

Agent-based modelling and simulation (ABMS) is a relatively new approach used to model complex systems composed of interacting "agents" (human or otherwise). These agents are often described by simple rules and behaviour for interacting with other agents and completing tasks. The main strength behind this approach is the principle of self-organization. Agents learn from their experiences, and adapt their behaviours so that they are better suited to their environment. As the models evolve, structures, patterns and behaviours can emerge that were not explicitly programmed into the original models, but instead surface through the agent interactions with each other and their environment [218]. An agent-based model (ABM) is one of a class of computational models for simulating the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) with a view to assessing their effects on the system as a whole.

A typical agent-based model is made up of three components:

1. A set of agents, their attributes and behaviours.
2. A set of agent relationships and methods for how to interact.
3. An environment 'i.e. a game'.

Agent-based modelling has been applied exhaustively in both the social sciences (economics, management, political and social psychology) and the formal sciences (computer science, biology, physics and statistics). This approach of modelling has proven to be useful for modelling phenomena which are not easily modelled by other approaches

[223]. The applications of agent based modelling are plentiful, ranging from modelling the stock market [104] to networking engineering (P2P file share) and predicting the spread of epidemics [412]. The interaction between a therapist and patient is clearly then a problem for which an agent based approach is well suited as the individual interacting elements are clearly non-linear decision making entities whose behaviour arises out of a complex series of interactions. These interactions are driven by a range of motivations, desires, beliefs and intentions which are difficult to quantify and simulate through any other means.

5.7 Modelling Patient-Therapist Interactions

The interaction between a therapist and patient is clearly then a problem for which a combination of an agent based approach and game theory are well suited, as the individual interacting elements are clearly non-linear decision making entities whose behaviour arises out of a complex series of interactions. These interactions are driven by a range of motivations, desires, beliefs and intentions which are difficult to quantify and simulate through any other means. Consequently we feel the approach will be of utility here and merits investigation, as so far as the authors are aware, the methods of agent based modelling or Game theory have not been previously applied to the design of automated controller systems for neuro-rehabilitation.

In this section we apply the ideas of the previous sections through very simple models of patient motivation and behaviour. Simple as the formulations are they demonstrate significant exploratory and explanatory power through the production of plausible patterns of behaviour in patient-therapist (therapist/agent/controller) interaction.

5.7.1 The Game

The interaction between a patient and their therapist can be considered as an instance of a competitive game in which the patient is seeking maximum success at the rehabilitation task but with minimal energy expenditure. The therapist on the other hand wishes to seek the patient deploy maximum effort or expenditure of energy during the rehabilitation tasks. However it is not obvious from the therapist's viewpoint how much effort the patient possesses and how much of it they are expending on a trial by trial basis. Consequently the therapist must balance giving assistance to complete the task and therefore maintain motivation with the need to engage the patient as fully as possible with the task. We start by defining each player's desires, objectives and outcomes according to a basic mathematical formulation.

5.7.2 The Patient Model

The patient's primary input to the game is the effort they exhibit during a therapy session. We called this parameter Ep (Patient Effort). Patient effort could be measured through energy exerted, force applied, measures of central nervous system activity etc. – the details of the physical measurement is not important at this stage as only an abstraction of the interaction is examined in this work. We also assume that the patient desires to recover the use of their effected limb, hence their objective is to successfully complete each motor task they are assigned, to the best of their ability. We can model this objective mathematically, see Equation (5.2).

The patient desires to maximize G where,

$$G = \sum_{i=1}^{N} T_i \tag{5.2}$$

where:

T = Task completion status: $T_i \epsilon$ [0,1].
N = Number of trails in therapy session.

In this case $T_i \epsilon$ [0,1] where 0 represents the task has not progressed at all and 1 represents the task is complete. For example, perhaps the task is to move a weight from one position to another. In such a case, patient effort might be measured in cm of movement that the patient generates (similarly for robotic effort) and therefore T can represent how far the patient movement task has progressed. In such a case $T = 1$ would correspond to the weight being successfully moved to the target position.

One could consider this desire to maximize G as reflecting the patient's motivation through gratification. Clearly this is something which could be experimented with in exploratory scenarios. We also need some measurement of the patient's recovery. A reasonable assumption would be that we can gauge the recovery of the patient based on the amount of effort Ep they offered during the complete set of rehabilitation therapy sessions. We can therefore say that a measure of the patient recovery is given by,

$$R = \sum_{i=1}^{N} E_p(i) \tag{5.3}$$

where:

Ep = Patient effort during i_{th} interval
N = Number of trials in therapy session.

5.7.3 The Therapist Model

The therapist's primary input to the game is the effort they offer to the patient in order to complete a task. We called this parameter E_r (Robot Effort). In a motor rehabilitation task this robotic effort could as in the therapist example be a physical measurement such as force applied, however as previously stated the details are not important in this example. The simplified formulation of the therapist's motivation is to assist the patient in completing a motor task. In the ideal situation the therapist desires to offer effort E_r described by equation 5.4,

$$E_r = [E_n - E_p] \tag{5.4}$$

where:

E_n = Effort needed to complete task
E_p = Effort offered by patient

Now that we have defined the preliminary models for our patient and therapist we can focus on designing a model of the interaction. The structure of this 'game' will determine how the agents interact with each other and will affect the behavioural patterns that emerge. In the following section we develop three different behavioural models for our robot therapist and describe the 'game' dynamics of each simulation which will control the agent's interactions.

5.7.4 Simulations

Our preliminary model defined above, which is admittedly very basic, can be used to demonstrate plausible patterns observed in real patient-therapist interactions. In this section we illustrate this by simulating interesting interactions between patient and therapist. We start by simulating a scenario in which learned dependency occurs; this simulation is of significant interest as its occurrence is quite common in rehabilitation therapy. However, we then proceed to show how through experimenting with alternative robotic agent (the model therapist) behaviour we can predict and limit its occurrence, thus optimizing the resulting recovery rate.

5.7.4.1 Simulation 1: Learned Dependency

In this instance we model the patient as being 'lazy', desiring to offer the minimal effort possible to complete a task. To simulate this effect we program the patients to offer less and less motor effort each turn so long as the task is cooperatively completed, see equation 5.5.

$$E_p(i) = [E_p(i-1) + \Delta E] \tag{5.5}$$

$$\Delta E = \begin{cases} +0.1, & \text{if T(i) = 0} \\ -0.1, & \text{if T(i) = 1} \end{cases}$$

Note: The values chosen for ΔE are arbitrary and only serve to reflect some change in the patient's effort.

We model the therapist in this instance (a naïve robotic actuator providing effort E_r) as a player who will always provide the additional assistance required to complete the task, see Equation 5.6.

$$E_r(i) = [E_n(i) - E_p(i)] \tag{5.6}$$

where:

En = Effort needed to complete task
Ep = Effort offered by patient

We then model the interaction through a round based game with N=100.

Given the rules as designed, it is clear that after several iterations the patient will offer almost no effort and yet still 'successfully' complete the rehabilitation task thanks to the additional effort offered by the 'over helpful' therapist. This can be observed in Figure 5.3. It is interesting to note that, whereas the patient received constant gratification of 'successfully' completing each motor task, their recovery R as defined as the sum of the patient efforts (area under the curve) is low. This result is as we would expect in the case of learned dependency.

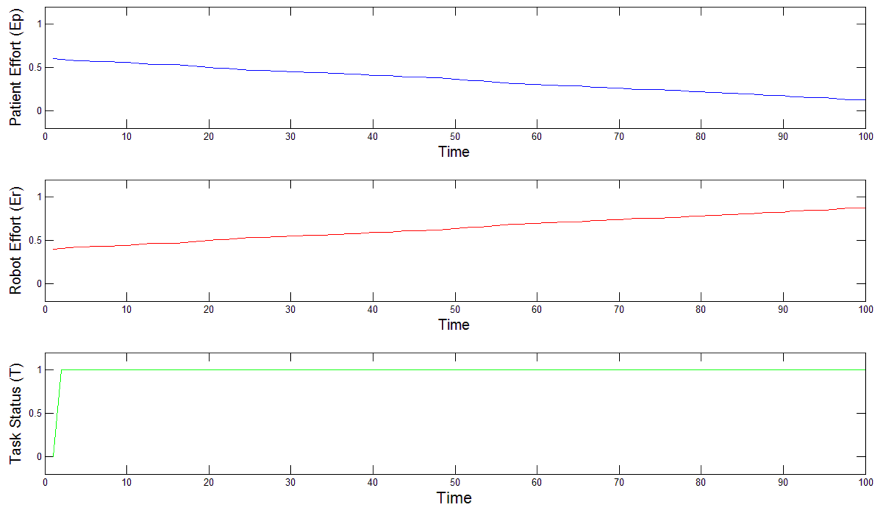

FIGURE 5.3: Learned Dependency

Now that we have observed a plausible behaviour we can experiment with developing alternative robot behaviour so as to reduce the likelihood of this occurrence through basing the robot's behaviour on its experiences of previous patient effort.

5.7.4.2 Simulation 2: Erratic therapist

The following simulations purpose is to explore how the patient will react to random bursts of no assistance while they are falling into the pattern of learned dependency. Instead of always assisting the patient to complete a task regardless of their input effort, we instead modify the robot to naïvely assist the patient only for the first half of our session. Then for the second half of the session we get the robot to randomly stop offering assistance to the patient for short periods of time. For this example, the moment of no assist will be chosen by generating a random number.

$$E_r = \begin{cases} E_n - E_p, & \text{if } x < 6 \\ 0, & \text{otherwise} \end{cases}$$

The results of this simulation are interesting as they still show the effect of learned dependency; however its occurrence is less severe and takes longer to manifest. This can be observed in Figure 5.4, since the gradient of the curve Ep is less linear than in Figure 5.3. We can clearly see the patient effort level Ep declining up until the halfway point (while the robot is still mindlessly assisting the patient). Then, as the robot behavior switches to randomly offer no assistance we see a drop in the task completion status. Consequently, as the patient loses the gratification of completing their task they react by starting to increase their effort levels again. Whereas this is a very simple simulation, it accurately replicates a plausible patient reaction. We can see that the recovery rate R of the patient under this robotic therapist model is higher than that in the previous model, since the patient was encouraged to offer more effort. In simulation 3 we take this model and try to advance it to show how we can effectively reduce learned dependency even further and regain positive efforts from our patient.

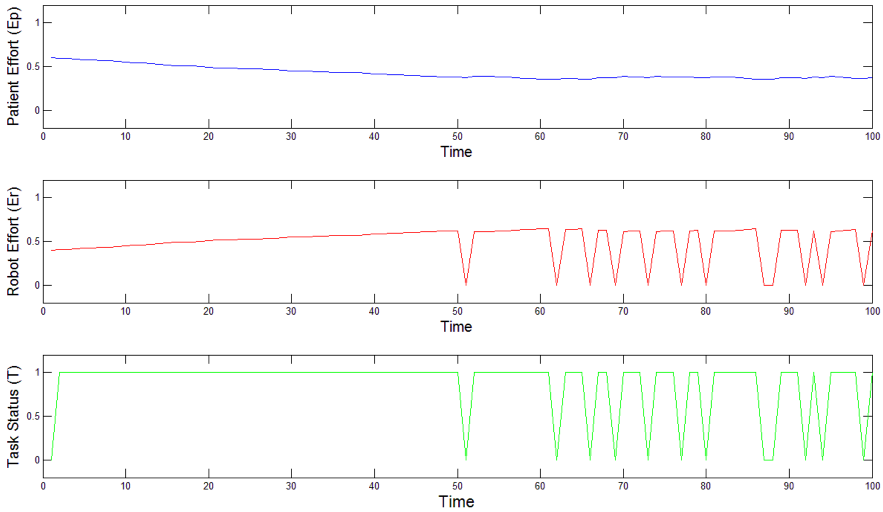

FIGURE 5.4: Learned Dependency

5.7.4.3 Simulation 3: Replicating Therapist Coaxing Effect

In this simulation we show how it is possible to replicate a desired behaviour which an experienced therapist might employ during periods of assistance when they realize a patient is no longer contributing sufficient effort to complete a task. We call this strategy 'effort coaxing'. To achieve this we take a similar approach as in simulation 2. However, this time instead of randomly reducing the robot's assistance to zero for short periods of time, we instead reduce the amount of assistance it offers by some small amount. We then hold this value constant for a random period of time, for example 10 trials.

$$E_r = \begin{cases} E_n - E_p, & \text{if } x < 6 \\ E_n - E_p - \Delta E, & \text{otherwise} \end{cases}$$

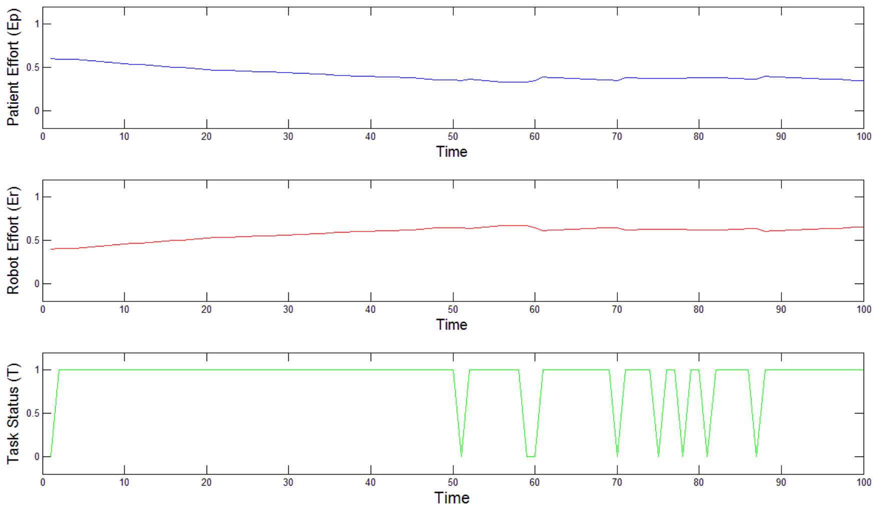

FIGURE 5.5: Simulation 3 results.

Figure 5.5 clearly shows the patient effort levels responding to the periods of lack of assistance. At these moment the patient loses gratification i.e. $T(i) = 0$, and therefore starts to increase their effort until they rebalance the completion status $T(i) = 1$. Since the assistance level is being held constant this coaxes the patient to keep increasing their effort until they match the effort need to complete the task. This effect can be observed as the slight rises in the plot of patient's effort. We can also observe a rise in the patient's recovery R, as would be expected in a real therapy session.

To compare the three therapist behavioural models developed above, we simulated 10 therapy sessions consisting of 100 iterations for each of the control strategies. We then computed the average recovery rate R as per Equation (5.3), for each of the models. The results of this experiment are described in Table 5.3. It should be noted that we are using the same patient model for each of the simulations and that only the therapist model has been modified between simulations. Therefore, we can simply examine the magnitude of the recovery R of the patient to determine how biasing the robots behaviour affected the patient's recovery.

TABLE 5.3: Statistical analysis of simulation results

	Simulation 1	**Simulation 2**	**Simulation 3**
Recovery (R)	33.82%	35.90%	38.68%
(R / Max Patient Effort)	56.36%	59.82%	64.46%

At first glance the difference between the patient's recovery rate R of the models might seem non-substantial. To better appreciate these results we need to examine the percentage difference of patient effort between the simulations. For example, there is approximately an 8 percentage point increase in patient effort between simulation 1 and simulation 3.

5.8 Discussion

A key objective of this Chapter is to investigate if agent-based models are a suitable approach for developing conceptual models of the interactions between a patient and their therapist with a view to improving the design of robotic assistance devices for automated therapy. As an illustration of this approach we have developed a simple model which demonstrates behaviour which could be described as 'learned dependency' – a phenomenon observed in real patient-therapist interaction. We have shown that it is possible to capture interesting patient-therapist dynamics with respect to patient effort through such simulations. We further show how through minor adaptation of the therapist agent we can alter the interaction elicited from the patient agent in a way that is commensurate with observed real patient responses. The results of this simulation show how appropriate interaction strategies for the therapist can reduce the manifestation of suboptimal interactions such as learned dependency and as a result increase the efficiency of the resulting therapy session (in this abstraction). Finally we demonstrate how such simple models can be further adapted to replicate a desired behaviour used by an experienced therapist to coax more effort out of their patient. Our results clearly indicate an increase in patient effort during this simulation. Whereas these simulations are admittedly simplistic, they serve to prove the potential of using an agent based modelling approach in replicating some of the phenomena observed in real patient-therapist dynamics.

The work described in this chapter is purely conceptual and is not intended to be put into practise in its current form. Instead, this work is an exercise in creative thinking, of aspiring to approach a well recognised problem from a distinct and innovate perspective. The author believes that an approach such as that described here has great potential merit and which might be put into practise to improve the current state of high-level control of therapeutic rehabilitation devices. It is hoped that the ideas described here will help promote and inform future work beyond this thesis, towards the development of more sophisticated control systems for assistive technology.

Chapter 6

Extrinsic Feedback for Automatic Rehabilitation Systems

Traditionally rehabilitation is managed, coordinated and facilitated by professional healthcare specialists. However, due to the increasing number of stroke survivors and the subsequent demand on healthcare systems, researchers are actively creating new technologies in the hope of enhancing and scaling conventional forms of therapy. The previous chapter described efforts already under way to enhance rehabilitation in the sub-acute stage of recovery after stroke, in which the physical therapist plays an active role in assisting with movement. In this chapter effort is made towards developing approaches to support the chronic stage of recovery, in which patients actively practise movement exercises independently, with no physical intervention from a therapist.

At this stage of recovery, it is common for the patient to only see a therapist once a week, if at all, and instead responsibility shifts towards the patient to continue their prescribed exercise routines independently. While patients can still make significant gains in the chronic stage of rehabilitation [228], emerging reports suggest that adherence to physiotherapy in home programs is a major problem with up to 65% of patients being either non-adherent or partially adherent, and with approximately 10% of patients failing to complete their prescribed course of physiotherapy [25, 164, 370]. As a result, recovery in the chronic stage often plateaus prematurely, not because of an inherent biological limit of plasticity but instead because of a reduction in voluntary motor activity [359].

An obvious innovation then is the development of automatic rehabilitation systems for the home setting which can be used to both monitor (and therefore measure compliance) and encourage patient engagement in therapy by providing feedback. Subsequently we would like to develop a form of “virtual therapist” which could help passively assist in the rehabilitation process by delivering concurrent feedback on performance during exercise training. The provision of such feedback has been shown to enhance motor learning and positively influences motivation, self-efficacy (i.e. patient belief in their ability to complete a task) and compliance with exercise programs [14, 222, 328, 392]. The precise nature of such schemes and their potential application for automatic rehabilitation systems are the focus of this chapter.

This chapter is divided into three parts. First, a brief introduction placing feedback in the context of motor learning is given, including an objective examination of the role of extrinsic feedback on implicit motor learning after stroke. Second, the design of a novel automated feedback platform and a low cost digital hand dynamometer for the investigation of feedback on motor performance are described. A preliminary investigation using this system to explore the effects of excessive feedback on motor performance during a repetitive grip exercise is performed and results are presented. Following this, a discussion of the shortcomings of the initial experimental protocol used in the previous investigation, highlighting concerns that the dynamics observed might simply be a result of local muscle fatigue. As a result, a secondary investigation of the effects of obfuscated feedback on motor performance is performed. For the purpose of fatigue assessment, additional custom designed, low-cost, hardware is described for the concurrent recording of EMG data, throughout the experiment. In addition, a commercial isometric hand dynamometer is used for this study and a more rigid experimental protocol is defined. Finally, statistical analysis is performed on the resulting data and conclusions are drawn regarding the affects of obfuscated feedback on motor performance.

6.1 Skill Learning

A skill is the learned ability to carry out a task with pre-determined results often within a given amount of time, energy, or both [152]. A motor skill is a specific type of skill resulting in the intentional movement of a body part that must be learned and voluntarily produced to proficiently perform a goal-oriented task [185]. The acquisition of new skills is made possible by the plasticity of the human brain and is an important part of everyday life, from learning how to walk, to riding a bicycle. These motor skills are acquired through the formation and development of sophisticated neuronal circuits which arise from the intense practise of those skills.

Motor impairment after neurological injury is fundamentally caused by damage to the normal organisation of motor circuits. Thus, after brain injury, neurological reorganization plays an important role in the restoration of motor function. Based on initial research in animal models Nudo et al proposed that changes occurring during motor learning, i.e. synaptogenesis and increases in synaptic strength, are likely the same type of changes that occur during the reorganisation period after stroke [268]. Since then a cohort of studies have confirmed this hypothesis and it is now well recognised that recovery of motor function after traumatic brain injury is fundamentally a process of relearning [117].

Regardless of the skill, learning how to ride a bike, to becoming a proficient golfer or a world class marksman, it is well known that task performance improves with practise [3, 110]. However, although mastering a skill requires repetitive training of that skill, there are other important factors, including the training conditions and quality of practise which can enhance the rate of learning and improve retention [328]. Feedback given during training is regarded as a critical variable for skill acquisition and has been shown to effectively enhance motor learning.

6.2 Feedback

6.2.1 Intrinsic Feedback

During independent learning, inherent feedback derived from sensory-perceptual information i.e. vision, audio and proprioception, help a learner to improve performance. This type of feedback is called intrinsic feedback as it come from within. Intrinsic feedback helps to formulate a person's internal representation of a movement task they are trying to achieve. For example, when first learning to throw a basketball, players miss the net very often, however as they practise they learn how to better judge the kinematics involved, i.e. the weight of the ball, the angle of the shot and the required power. The learner can achieve a certain level of proficiency from task-intrinsic feedback, however in order to attain a higher level of skill, augmented feedback is often required. When intrinsic feedback is no longer good enough to provide information about the appropriateness of the performance, or when the information required cannot be accessed by the learner, then augmented feedback can play an essential role in effective skill learning.

6.2.2 Extrinsic Feedback

Augmented task-related feedback, or extrinsic feedback comes from an external source and usually provides information which is not generally available to the user from intrinsic sources. For example, returning to our original basketball analogy, extrinsic feedback might be derived from a coach providing information which helps to correct the players posture, or release timing, while watching the player make free throws. Extrinsic feedback is commonly categorized as either knowledge of performance or knowledge of results. Knowledge of results (KR) is defined as extrinsic or augmented information provided to a performer after a response, indicating the success of their actions with regard to an environmental goal [315]. For example, a tennis player might be told they served a ball with a speed of 80 mph. Knowledge of performance (KP) or kinematic feedback refers to information provided to a performer, indicating the quality or patterning of their movement [328]. KP tends to be distinct from information which can be obtained through intrinsic feedback, such as information which can be used to directly improve a tasks. In contrast to KR, an example of KP would be information regarding how the tennis player might have hit the ball too early, i.e. before it reached its maximum height, resulting in an off center collision with the racket and subsequently a sub-optimal serve speed. While it is possible to make significant learning gains without extrinsic feedback, studies show that extrinsic feedback improves learning rate and retention [379].

6.2.3 Feedback Scheduling

Feedback scheduling is an important parameter in providing feedback, that is the timing and frequency with which extrinsic feedback is provided during practise, and has been shown to affect motor skill acquisition and retention [186, 202]. A brief discussion of feedback scheduling modalities is given here, mainly to highlight the significance of obfuscated feedback for motor learning, for a more thorough discussion of different feedback modalities, see Literature review Chapter 3.

Concurrent or continuous feedback is a form of feedback which is given in real time while a participant is performing a task. Intrinsic feedback can be considered a form of concurrent feedback, however concurrent feedback can also come from external sources such as manual guidance, where a therapist provides tactical cues to help guide movement. Continuous feedback has been utilised for decades in physical rehabilitation therapy as a means of training injured limbs. Superficially, continuous feedback appears to be an effective method for augmenting the learning process as it strongly guides the learner to the correct or desired response, minimises errors and holds behaviour on target. However, mounting evidence suggests that the gains observed during training do not carry over to retention tests or transfer tests in which feedback is withdrawn [322]. It has been suggested that one reason for the detrimental effects of concurrent feedback might be that they prevent spontaneous error estimations that might occur during or after the movement. Additional findings suggests that concurrent feedback has a negative effect on learning because it provides feedback too frequently, such that the learner becomes dependent on it, thereby degrading learning [285, 315].

In contrast, research suggests that methods which obfuscated direct performance (i.e. summary/averaged feedback, delayed feedback or bandwidth limited feedback) improve learning as they increase movement stability and yield better performance in retention tests when compared to concurrent feedback [50, 57, 334].

In both summary and average feedback, feedback is provided at the end of a set of trials. Summary feedback refers to feedback which is given on each trial in the set, while average feedback refers to feedback given about the average performance over the course of the entire set. The benefits of both summary feedback [327, 330] and average feedback [407] relative to single-trial feedback has been demonstrated in many studies.

Bandwidth feedback involves giving qualitative feedback when task performance is within some acceptable range of error (e.g., 10%), and quantitative feedback when performance is outside that range (e.g., 70 ms too fast) [379]. The capacity of bandwidth feedback as a tool for augmenting motor learning is well documented and has been shown to be highly effective in enhancing learning during physical practice [39, 50, 79, 202, 203, 334, 342].

6.2.4 Feedback after Neurological Injury

An important question is whether or not the research findings described above for healthy subjects apply to persons with neurological injury after stroke! After stroke, intrinsic feedback pathways may be damaged making it difficult for the learner to determine what needs to be done in order to improve performance. For example, a patient suffering from hemiparesis of the hand will more often than not also have proprioceptive impairment of the hand and subsequently a loss in sensation. Therefore, extrinsic feedback might even be more important for people with stroke.

While there is some research which indicates that feedback can enhance motor learning after stroke, there are many areas as yet not examined and there is clearly a need for considerably more research in the area. An extensive review of extrinsic feedback for motor learning after stroke undertaken by Vliet et al. suggests that there is a distinct lack of research which analyses if variables which have been shown to positively influence learning in healthy subjects are transferable to stroke patients [379].

6.2.5 Discussion

During the early stage of training high frequency feedback might be necessary when a participant is learning how to perform an exercise or functional task, however, in general a basic principle of augmented feedback is that less is better! In support, studies suggest that while concurrent feedback on performance has shown strong performance-enhancing effects during practise, it typically results in clear performance decrements when it is withdrawn in retention or transfer tests. Furthermore, erroneous extrinsic feedback on performance has been shown to override a person's own correct intrinsic feedback during training with detrimental implications for learning. Therefore, mechanisms which deliver extrinsic feedback on performance should encourage the development of desired patterns in such a way that doesn't completely override information coming from intrinsic pathways, thus allowing for innate self-correction and the development of internal models of the task requirements. In addition, to be optimal, extrinsic feedback scheduling should be dynamic, with less frequent feedback given as progression is made. In this respect, the application of bandwidth feedback is of particular interest as it is an ideal mechanism for delivering adjustable, obfuscated feedback on performance. What we mean here by obfuscated feedback is that the feedback presented to the learner masks or obscures direct performance by substituting it with more loosely defined contextual feedback. For example, a performance bandwidth, i.e. the amount of error that will be tolerated before providing feedback, can be established which best matches the skill level of a performer attempting to learn a new skill. As long as the participant's performance falls within this tolerance zone, there is no need to give feedback on performance. As the novice performer get better at completing the task, you can then narrow the bandwidth, thereby increasing the difficulty of the task and better challenging the performer.

From the perspective of developing applications for enhancing home-based rehabilitation, a bandwidth based feedback mechanism might be an ideal means of incorporating dynamic feedback into conventional training programs. Such feedback could easily be administered by an application running on a desktop PC which presents feedback (eg. visual, verbal, etc.) on task performance, based on some metric of performance measured through an input signal, for example, grip strength measure from a digital hand dynamometer, or muscle activity represented by an EMG signal.

In the following section we describe the development of such an experimental platform which integrates both a low cost, custom designed hand dynamometer and an experimental bandwidth based feedback platform. We then demonstrate the use of this platform for investigating the affects of bandwidth limited feedback on motor performance during a repetitive motor task. We are particularly interested in whether the obfuscation of performance, as presented by bandwidth delimited feedback, might cause any behavioural dynamics which seek to minimise effort, described previously as motor slacking.

6.3 A Low Cost Hand Dynamometer and Custom Feedback System

Grip strength is commonly used as a quantifiable measure of effort/performance and is an accepted indicator used as a measure of recovery after neurological injury [403]. The ability to grasp is also a fundamental hand skill, used in a variety of activities of daily living (ADLs). Studies have shown that increased use of arm and hand activity early after a stroke can and does have significant impact on improving functional movement recovery outcomes. So important is the ability to grasp that an initiative by the faculty of medicine, funded by a Heart and Stroke Foundation of BC, has developed a program called GRASP (Graded Repetitive Arm Supplementary Program), developed for stroke patients with upper extremity impairments. GRASP is a stroke rehabilitation intervention that anecdotally has had rapid translation from research to clinical practice [63]. Studies have shown that patients who supplemented standard rehabilitation exercise with GRASP had better arm and hand function than control groups who only had standard rehabilitation care [136]. Better function was demonstrated when patients were discharged from the rehabilitation hospital and also at 5 months post-stroke. However, the study concluded that better outcomes were achieved if the patient was supervised by family, friends or a caregiver throughout the GRASP program. This again highlights the importance of the presence of an external administrator, be it a care giver, family member or artificial therapist, to stimulate and motivate the patient in an attempt to maintain adherence with the therapeutic exercise program.

For the purpose of grip strength measurement and assessment a hand dynamometer is often used. There are many commercially available dynamometers for measuring grip strength [224], however a computerized dynamometer which can graphically represent force in real time and store the results is prohibitively expensive. The Jamar hand dynamometer (Lafayette Instrument Company, USA) is the most widely cited in the literature and accepted as the gold standard by which other dynamometers are evaluated [304] and costs upwards of €500. As one of the main aspirations of this thesis is to endeavour to help make rehabilitation tools more affordable and accessible, a custom designed affordable hand dynamometer is described next.

6.3.1 Custom Hand Dynamometer

This simple yet satisfactory hand dynamometer was made by attaching a strain gauge to an easily available hand exercise device. The strain gauge sensor was positioned and epoxied to a curved section of the apparatus' spring, see Figure 6.1. When force is applied to the device's handle, the spring is slightly deformed causing the strain gauge itself to undergo deformation.

FIGURE 6.1: Photograph of custom designed hand dynamometer, showing A) Strain gauge sensor, and B) Terminal connections.

The strain gauge consists of an insulating, flexible material on which a metallic foil pattern is etched. When stress is applied the electrical conducting foil becomes narrower and longer causing its electrical resistance to change. However, strain gauges present a measurement challenge because the typical change in resistance over the entire operating range may be less than 1% of its nominal rest valve. An appropriate set-up is therefore to connect the gauge as a varying resistor in a Wheatstone bridge configuration, see Figure 6.2. One side of the bridge consists of two well-balanced, identical fixed resistors while the other side consists of a sensitive multi-turn potentiometer and a strain gauge. The potentiometer allows for precise balancing of the bridge under null conditions (no force applied to strength trainer). At this point the voltage difference between the two sides of the bridge is zero. When force is applied the resistance of the strain gauge changes thus unbalancing the bridge and generating a proportional voltage. The output of the bridge is typically very small (a few millivolts) and so must be amplified greatly before being converted to a digital signal. The amplification is handled using an instrumentation amplifier, the AD620AN (Analog Devices Inc, Norwood, USA).

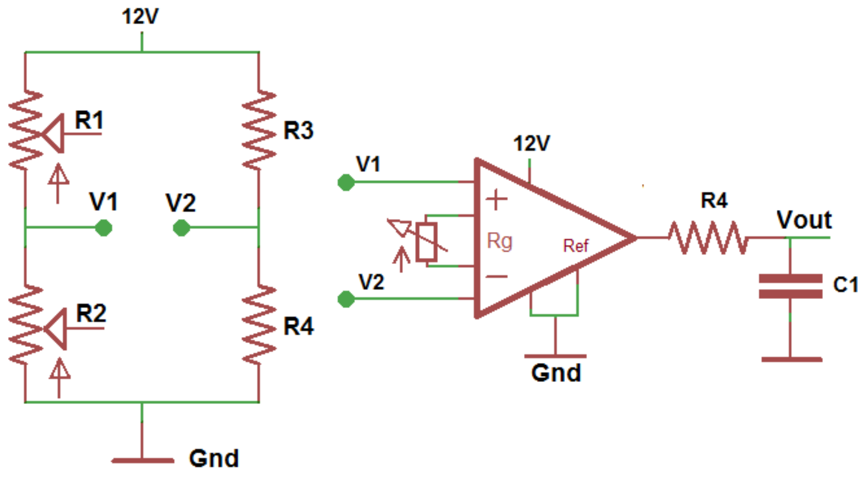

FIGURE 6.2: Quarter bridge Wheatstone bridge and amplifier circuit

After amplification the signal is filtered using a low pass anti-alising filter (determined by R4 and C1, see Figure 6.2) to half the max sampling frequency. The filtered signal is then processed by an open-source electronics prototyping platform the Arduino Uno (Arduino, Smart Projects, Italy), sampled using an embedded 10-bit analog to digital converter (ADC) at a rate of 1000 samples/s. The final output signal is then transmitted to a receiving PC over USB through a virtual serial port connection, established through the Arduino's FDTI and UART hardware.

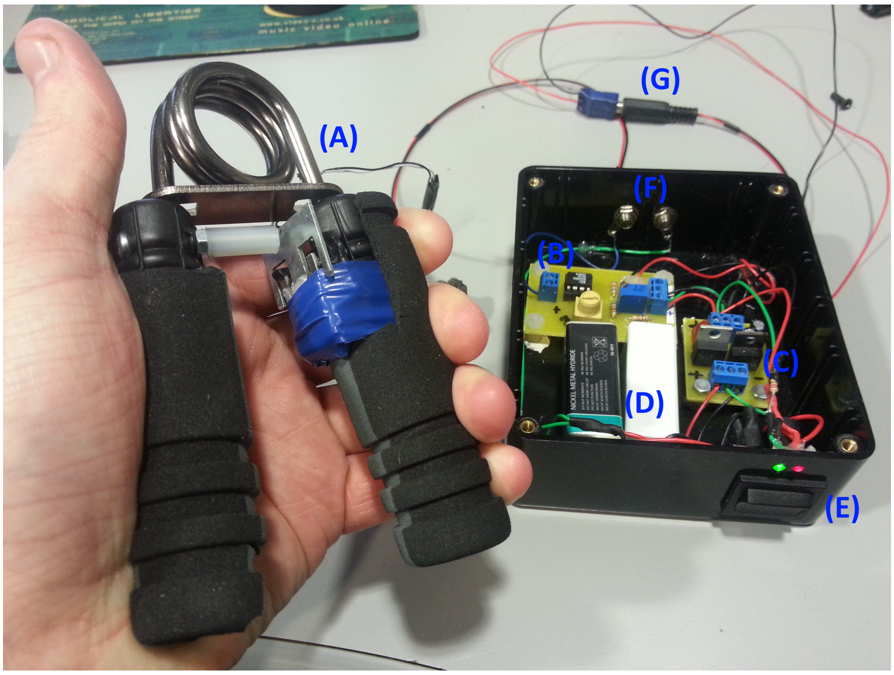

FIGURE 6.3: Photograph of custom designed hand dynamometer and acquisition circuit, showing; A) Custom hand dynamometer (V.1.), B) Wheatstone bridge amplifier and filters, C) Power regulation electronics, D) Isolated power supply, E) Status LEDs and switch, F) Output signal to digital acquisition board, and G) Load cell input connector.

6.3.2 Visual Representation and Recording Software

Custom software written in C# instigates a serial port connection with the Arduino to facilitate the streaming and recording of data from the hand dynamometer. An open source library, ZedGraph[1], is used to visualize the incoming data and to allow plotting of the sensor data in real time. The software also controls and produces appropriate visual feedback depending on the selected error to feedback mapping chosen. All captured data is labelled and time stamped before being saved to files which are later analysed using Matlab (Math Works, Natick, Massachusetts, U.S.A). A system overview diagram is shown in Figure 6.4 for reference.

[1]ZEDGraph - url: http://sourceforge.net/projects/zedgraph/

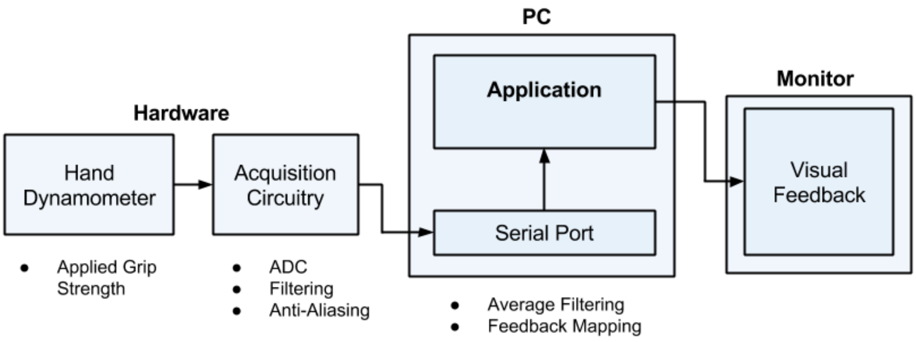

FIGURE 6.4: System diagram of custom hand dynamometer and feedback System.

The software system integrates two different feedback modalities, concurrent feedback and contextual feedback.

6.3.2.1 Concurrent Feedback Mode

This mode presents concurrent (i.e. real-time) feedback, which shows direct highly accurate feedback of grip strength through a moving window that plots "effort" against "time", with time on the horizontal axis and effort on the vertical axis, see Figure 6.5.

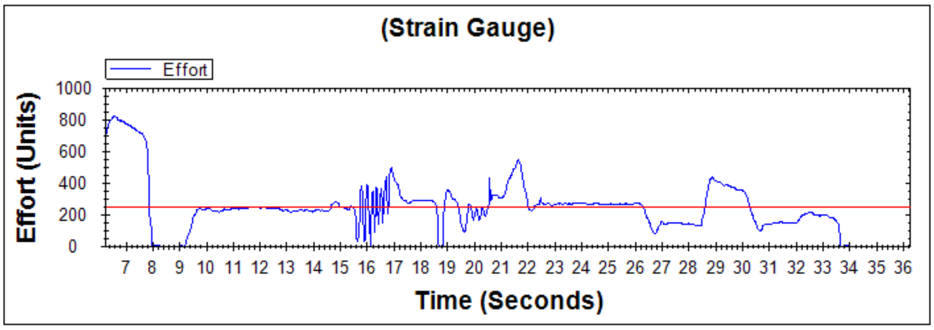

FIGURE 6.5: Real time plotting of Hand Dynamometer data.

6.3.2.2 Contextual Feedback Mode

This mode presents contextual feedback on performance using a vertical column of linguistically defined satisfaction assessments of effort, i.e. the words ("poor", "fair", "good", "very good" and "excellent"). In this mode, the current feedback which best describes performance is highlighted in bold text with an adjacent yellow arrow pointing to it, see Figure 6.6.

FIGURE 6.6: Contextual feedback on performance.

6.3.3 Feedback Mapping System

The resulting feedback which is presented to the learner using the contextual feedback mode is determined by a bandwidth mapping system. Typically, in conventional bandwidth feedback systems no feedback is given when task performance is within some acceptable range of error, i.e. when error falls between a specified upper B_U and lower B_L bandwidth limit, and quantitative feedback is given when performance is outside that range, see Figure 6.7.

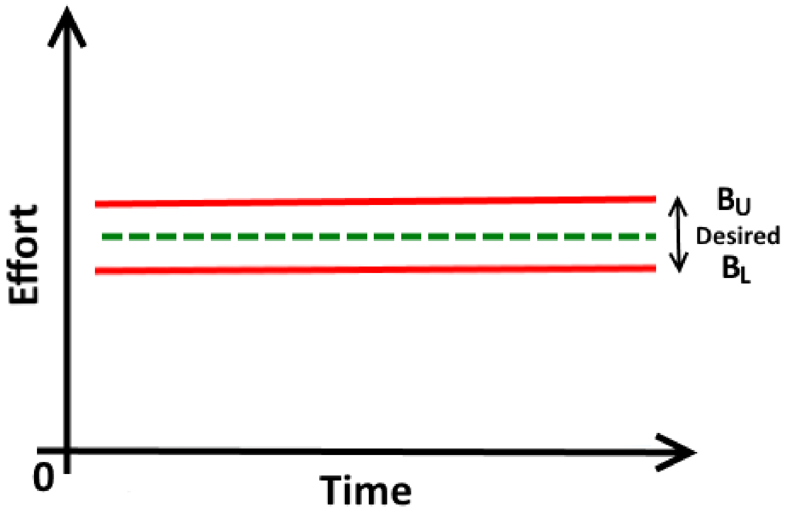

FIGURE 6.7: Conventional Bandwidth feedback paradigm, illustrating desired performance with a dashed green line, and with upper B_U and lower B_L bandwidth limits with a continuous red line.

This approach to feedback might be suitable for delivering feedback on performance in healthy people but we speculate that for stroke, a more suitable feedback system which can better help the patient to quantify their effort and understand what needs to be done to improve their performance can be achieved through the inclusion of multiple, sequential bandwidth zones. Hence, in this work we experiment with a multi-level bandwidth system. To achieve this, the potential force spectrum (i.e. from 0 (Kg) up to the subject's recorded MVC(Kg)) is divided into N adjacent bands. Bands are allocated by limits which set the upper B_U and lower B_L error boundaries for that band. It follows that the bandwidth of each band is given by the distance between its upper and lower limits. See Figure 6.8 for illustration.

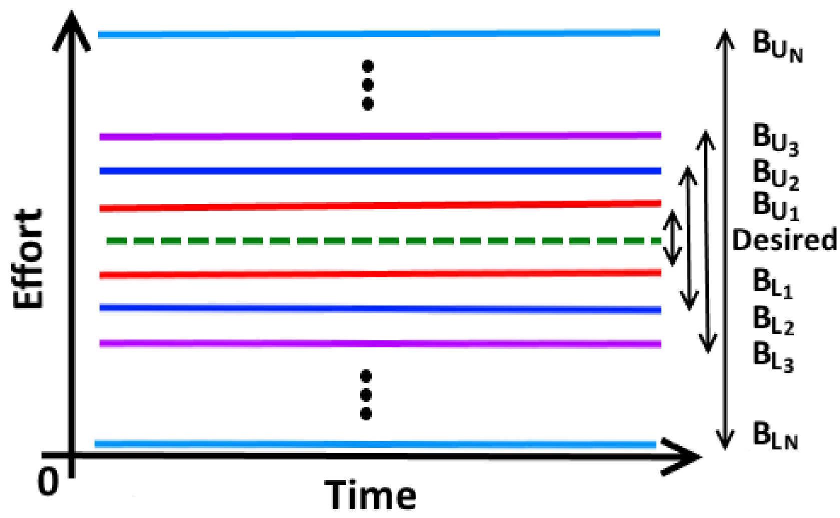

Figure 6.8: Custom bandwidth feedback paradigm, illustrating desired performance with a dashed green line, and with upper B_U and lower B_L bandwidth limits for each bandwidth zone with a additional continuous coloured lines.

A look-up table relates performance effort with feedback reward depending on which band the current effort falls into, see Table 6.1. For example, for the inner band around zero error the user might be presented with the feedback "Excellent". If their performance error outgrows this band into an adjacent band the feedback will then change to be of lesser quality "Very good".

6.3.4 Experimental Protocol

4 subjects, 3 male & 1 female, ageing between 23-27 years old, all right handed, willingly participated in the experiments. Each subject was tested to ensure they could achieve momentary grip strength which saturated the upper bounds of our recording device. A preliminary test was then done with each subject to ensure they could easily maintain a

TABLE 6.1: Agent output in response to quantitative task performance measures (normalised error). The values indicate breakpoints above which the associated row label is produced for each therapist. For example, only a score of 0.1 or above will elicit the response "Excellent" for Therapist 1

Linguistic Feedback	Therapist 1 "demanding"	Therapist 2 "affirmative"
Excellent	0	0
V. Good	0.10	-
Good	0.20	-
Fair	0.35	-
Poor	1	1

constant grip target set at 15% of the maximum recordable value, without discomfort, strain or fatigue (self-reported) for a prolonged contraction longer than the duration of that required in the experiments. Using direct feedback as manual guidance Figure 6.5, all subjects were given adequate time to become familiar with the mechanics of the task and the relationship between error and effort, before commencing the experiments.

The experiment is divided into three parts, each consisting of a single sustained grip contraction for 15 seconds. A target grip strength was set equal to 15% of the subject MVC which stays constant throughout the experiment. The subjects are first given a couple of minutes to get acquainted with both feedback systems (i.e. concurrent and contextual) and to better understand the relationship between error and effort, during this period a series of random grip targets are set, which the subjects practise achieving.

Before commencing the experiment, the subject is informed that their objective is simply to attempt to achieve a static grip strength equal to the specified target and that feedback would be given to assist them in achieving this.

6.3.4.1 Set (1) - Direct Error Feedback

In this set the subject is given direct (continuous and real time) visualization of their applied force as feedback using the system described in Section 6.3.2.1 while attempting to achieve the specified grip strength.

6.3.4.2 Set (2) – Demanding Therapist

In this set the subject is given obfuscated feedback on their performance using the feedback described in Section 6.3.2.2. A mapping system, described as a "demanding therapist" is used to control how error relates to feedback, see (Therapist 1, Table 6.1).

6.3.4.3 Set (3) – Excessively Affirmative Feedback

In this set the subject is given obfuscated feedback on their performance using the feedback described in Section 6.3.2.2. Initially a mapping system described as a "demanding therapist" is used to control how error relates to feedback, however 5 seconds into the session, the mapping system is instead switched to an "excessively affirming therapist" see (Therapist 2, Table 6.1).

6.3.5 Results and Analysis

The results of the first Set show that when given direct access to performance all subjects easily maintained their grip strength for the duration of the task, i.e. subjects had relatively low error and average grip strength close to the target, see Figure 6.9 and Table 6.2. The results of the 2nd Set show that similar results were obtained when subjects instead received verbal feedback from a 'demanding' virtual therapist. Interestingly, all subjects initially overshot the target; however their overall performance during the task had low error and average grip strengths close to the target, see Figure 6.10 and Table 6.3. The results of the 3rd Set show that subjects significantly reduced their performance (much greater accumulative error) when we switched (after 5 seconds) from a 'demanding' therapist to an 'unconditional' therapist, i.e. one who always reported 'excellent' regardless of the error, see Figure 6.11 and Table 6.4.

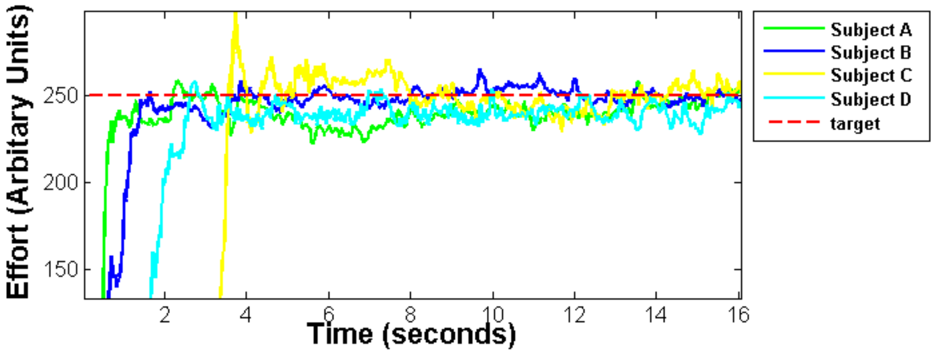

FIGURE 6.9: Experiment 1 results - effort over time for each subject while being given direct access to performance.

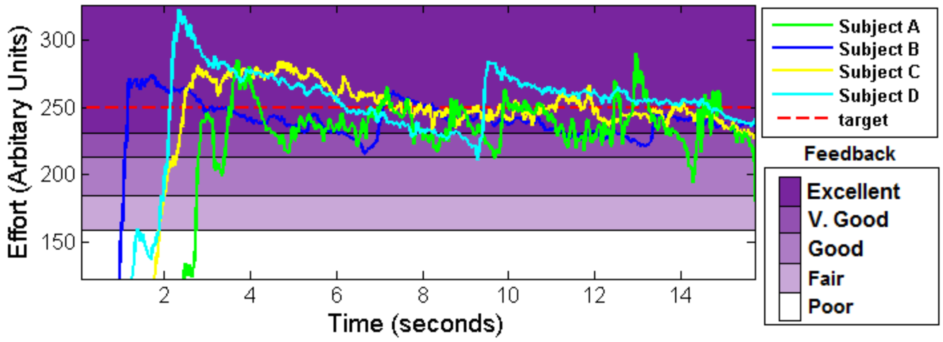

FIGURE 6.10: Experiment 2 results - effort over time for each subject while receiving feeback from a 'demanding' therapist (therapist 3, table 1).

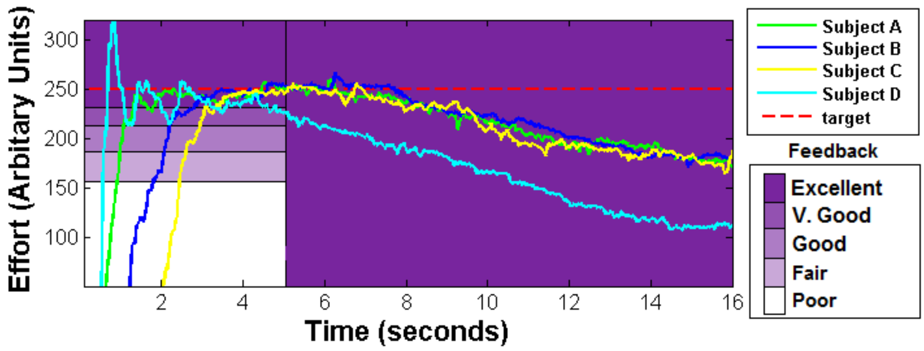

FIGURE 6.11: Experiment 3 results – switching after 5 seconds from a 'demanding' therapist (therapist 3, table 1) to a 'unconditional' therapist (therapist 4, table 1) who reports 'excellent' feedback regardless of the error.

TABLE 6.2: Experiment 1 – Quantified Results

		Effort		**Error**
	Min	Max	Avg	Sum
Subject A	222.59	270.48	238.99	1.067*
Subject B	238.50	270.43	250.05	1.288*
Subject C	205.46	270.57	233.28	4.699*
Subject D	229.79	271.43	240.03	3.232*

Table 6.3: Experiment 2 – Quantified Results

		Effort		**Error**
	Min	Max	Avg	Sum
Subject A	204.32	277.31	239.07	1.328*
Subject B	217.43	280.57	238.03	2.117*
Subject C	204.32	277.31	239.07	2.237*
Subject D	218.04	316.17	255.19	-1.890*

Table 6.4: Experiment 3 – Quantified Results

		Effort		**Error**
	Min	Max	Avg	Sum
Subject A	179.45	267.95	221.52	3.748*
Subject B	175.08	281.07	224.96	4.597*
Subject C	179.58	267.35	218.79	6.075*
Subject D	108	259.04	173.73	6.930*

6.3.6 Discussion

In the first experimental set, not surprisingly the subjects produced low error when confronted with such a direct accurate measure of performance. These results might suggest that to maximize performance we simply need to give subjects direct access to error. However, as previously elucidated direct concurrent feedback of this form is detrimental for learning. In addition, direct error does not capture effort in a comprehensive or forgiving fashion and therefore might be unsuitable for use in patients with neurological injury. A patient, particularly one recovering from stroke may produce initially low error but as they progress their error may increase despite the patient's best efforts. Instead, the results from this set should be considered a reference which both validate the ability of our custom hand dynamometer to accurately capture grip strength and as an experimental control for comparing and contrasting the results of set 2 and 3.

The second and third experimental sets replace this unrealistic direct measure of performance with a more appropriate form of obfuscated feedback that we feel better resembles that given during real therapy situations, i.e. verbal feedback given intermittently by a therapist to coax effort and to reinforce positive behaviour. In set 2 and 3, it is interesting to note that subjects initially over shot the required target force even thought the target force required was identical to that in both the training session and first set. Perhaps from a motor program perspective this makes sense, since by purposely over shooting and then slacking, the optimal level can be found quickly. Additionally, in Set 3 the mapping between error and performance is gradually relaxed making it easier to obtain a score of excellent over time. What is interesting here is that all subjects initially over shot the target, gradually reduced their force below that of the target to the minimum required to achieve "excellent" feedback (except one who greatly overshot) and then held at the boundary between "excellent" and "very good", i.e. the minimum effort required to achieve the objective goal. After 5 seconds the feedback system then switches to an "unconditional" therapist, essentially removing the lower bandwidth limit and therefore always giving the feedback "excellent" regardless of error, subjects gradually reduce their efforts to levels far below that required.

An interesting dynamic which is not captured in the data presented here is the subjects perception of their performance across the three experimental sets. Surprisingly, immediately after completing the experiment subjects were asked to assess their own performance in each set. All subjects reported that they felt they managed to maintain a sufficient and steady grip over the course of each set. These experimental results suggest that once given overly affirming feedback on performance, even in the presence of errors subjects exhibited "slacking" like dynamics.

6.4 A Low Cost EMG System and a Secondary Investigation

While the initial investigations suggest there are interesting dynamics at play which are similar to those described as slacking, there are some concerns about the original experimental protocol used in this investigation. Firstly, the custom hand dynomometer used to collect data is an isotonic device, i.e. the device physically changes shape when force is applied. Since the device is essentially a spring, it creates a non-linear reaction force proportional but opposite to the applied force. This is problematic because the reactive force works against the user and constantly attempts to restore the device to its rest position, putting stress on the user to maintain force and causing fatigue. Second, the experimental protocol adhered to during testing was not well defined. No strict guidelines were followed to ensure consistency between grip attempts, for example to ensure the measuring device was held in the same manner, or that subjects posture was consistent throughout the experiment. Only a single sub-maximal grip attempt was attempted in each set and all subjects attempted to achieve the same target force. While this target force was selected to be achievable by each subject, i.e the required force was much lower than the weakest participants MVC, a more suitable target would have been to set an individual target for each user, equal to a fixed percentage of their own MVC. Finally, no estimation or indication of muscle fatigue was measured throughout the experiment, thus the force dynamics observed could simply be a resultant of natural peripheral fatigue, accumulated during the sets or throughout the experiment.

A second more rigorous experiment was therefore undertaken to more thoroughly investigate the effects of obfuscating feedback on performance during a repetitive motor task. This objective is approached through three processes. First the introduction of additional hardware; a commercial isometric hand dynamometer and a low cost EMG recording system. Second, through a revised more rigid experimental protocol. And third, through a more stringent statistical analysis of the accumulated data.

6.4.1 Revised Hardware

The original custom designed isotonic hand dynanometer was replaced with a commercial hand dynamometer, the Biopac-SS25L (BIOPAC Inc., CA, USA). The SS25L is an isometric dynamometer that measures a variety of gripping strengths for several muscle groups; clench force range (0-50)Kg. The isometric design improves experiment repeatability and accuracy. Typically a proprietary data acquisition unit, the DA100C general-purpose transducer amplifier, is used in conjunction with the SS25L hand dynamometer which facilitates the processing of the underlying sensor, a strain gauge, into a digital quantised signal. However, the DA100C did not meet the requirements for the work we wished to undertake. For this study we required direct access to the SS25L sensor output in order to drive our feedback platform in real time. Furthermore, we required some means of concurrently recording muscle activity during experimentation. While Biopac offer a comprehensive modular solution for acquisition of bio-potential data (i.e. Grip strength, Electrogastrogram, Microelectrode Recording, Noninvasive Blood Pressure Measurement, and Electrical Bio-impedance) the cost of such systems are prohibitive. Subsequently we developed our own custom designed data acquisition unit, incorporating both the concurrent recording of EMG from two separate channels (surface electrode pairs) and the recording of grip strength data from a hand dynamometer. In conjunction, we also developed an accompanying real time visualisation tool for the analysis and representation of the acquired physiological data (muscle activity and grip strength).

6.4.1.1 Grip Strength Measurement

Measuring the strain applied to the gauge requires accurate measurement of very small changes in resistance. Hence, the strain gage R_s is used in a bridge configuration with a voltage excitation source (±5 V). The resulting output V_w is very small (typically μV) and requires amplification before it can be digitally sampled. This was accomplished using an instrumental amplifier with a gain (G) of 1122.5. The resulting circuit is illustrated in Figure 6.12 and described by Equations (6.1) to (6.3).

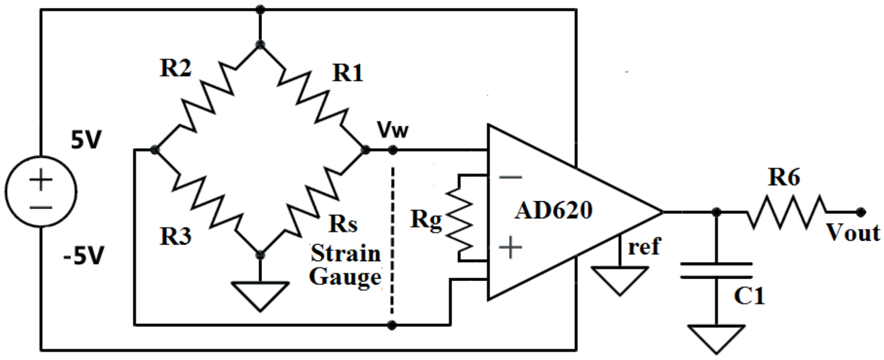

FIGURE 6.12: Electronic schematic of custom hand dynamometer interface

$$V_w = V_{in} \cdot (\frac{R_s}{R_s + R1} - \frac{R3}{R2 + R3}) \tag{6.1}$$

$$G = \frac{49.4k\Omega}{R_g} + 1 \tag{6.2}$$

$$V_{out} = V_w \cdot G \tag{6.3}$$

The analog output of the circuit V_{out} is subsequently digitized, using a 10-bit analog-to-digital conversion.

The SS25L isometric range is 0-90 Kg with a nominal output of 13.2μV/Kg per volt excitation. Therefore, at 5 V excitation, the nominal output is 66μV/Kg. Using Equation (6.4), a resulting force F measured in Kg can be obtained.

$$F = \frac{V_{out}}{66x10^-6V \times G} \tag{6.4}$$

Note, from here onwards all results presented in this section describing effort (i.e. grip strength) are giving in (Kg) derived using the equations above.

6.4.1.2 EMG Acquisition

Electromyographic data (EMG) was collected with the intention of providing a measurement of muscle fatigue and is used in the interpretation of our results. A fatigue measurement was necessary in order to distinguish between back-off in effort due to peripheral phenomenon in the muscles involved versus any speculated central component.

EMG was recorded using a modified open source Electroencephalogram (EEG) system, the ModularEEG[2] device. This is possible since the principle recording methodology of EEG and EMG are fundamentally the same. Both techniques measure bio-electric potentials provoked by active tissue, measured through electrodes placed on the surface of the skin. The two main differences between EEG and EMG are the source location and frequencies of the underlying signals. EMG measures electrical activity in muscles and is characterised by the frequency range 0-500 Hz. EEG on the other hand measures electrical activity in the brain which is characterised by lower frequencies in the range of (0-100)Hz. There is also a slight discrepancy in the related signal strength of EEG and EMG. EEG typically ranges between 10-100 μV while EMG potentials range between 50 μV and up to $30mV$, however this is not a concern since the gain of the system is low enough not to cause acquisition saturation. Therefore, the main difference in the equipment used to record EMG and EEG lies in the design of the active filters used and the rate at which data is sampled. The ModularEEG device is made up of two main acquisition boards, an analogue board and a digital board. The analogue board supports two separate differential input channels from an electrode pair and facilitates the isolation, amplification and filtering of these signals. The digital board supports up to 6 input channels and facilitates the high speed sampling of these inputs signals and communication with a PC via a standard serial cable.

Analogue board description

A bioelectric potential is acquired through silver-chloride common mode sense (CMS) active electrodes. The resulting signal is potentially only a few microvolts in amplitude and needs to be amplified several thousand times before it can digitalised, see Figure 6.13. Since the amplitude is so small, the signal can very easily drown in noise, particularly 50/60Hz hum from the mains which is transmitted capacitively (i.e by an electric field). Hence a low pass filter is applied before amplification. Afterwards the signal strength is

[2] hrefhttp://openeeg.sourceforge.net/doc/modeeg/modeeg.htmlModularEEG device - url: http://openeeg.sourceforge.net/doc/modeeg/modeeg.html

boosted first by a low noise instrumental amplifier and then by successive operational amplifiers. Between the two stages there is a high-pass filter which removes undesirable DC-voltage offsets which can occur due to electric charge accumulating on the surface of the electrode. The resulting amplified signal is then passed through a low-pass filter. This final filtering stage prevents distortion caused by the aliasing effect as a result of the sampling process. Below the signal amplifiers, and the filter, sits a third amplifier pointing in the opposite direction. This is called the Driven Right Leg (DRL) circuit. The purpose of the DRL is to reduce common-mode signals such as 50/60Hz mains hum, by cancelling them out. It replaces a ground electrode which older EEG designs use, and can attenuate mains hum up to 100 times more than the instrumentation amplifier can do by itself. A simplified block diagram of the analogue board is shown in Figure 6.13 for reference.

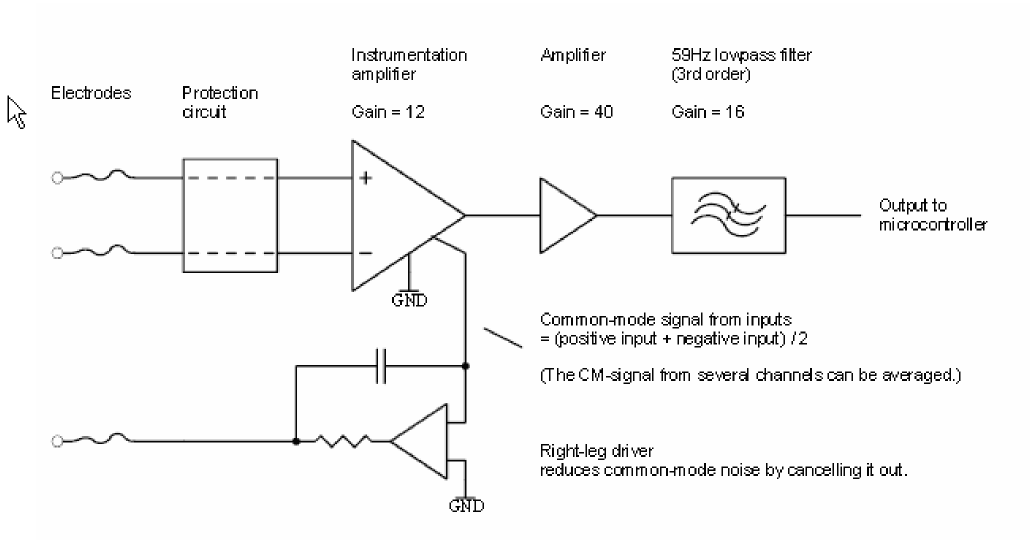

FIGURE 6.13: Simplified block diagram of the ModularEEG analogue board

Digital board description

After leaving the analogue board the signal is passed into the digital board. At this stage the signal is ready for acquisition by an analog-to-digital (ADC) converter of the embedded microcontroller. In the original design the sampled signal was then transmitted to a PC via a standard serial cable. However, to improve noise immunisation and to protect the user from electrical faults a bluetooth module was retrofitted instead, isolating the user from the PC and external power sources. A simplified block diagram of the digital board is shown in Figure 6.14 for reference.

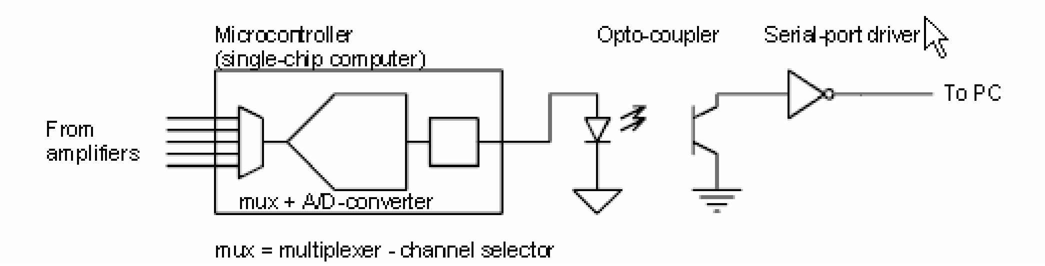

FIGURE 6.14: Simplified block diagram of the ModularEEG digital board

6.4.1.3 SPICE Modelling and Filter Response

As discussed in the previous section, in order to use the modularEEG board to record EMG signals the original filter design needed to be modified. Analysing the analogue filter schematics Figure 6.13 illustrates that there are three distinct filter stages. The first two filter stages simply add a total gain of 640, or roughly 56dB to the captured signal. The third filter stage, referred to previously as an anti-aliasing filter is in fact a combination of a Bessel filter and a Butterworth filter. This filter is essentially a notch filter, also known as a band-stop filter or band-rejection filter. However, in contrast to a standard notch filter which simply passes most frequencies unaltered, but attenuates those in a specific range to very low levels, the filter described here instead both amplifies frequencies within the bandpass range and attenuates those outside this range. To understand this filter better and in order to modify its effective bandpass frequency range, the filter was modelled using SPICE (Simulation Program with Integrated Circuit Emphasis) simulation software, LTspice[3] (Linear Technology Corporation, California, USA), see Figure 6.15.

From the frequency response of the filter we note that there is an approximate 19.2dB rolloff per octave, and a cut-off point of effectively 500 Hz. The cutoff frequency referred to here is the half power point of an electronic amplifier stage which is the frequency at which the output power has dropped to half of its mid-band value, that is a level of -3 dB. It is also important to note that the unaltered filter amplifies frequencies which fall within the respective frequency range of EEG, i.e. approximately 0-50 Hz. As is, this filter cannot be used for the acquisition of EMG which falls between 0-500 Hz.

6.4.1.4 Analog Board Modifications

Tweaking the modelled filters coefficients can be achieved by modifying the capacitor C9, C10 and C12, altering the filters response to instead match the desired EMG range,

[3]LTspice: - url: http://www.linear.com/designtools/software/

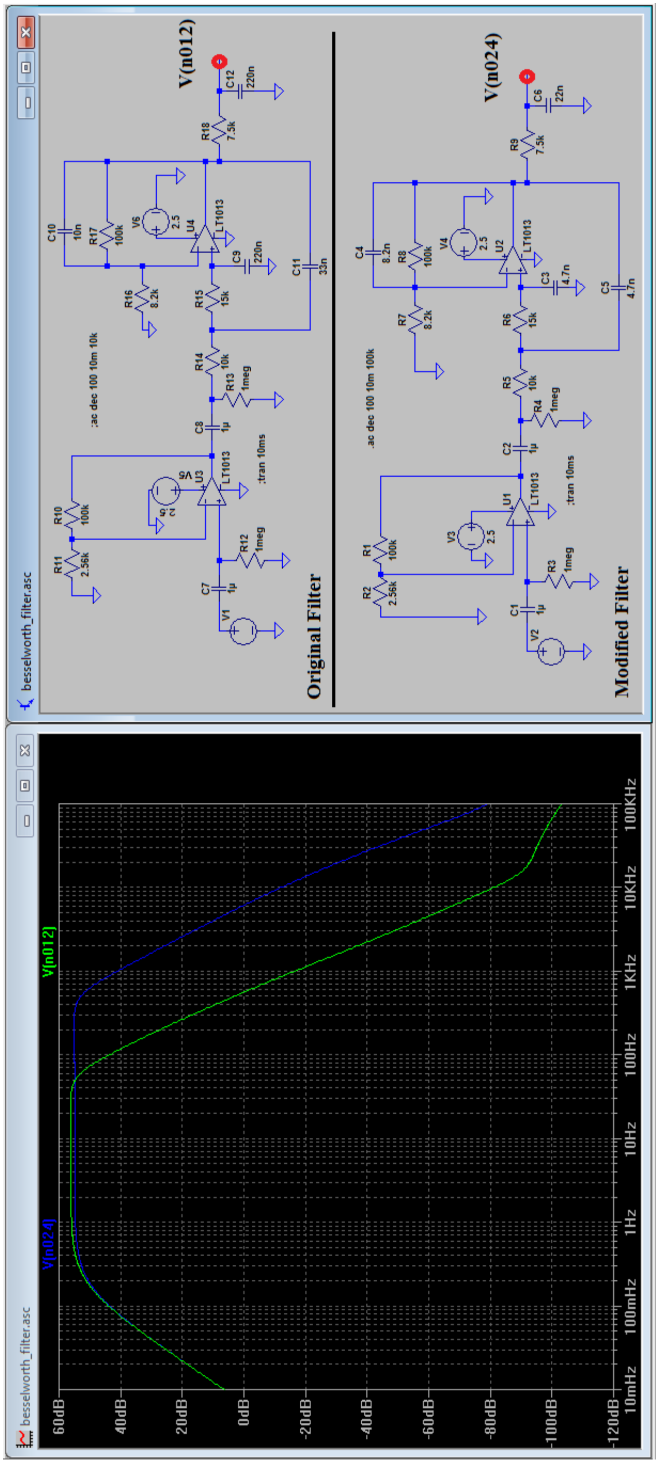

FIGURE 6.15: LTspice Simulation of Besselworth filters showing, plot of filter's response on left and filter schematics on right.

see Figure 6.15. Note that the resulting filter shape is identical, however the cut-off frequencies are now different.

6.4.1.5 Digital board Modifications

The second modification which needs to be made to the modularEEG system is increasing the sampling rate of the digital board. This is achieved through modifying the digital boards firmware[4] to increase the ADC sampling rate, see footnote. First, the original now obsolete AT90S4433P micro-controller was replaced with the newer pin compatible ATmega8 microcontroller (Atmel Corporation, CA, USA). The ATmega8 supports a faster 16Mhz external crystal oscillator, doubling the original ADC acquisition speed. Adjustments were also made to the original source code, see AppendixB, to modify the overflow counter used in triggering an ADC interrupt event, increasing the ADC acquisition rate from 256Hz to 1000Hz.

6.4.1.6 EMG Software Filtering

The resulting raw EMG signal captured by the acquisition system is inherently noisy and includes both movement artefacts and baseline noise contamination, including an unwanted DC offset, potential interference from mains (50Hz hum) as well as both high and low frequencies outside the effective range of EMG. Therefore, the resulting raw EMG signal requires some additional software filtering. Subsequently, the raw EMG signal is treated by multiple filtering stages.

1. De-trending (removal of DC offset)
2. Notch filtering (suppress 50Hz interfere)
3. Butterworth filter (bandpass filter EMG frequency range)

Figures 6.16 and 6.17 illustrate the various applied filter stages and demonstrates their effect on both the raw EMG signal and the resulting power spectral density (PSD) of the EMG data.

[4] modeeg firmware - url: http://openeeg.sourceforge.net/doc/modeeg/firmware/modeeg-p3.c

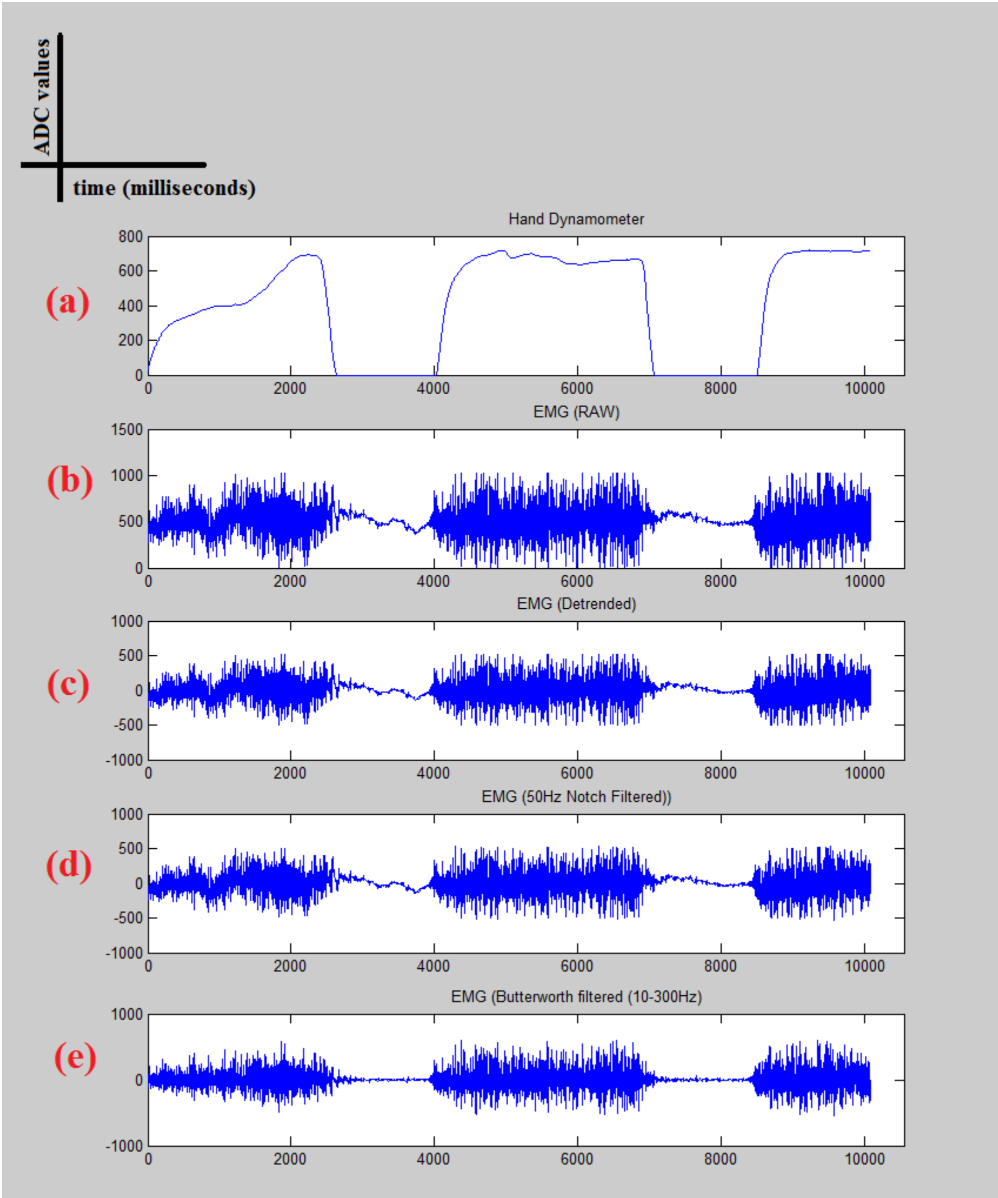

FIGURE 6.16: Demonstration of EMG filtering stages, including plots of; A) Hand dynamometer recording for reference, B) Raw unfiltered EMG signal, C) De-trended EMG (removal of DC offset), D) 50Hz notch filtered EMG, and E) Bandpass filtered (10-300Hz) EMG using a Butterworth filter

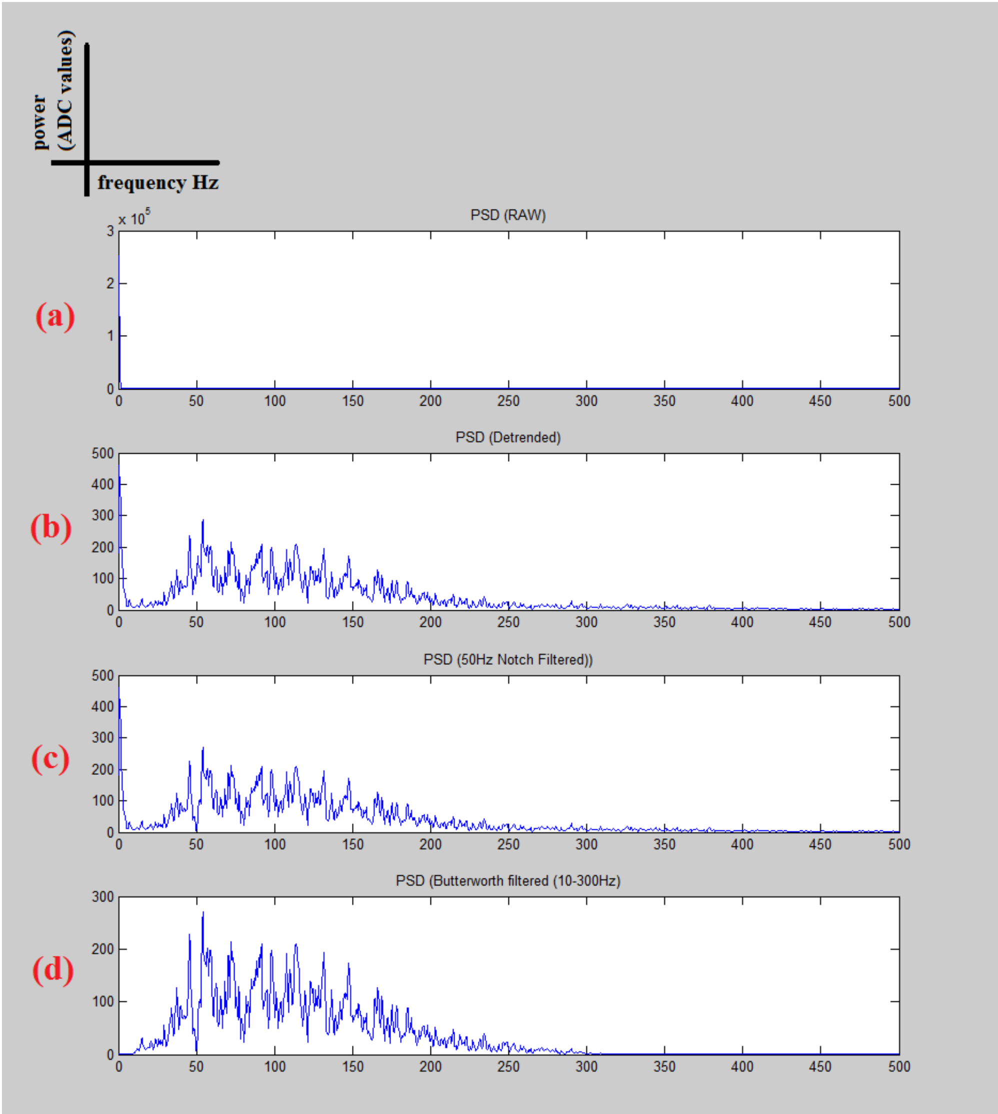

FIGURE 6.17: Demonstration of EMG filtering stages, including plots of; A) PSD of raw EMG, B) PSD of De-trended EMG, C) PSD of notch filtered EMG, and D) PSD of butterworth filtered EMG.

6.4.1.7 EMG System Testing

Figure 6.18 illustrates a simplified system overview diagram of the hardware used. For reference, photographs of the actual hardware are shown in Figure 6.19 and Figure 6.20.

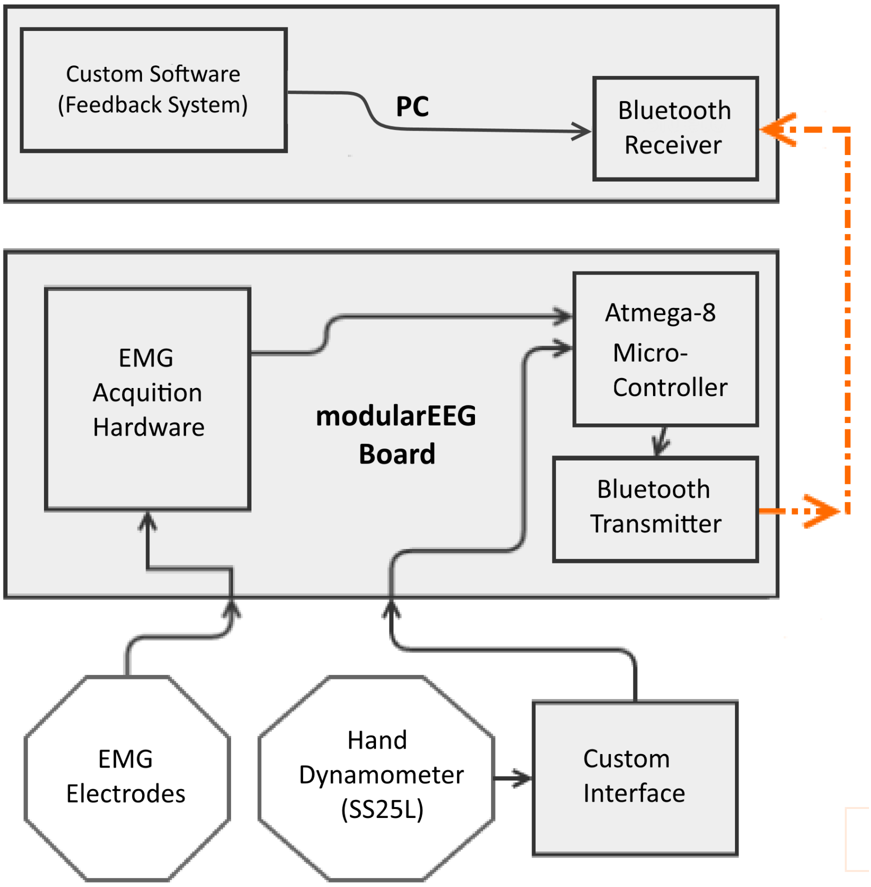

FIGURE 6.18: Simplified system overview diagram.

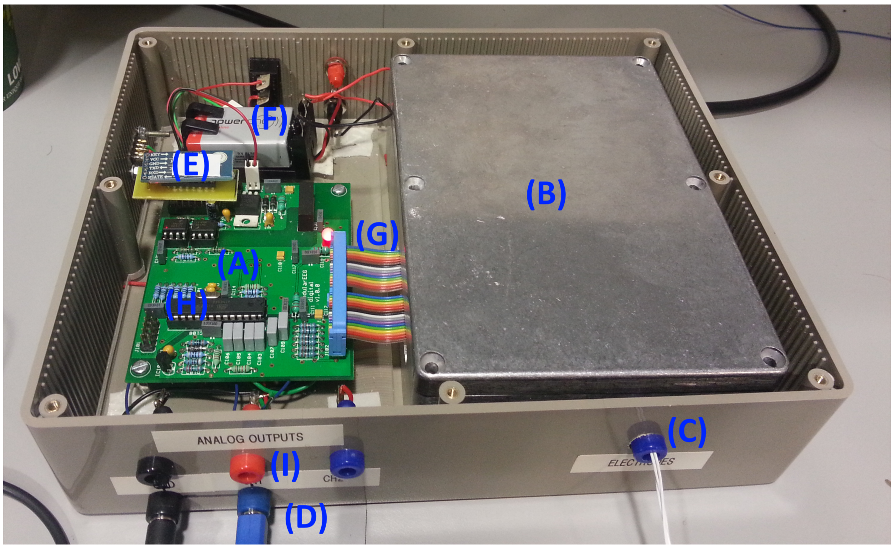

FIGURE 6.19: Picture of custom EMG rig, showing; A) Digital Board, B) Analogue Board encased in RF shielding, C) Electrode interface, E) Bluetooth module, F) Isolated power supply, G) Interface bridge between Analogue and Digital boards, H) Micro-controller, I) Hand Dynamometer interface.

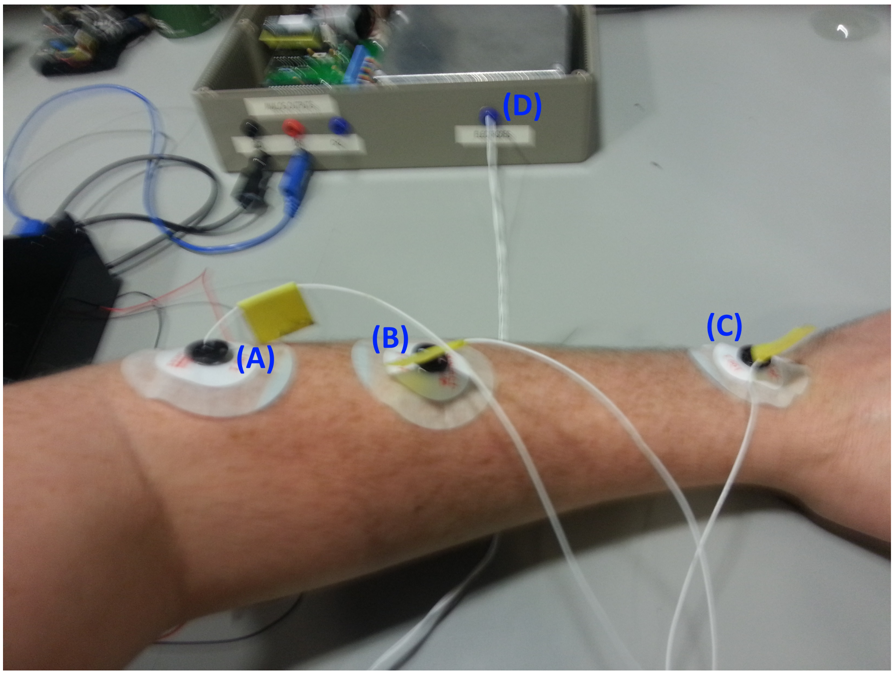

FIGURE 6.20: Electrodes attached to arm connected to EMG rig, showing; A) CMS active (+) electrode and B) CMS active (-) electrode, and C) DRL reference electrode position on bone.

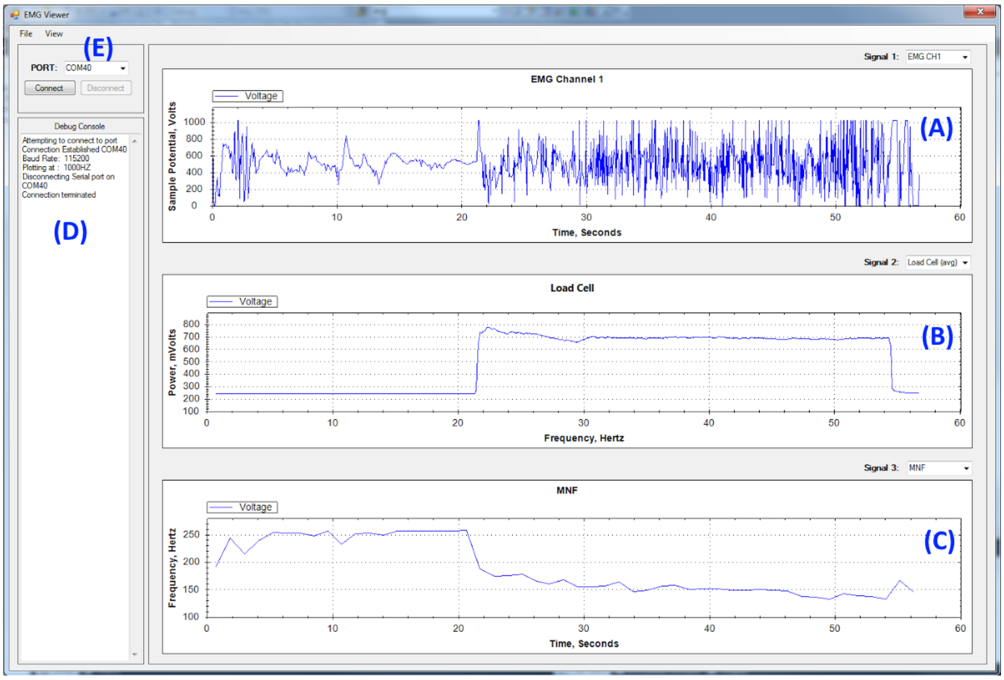

FIGURE 6.21: Screen cast of custom physiological data visualisation software, showing; A) Plot of EMG Amplitude over time, B) Plot of load-cell output over time, C) Calculated MNF over time, D) Debug window showing status output, and E) Virtual COM port selection menu.

A comparison test was done against the Biopac DA100C amplifier to validate the capability of our custom designed EMG amplifier. This test consisted of performing a unilateral maximum voluntary contraction grip while recording EMG data with identical electrode placement using both systems. The corresponding power spectral density (PSD) and frequency range were assessed for both devices.

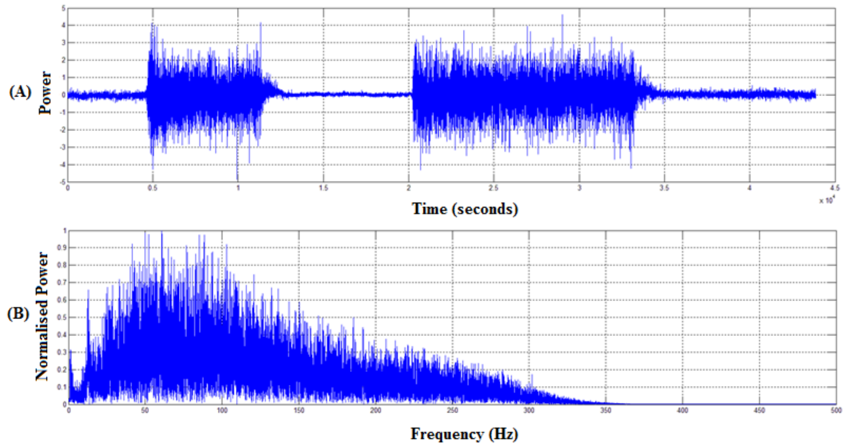

FIGURE 6.22: Results of test using Biopac DA100C amplifier illustrating, A) Power (EMG amplitude) against time and B) Power spectral density of EMG data.

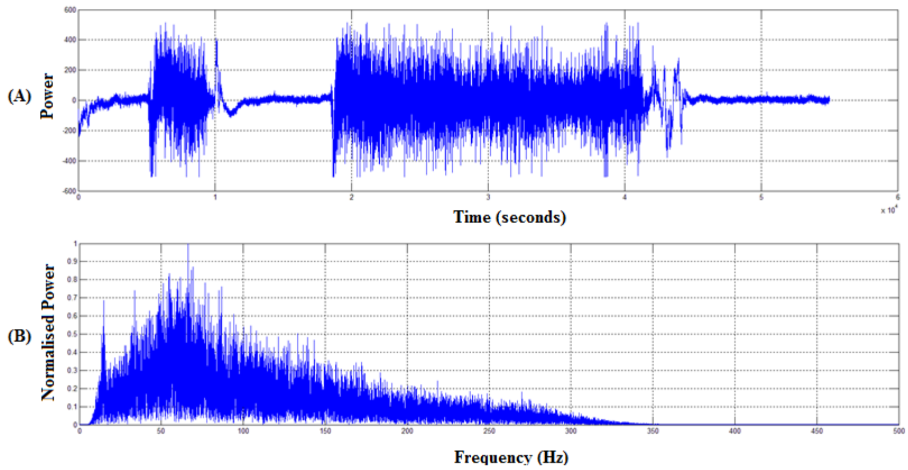

FIGURE 6.23: Results of test using custom EMG amplifier illustrating, A) Power (EMG amplitude) against time and B) Power spectral density of EMG data

6.4.2 Revised Feedback and Mapping System

A revised feedback mapping system was devised which improves upon the original system described in Section 6.3.2.1. The feedback mechanism used here is essentially the same as before, except now additional information is given which helps the user distinguish whether too much or too little force is being applied.

The new feedback interface consists of a vertical column of adjectives (i.e. 'Poor, Fair, Good, Very Good, Excellent'), centred around the most desirable adjectives 'Excellent', see Section 6.4.2. Feedback is given by highlighting the adjective that currently best describes the effort of the subject compared to some set target force, with effort being applied by squeezing the hand dynamometer. The error signal in this case is the difference between some set target force (i.e. a grip strength the subject is attempting to produce) and their applied grip strength.

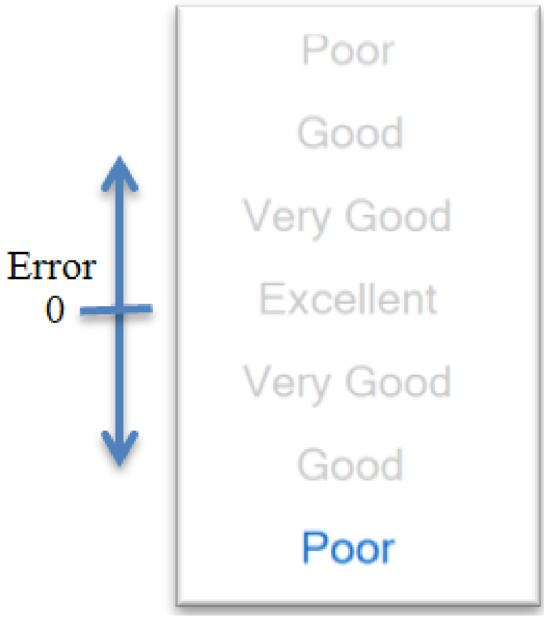

FIGURE 6.24: Mechanism for delivering extrinsic feedback during training.

A band-width delimited mapping system determines the relationship between performance and feedback. To achieve this, the potential force spectrum (i.e. from 0 (Kg) up to the subject's recorded MVC(Kg)) is divided into N adjacent bands. Bands are allocated by limits which set the upper and lower error boundaries for that band. It follows that the bandwidth of each band is given by the distance between its upper and lower limits. A look-up table relates performance effort with feedback reward depending on which band the current effort falls into. For example, for the inner band around zero error the user might be presented with the feedback "Excellent". If their performance error outgrows this band into an adjacent band the feedback will then change to be of lesser quality "Very good". See Figure 6.25 for an illustration of this mapping system.

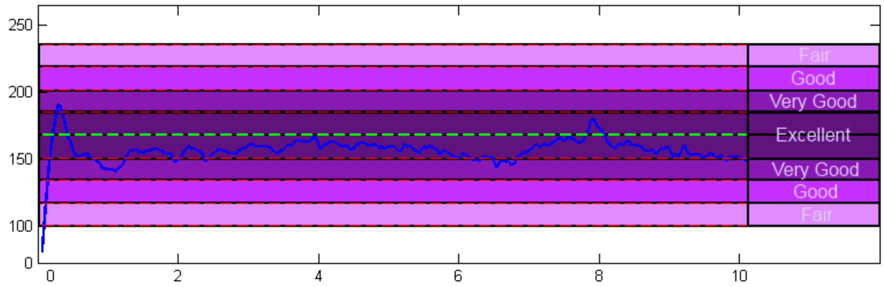

FIGURE 6.25: Illustration of feedback and grip strength mapping, showing grip strength in blue, target force in green and bands in purple with correlating textual feedback between bands.

6.4.3 Experimental Protocol

The experiment consists of attempting 24 repetitions of a unilateral sub-maximal grip for 10 seconds. The procedure is broken down into three sets each containing eight repetitions. A rest period of 60 seconds is included between attempts. The target grip force is constant throughout the experiment and is set to 20% of the subject's maximum voluntary contraction (MVC), calculated as the mean of three sustained maximum grip attempts measured before the experiment commenced. The subjects MVC is re-assessed between sets with the intention of detecting any reduction in ability to produce force as a result of muscle fatigue.

The subject is instructed to sit in a rigid chair with their feet firmly positioned flat on the floor, their back straight, shoulders abducted and neutrally rotated with their elbow flexed at 90%, with forearm and wrist in neutral position. The subject rests their non-dominant hand on their lap and holds the hand dynamometer in their dominant hand. The hand dynamometer is held according to best practice instructions close to the bracket but not touching with the Dynagrip crossbar pointing towards the body. The holding position and subject's posture is checked before each trial to ensure consistency.

Muscle activity is recorded using the system described in Section 6.4.1.2. The subject's dominant arm is prepared using alcohol based wipes with skin electrodes applied according to a study on optimal electrode positioning for grip strength analysis [281].

Feedback is given on screen throughout the duration of the experiment as described in Section 6.4.2. The subject is informed that their objective is simply to attempt to match a target grip strength and that feedback will be given to them as assistance in achieving this goal. However, unknown to the subject, the mapping system relating the feedback and effort is altered between sets. For each consecutive set the band widths are increased by 2.5%. Therefore, Set 1 has a band width of 5%, Set two has a band width of 7.5% and Set 3 has a band width of 10%.

6.4.3.1 Subjects

Eight subjects (6 male and 2 female, aged 23-27) participated in the experiment. Subjects were tested for dominant handedness using the Edinburgh handedness inventory [276], resulting in 6 right and 2 left hand individuals. Subjects were recruited from the National University of Ireland Maynooth and all gave written consent. Ethical approval for this body of work was obtained from the Biomedical and Life Sciences Research Ethics Sub-Committee at the National University of Ireland Maynooth, reference number BSRESC-2014-006.

6.4.4 Results and Analysis

6.4.4.1 Data Preparation

In total, 48 individual data-sets were recorded per subject (24 grip strength data-sets and 24 EMG data-sets). This data comprises of 3 sets each containing eight 10 second grip attempts. Each grip attempt contains approximately 10,000 sample points. Recording of grip strength and EMG data was automatically initiated after the detection of a nominal applied force (greater than 5% of the subjects MVC). This mechanism ensures consistency in the length of recorded data and removes any ambiguity from when a trial starts and ends. However, as a consequence each trial contains a transient period in which force increases from rest to the target force. Accordingly, the first 1.5 seconds of data from both the grip strength and EMG recordings are removed before analysis.

6.4.4.2 Grip Strength Analysis

Statistical analysis was performed on each set including analysis of the (minimum, maximum, mean, median, mode and variance) of grip strength. In addition, the accumulated sum of effort and sum of absolute error were also calculated. Since there is too much data to present all the results in a comprehensive way bar charts and box and whisker plots are used to illustrate the results, see Figures 6.26 to 6.31.

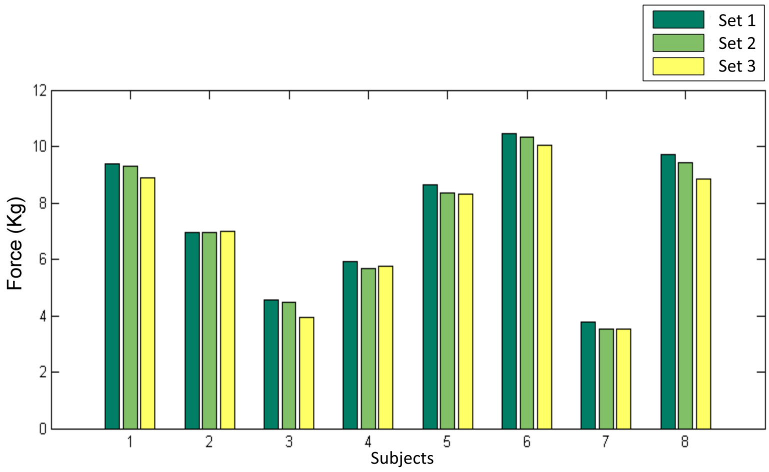

FIGURE 6.26: Minimum effort (Kg)

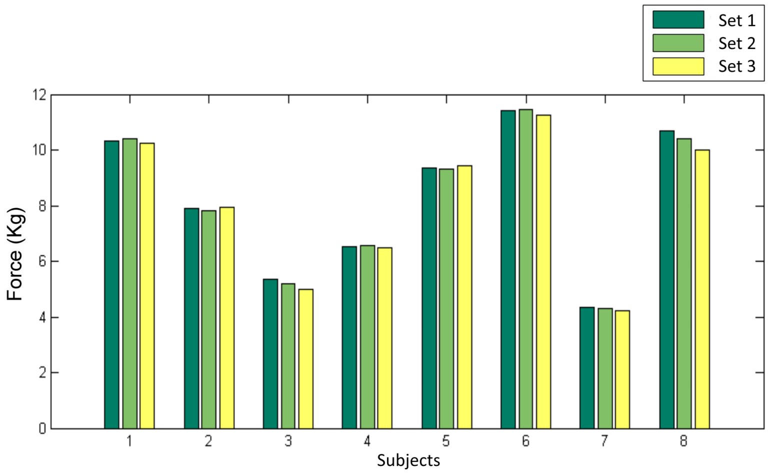

FIGURE 6.27: Mean effort (Kg)

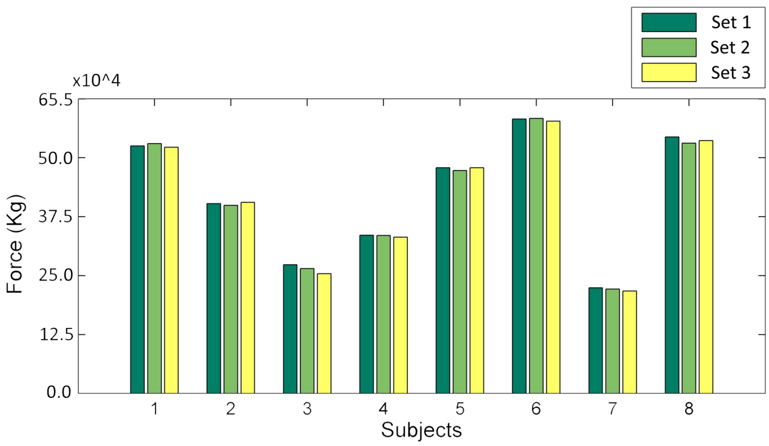

FIGURE 6.28: Sum of effort (Kg)

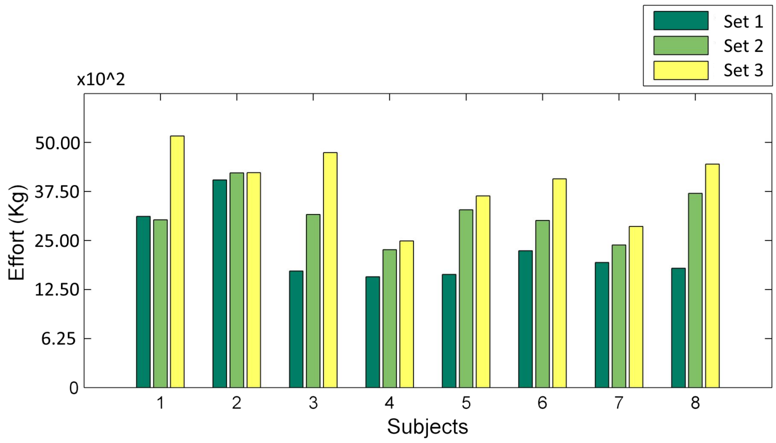

FIGURE 6.29: Sum of absolute error (Kg)

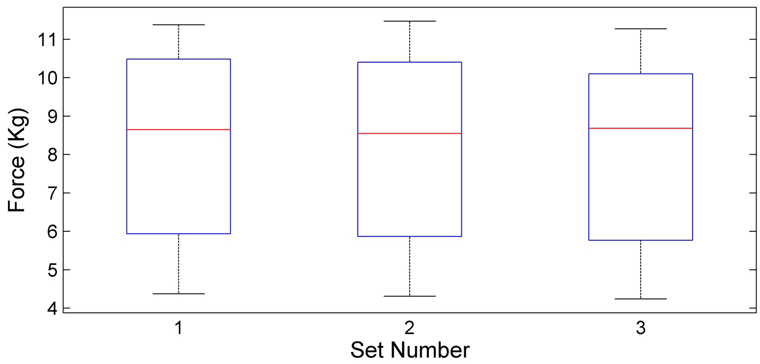

FIGURE 6.30: Mean group effort (Kg) across Sets

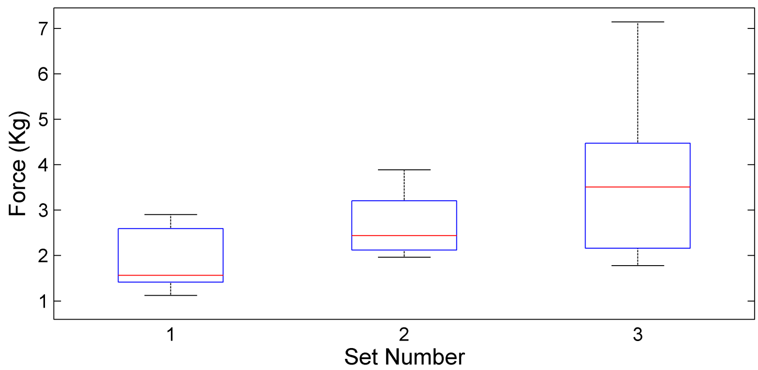

FIGURE 6.31: Variance of group effort (Kg) across Sets

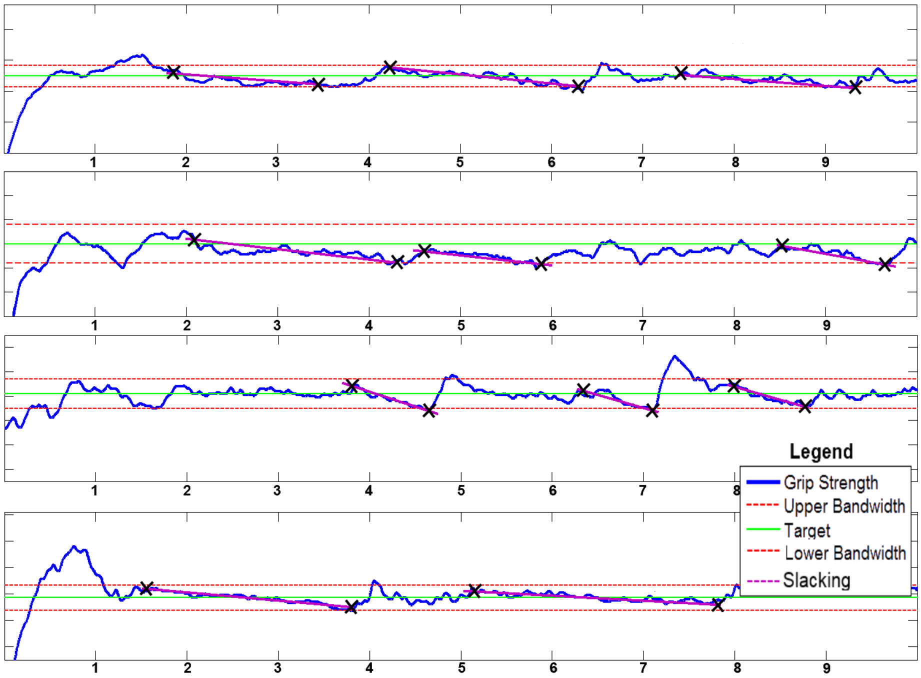

FIGURE 6.32: Random sample of trials chosen from Set 3 (i.e. Bandwidth = 20%) illustrating reduction of force over time if feedback is optimal, illustrating grip strength in blue, target force in green and bandwidth (upper and lower) dashed red line and slacking in Purple.

An ANOVA test [372] was performed on the above results in order to gauge their significance. Accordingly, a test for homogeneity of variance using the Levene's test and a test for normality using a Welch's test were first conducted. The results show that there were no statistically significant differences in group means ($F(2,12) = 0.00829$, $p = 0.992$) or the group sum of efforts ($F(2,12) = 0.00326$, $p = 0.997$) across sets. However, there was a significant difference between group variance ($F(2,12) = 4.332938$, $p = 0.027$) and between groups absolute sum of error ($F(2,12) = 16.74603$, $p = 0.000$) across sets.

6.4.4.3 Fatigue Analysis

Intermediate recordings of MVC were obtained before and after each of the subsequent sets, calculated from the average of three transient maximum contraction attempts, Table 6.5. If significant fatigue has occurred throughout the experiment, there should be a reduction in the ability to produce levels of force equivalent to that recorded at the beginning of the experiment.

A secondary index of fatigue was generated using data collected from EMG. This index was obtained by first generating a series of MNF values for each movement attempt and then calculating the slope of the best fit line for that series, see Table 6.6. For comparison and to put the calculated results into context we have included the analysis of an extended grip exercise in which fatigue is evident (20 second grip attempt at 80% MVC), see row (REF) in Table 6.6. Since fatigue is characterised by a reduction in the median frequency over time, it follows that the calculated slope can be used as an indication of fatigue over the course of an entire set, see Figure 6.33 for illustration.

TABLE 6.5: Intermediate MVC recordings (Kg)

Subjects	*Initial*	*Post Set 1*	*Post Set 2*	*Final*
A	52.97	57.23	52.95	54.31
B	33.90	28.21	30.10	30.03
C	27.79	27.75	27.07	26.39
D	41.81	35.92	36.67	37.63
E	47.70	56.90	60.00	58.26
F	57.78	64.41	61.40	52.44
G	23.00	24.87	25.33	25.22
H	54.15	54.13	53.76	53.89

TABLE 6.6: MNF results - slope of best fit line

Subjects	*Set 1*	*Set 2*	*Set 3*
A	-0.0771	-0.1416	-0.0201
B	-0.0650	-0.1368	-0.1579
C	-0.0772	-0.0946	-0.0726
D	+0.0312	+0.0408	-0.0409
E	-0.0301	-0.0496	-0.0696
F	-0.0964	-0.0537	-0.0659
G	+0.0535	-0.0481	-0.0342
H	-0.0578	-0.0484	-0.0670
REF	-0.5652	-0.5652	-0.5652

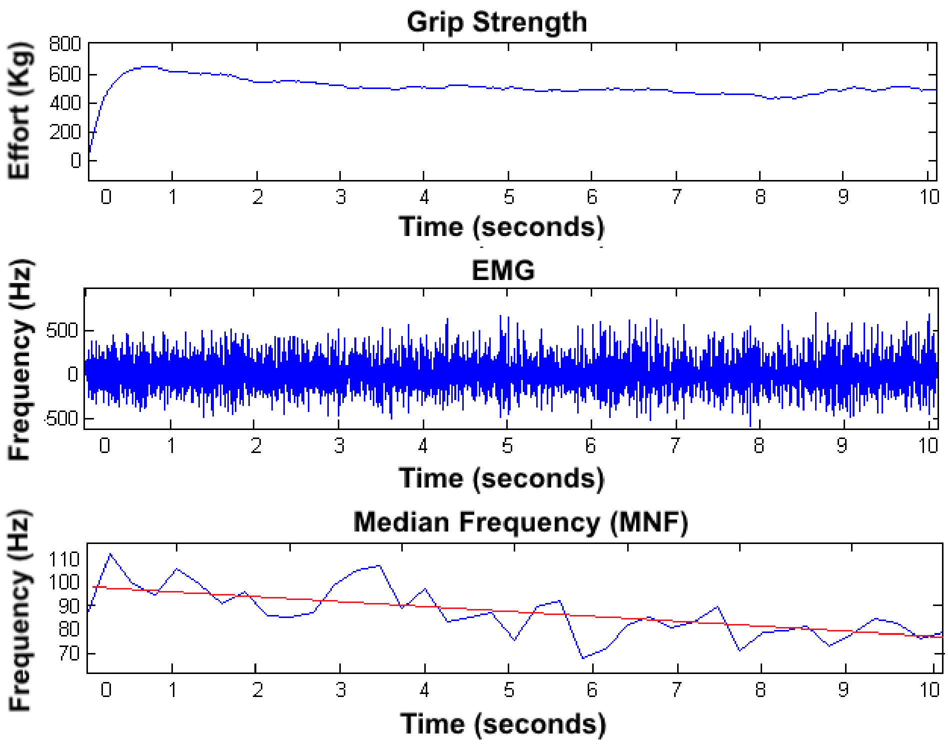

FIGURE 6.33: Reference signal showing extended grip exercise containing muscle fatigue and the response of MNF.

6.4.5 Discussion

The results as outlined in Section 6.4.4 show that increasing the width of the band widths had no significant effect on subjects mean (average) effort and subsequently there was no significant difference in the accumulated effort over an entire set, see Figure 6.27 and Figure 6.28. In contrast, increasing the widths of the bands did have a statistically significant effect on the variance of effort produced and subsequently the absolute sum of error with respect to the target force, see Figure 6.29 and Figure 6.31. At first glance these results might suggest that the relevant band width allocations and therefore the extent of obfuscation, had little effect on the performance of the subject throughout the experiment. However, time series analysis of the collected data indicates that the allocated band widths have a distinct impact on the intermediate production of effort. An intersection of motor performance against feedback reward shows that there is a tendency across subjects to gradually reduce effort once feedback reward is optimum, see Figure 6.32.

Studies of motor adaptation by the human motor system suggest that the motor program incorporates a forgetting factor into an error-based learning law as it adapts to novel dynamic environments, in order to minimize its own effort [98, 303]. Initial attempts to model the human motor system thus included a gain F, to account for the attenuation in effort observed. This forgetting factor was rationalised as some form of error in neural-recall from memory. However, Reinkensmeyer et al. [303] proposed that this forgetting factor was instead an intentional effort by the motor program to reduce effort when error was small, in an attempt to optimise energy efficiency. A compelling computational model of slacking was described by Reinkensmeyer et al., and the implications of slacking for assisted robotics was discussed. It was suggested that slacking by the human participant could cause a naive robot controller to gradually take over force production during assistive training, with negative consequences for use-dependent rehabilitation.

We speculate that the attenuation in effort observed in our experiments might be the result of motor control dynamics which are concerned with the minimisation of effort once the error is small. However, this begs the question of why then is there no reduction in mean effort and subsequently a reduction in accumulated effort in our experiment as the band widths are increased between sets. Insight from motor control experiments might provide an answer to this question as it is suggested slacking can be difficult to detect because it typically increases movement errors as it progresses, triggering error-corrective motor processes that raise muscle activation, resulting in no net decrease in effort [302]. In a similar fashion, a reduction in feedback causes error correction when effort falls below the lower band width limit. Subsequently, the sudden change in feedback causes the subject to increase their effort, typically over estimating the additional required "top-up" effort needed to correct the error. This effect is illustrated by Figure 6.32 which clearly shows distinct periods in which there is an initial surge in effort after the reduction of feedback reward, followed by a gradual reduction of force which reduces effort back down towards the lower bandwidth limit. Therefore, slacking followed by a tendency to over estimate the required error correction could account for both the stable mean effort and the increase in effort variance seen in our results.

Of course, there might instead be alternative explanations for the gradual reduction in effort as seen in our experiment. A gradual reduction in force could be explained by physiological changes in the muscle's dynamics, such as peripheral muscle fatigue. However, care was taken when designing the experiment to reduce the onset of fatigue. The target grip strength selected for the experiment was set at a fraction of the subjects MVC, the time period required to sustain this force was kept short and ample rest periods were scheduled between grip attempts. During the experiments the subjects MVC was reassessed between sets as an indication of any reduction in the ability to produce force. No significant reduction in the ability to produce force was observed as can be seen from Table 6.5. Furthermore, analysis of concurrently collected EMG data suggests that no significant fatigue occurred throughout the experiment, this can be inferred from the shallow slopes presented in Table 6.6, indicating a relatively static MNF throughout the experiment.

In their experimental simulations, Reinkensmeyer et al. proposed that to counteract slacking by the human motor system the robot should also contain a similar slacking term in its controller, designed to reduce its assistance when the error is small. They show that if the robot's slacking term is greater than that of the human participant then it should offset the effects of slacking. However, we speculate that to be effective the robotic slacking rate would need to be dynamic, to allow for variation in the patient's performance caused by psychological factors (i.e. mood, state of mind, concentration levels etc.) and physiological factors (i.e. weakness, fatigue, pain etc.). Furthermore, we speculate that including a robot slacking term might prompt the human to effectively lower their own slacking rate, learned through iterative encounters with the robotic controller, allowing the human to effective "game" the robotic controller into once again taking over force production.

Hence, we contend that a game theoretic approach to designing an automated therapist system, as described previously in Chapter 5 might be an appealing solution to this problem. A game theoretic controller, with access to multiple sources of information about a patient, for example effort afforded by a hand dynamometer, an indication of fatigue afforded by an EMG signal, information regarding the patient's history pertaining to their abilities (i.e. their previous MVC, concentration levels, pain assessment etc.) might be better suited to optimising performance.

6.5 Summary

The provision of extrinsic feedback during motor learning has been shown to enhance motor learning and positively influence motivation. However, studies suggest that to be optimal, mechanisms which deliver extrinsic feedback on performance should encourage the development of desired movement patterns in such a way that supports information coming from intrinsic pathways, thus allowing for implicit self-corrections to be made and for the development of internal models of the task dynamics. Additionally, to be optimal feedback scheduling should be dynamic, with less frequent feedback given as progression is made. Therefore, methods such as bandwidth feedback are of particular interest, as they both obfuscate direct performance and are easily adjustable.

There is currently a dearth of tools which can supplement the loss of feedback during therapeutic exercise training, previously afforded by a physical therapist, after patient leave primary care and return home. Instead, patients are charged with continuing their arduous training programs with little or no external support. In this chapter, efforts are described towards developing automated solutions for supporting and complimenting home based motor intervention programs.

Towards this goal, the design and development of two complimentary tools for the acquisition and analysis of grip strength and muscle activity, two physiological signals commonly used to assess motor recovery and as a prognostic indicator [34, 301], were described. First, a low-cost, reproducible, digital hand dynanometer system, including a grip strength measuring apparatus and acquisition unit. Second, an affordable, satisfactory, two channel EMG acquisition unit, built from open source hardware for measuring muscle dynamics. In addition, a supplementary software system for the real-time data capture and plotting of these two systems was presented.

Using the above systems, a novel bandwidth based experimental feedback paradigm was designed as a means of delivering obfuscated feedback on performance during a grasp and release exercise. This solution incorporates a band width based mapping system which determines the relationship between performance and feedback reward. To assess the potential of such a feedback controller, two separate experiments were conducted to investigate the effects of obfuscated feedback on motor performance.

However, preliminary results suggest that feedback systems which obfuscate performance errors might encourage motor control processes which seek to minimise effort, a variable believed to be critically important in the success of any motor function rehabilitation program. Therefore, care should be taken when designing feedback systems which obfuscate direct performance as they might reduce the effectiveness of the exercise program. Subsequently, further research is required to better understand the underlying interaction dynamics observed here and to elucidate the potential of obfuscated feedback for improving the efficacy of automated solutions for rehabilitation.

Chapter 7

Machine Learning for Augmented Biofeedback

Machine learning refers to a sub field of computer science that deals with the development of models which can learn from and make predictions on data. Machine learning algorithms operate by formulating models based on example input data in order to make "intelligent" data driven predictions or decisions of future events. Initially a machine learning model is essentially blank and needs to be trained to do a certain task. During training new data is fed to the "machine", which in reality is an algorithm, that then generates an output which is subsequently graded by a human expert. The machine then uses this expert assessment to adjust its internal algorithm to better model the desired response. After a while the model becomes sufficiently complex so that the machine becomes adept at completing the task automatically. The power behind machine learning is that rather than following some strict predefined static program instruction, these models are designed to change and adapt, allowing the machine to essentially learn over time.

Biofeedback is the process of providing information regarding the physiological functioning of systems of the body, in an attempt to help control the activity of those systems. For example, an electrocardiogram (ECG) presents feedback regarding the electrical activity of the heart, which could be used by an individual to control their heart rate, through decisive manipulation of breathing. Biofeedback has many potential applications for rehabilitation and can be particularly useful in situations where there is little or no information originating from intrinsic sources that can help inform a person how to better their performance. For example, when practising a photogenic smile, it can be useful to practise in front of a mirror since the bodies sensory apparatus provides no inherent feedback about the quality of the performance of a facial expression. In a similar manner, after neurological injury damage to the somatosensory system or motor system can impair normal feedback pathways, making it difficult for an individual to improve their performance of a movement task.

The work in this chapter draws on elements of both machine learning and biofeedback to develop two separate applications for enhancing rehabilitation post stroke. The first part of this chapter introduces a portable and inexpensive, EEG based biofeedback brain computer interface (BCI). This system uses machine learning techniques to develop a prediction model based on common spatial patterns (CSP), to distinguish between different brain states relating to two different classes of motor activity, (i.e movement and rest). The output of this model is then used in deciding weather or not sufficient effort has been contributed by an individual during a movement attempt, in order to trigger haptic feedback to help complete the movement task. The focus of the work here is on the development of the biofeedback system as a whole and not on the advancement of the machine learning techniques employed therein.

The second part of this chapter investigates the potential application of active appearance models (AAMs), a machine learning technique used for matching a statistical model of object shape and appearance to locate objects of interest in new images. The system described here utilises AAMs to tracking key facial features with the objective to automatically assess facial paralysis according to the House Brackmann (HB) scoring system. The aspiration of this work is to provide a proof of concept for the design of an intelligent feedback mirror, suitable for use in the home setting, that can provide subdued visual feedback during training in an attempt to enhance facial motor system (FMS) rehabilitation.

7.1 A Portable and Inexpensive Biofeedback BCI

After stroke, most patients suffer from some form of motor disability, typically weakness on one side of the body and/or partial loss of functional movement of a limb. In such cases, motor therapy comprising task-specific, repetitive, prolonged movement training with learning, often guided by a therapist who assists in the completion of movement tasks [112], may have significant impact on recovery. However, in the case of severe impairment where motor skills have been highly affected there is often little or no movement available which the therapist can work with. Patients with such severe disability then have few if any therapy options for the required type of motor rehabilitation. In such cases the application of a brain-computer interface (BCI) may provide an alternative approach for neurorehabilitation [333]. A BCI can serve a number of rehabilitation purposes for recovering stroke patients, for example a BCI can be used to substitute for loss of neuromuscular functions by using brain signals to interact directly with the environment. Another mode of application is to provide a means by which a severely disabled patient can engage in activities that may help restore function. In such an application coincident activation of sensory feedback loops and the primary motor cortex may reinforce previously dormant cortical connections through Hebbian plasticity and thereby support functional recovery [300]. A BCI can help achieve this through a neurofeedback process in which measures of motor program engagement can be detected with appropriate feature extraction and machine learning, to produce a control signal which is then used to close the feedback loop through triggering of appropriate feedback [125]. Such an approach may have tremendous utility in providing closed loop neurorehabilitation to patients with severe deficits.

For a detailed discussion of BCI for neurofeedback, see Chapter 3.

7.1.1 Motivation

Recently, there has been much interest in neurofeedback with many researchers attempting to incorporate aspects of neurofeedback into robotic or haptic rehabilitation systems. However, current commercially available devices for Brain Computer Interface (BCI) controlled robotic stroke rehabilitation are prohibitively expensive for many researchers who are interested in the topic, and physicians who would utilize such a device. In addition, while these systems represent the state of the art in clinical rehabilitation and are capable of fine measurement and performance, they are however unsuitable for home deployment given their costs, complexity and technical operation requirements.

There are two costly elements of a BCI biofeedback system; the haptic feedback component, typically a robotic end effector, and the BCI component, usually an EEG acquisition system. While much effort has been made to develop cost effective methods to record electrical activity of the brain, less progress has been made on developing affordable biofeedback devices. As a consequence, the BCI component of such systems is now relatively inexpensive in comparison to the haptic feedback component.

As discussed in the previous chapter, one of the major disadvantages of home-based rehabilitation programs is the current lack of specialized equipment and insufficient data as to their efficacy. Unfortunately this lack of data makes it difficult for companies which might provide BCI-driven robotic systems to justify the investment required to make this technology widely available. This, in turn, makes collection of the required evidential data even less likely to happen. Therefore, presented in this section is the proof of concept design, implementation and test of an inexpensive, portable BCI-controlled hand therapy device, which provides haptic feedback using a lightweight inflatable glove. We believe that the relatively inexpensive, albeit very simple, BCI-driven haptic system described here is an example of the type of approach which may help "bootstrap" the process of creating the necessary studies which can build evidence as to the effectiveness and utility of home-based BCI rehabilitation systems.

7.1.2 Pneumatic Glove

The haptic feedback component of the system is a pneumatically controlled hand therapy glove which provides finger and wrist extension to a limp or paralysed hand. The glove consists of numerous air pockets, located along the spine of the glove and along each digit. The hand is secured to the glove by a series of Velcro™ straps, at the wrist and at each digit. When deflated, as shown in Figure 7.1 the glove is completely flaccid. When inflated the glove becomes rigid, encouraging the hand to conform to the shape of the glove as shown in Figure 7.2.

Figure 7.1: Photograph of hand in pneumatic glove when fully deflated, illustrating rest state of the hand and fingers.

FIGURE 7.2: Photograph of hand in pneumatic glove when fully inflated, illustrating wrist extension and flexion of digits.

The glove (Romover Exercise Air Glove, Model: RA-100A, Nitto Kohki CO LTD) utilised here is re-purposed and is no longer in production. However, a similar pneumatic glove, the PneuGlove, has been described elsewhere [64, 65] and would be a suitable low-cost replacement.

7.1.2.1 Pneumatic Control System

A custom air control system, shown in Figure 7.3, was designed to facilitate the inflation and deflation of the glove through a computer-controlled interface.

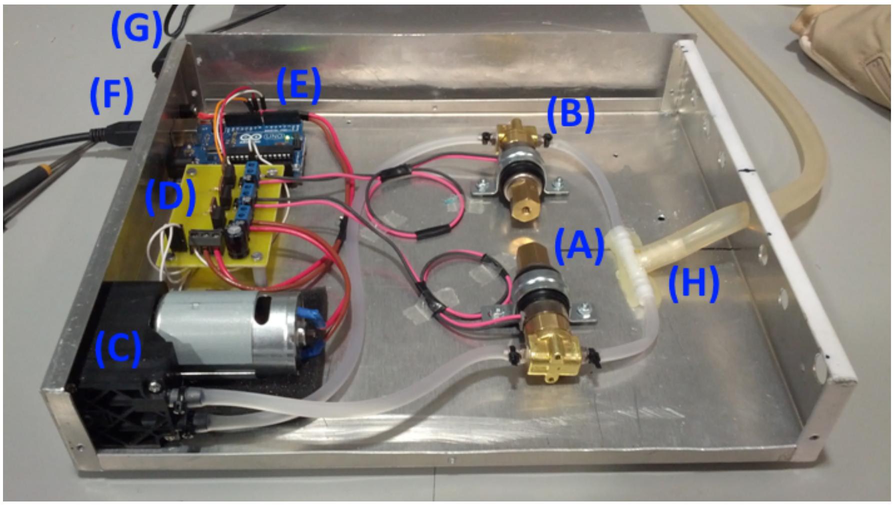

FIGURE 7.3: Custom pneumatic control system, showing; A) Air inlet valve, B) Air outlet valve, C) Vacuum pump, D) Electronic control system, E) Arduino, F) USB data interface, G) Power supply, H) Intersection to air glove.

A 12 V DC diaphragm vacuum pump (Airpo-D2028B, Ningbo Forever Electronic Appliance Co., China.) supplies both pressure and vacuum to our system. Inflation and deflation of the glove is determined by control of two electro-mechanic 3/2 solenoid valves (SMC Corporation, Japan. S/N: VDW250-6G-1-01F-Q). The valves exhibit binary control allowing for the selective routing of air from their input port to one of their two output ports. For both valves, the input port is connected to the vacuum pump, one output port is connected to the glove and the other is connected to the atmosphere. The set-up configuration is illustrated by Figure 7.4.

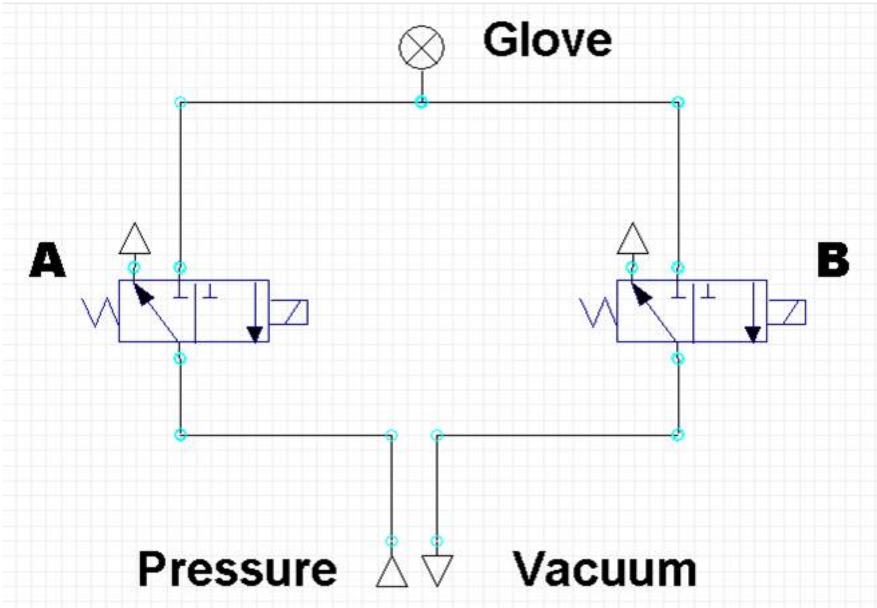

FIGURE 7.4: Illustration showing configuration of pumps, (A) intake value, (B) outlet value, arrows show the direction of airflow.

7.1.2.2 Electronic Control System

An open-source prototyping platform, the Arduino Uno (Arduino, Ivrea, Italy), acts as a mediator between the BCI and pneumatic glove system. The Arduino receives instructions over a serial communication link from the PC and carries out appropriate control of the pump and solenoid valves. Thus, inflation and deflation of the glove is controlled via serial communication with the PC. The system incorporates two independent power supplies: 5 V DC supplied by USB to power the Arduino platform and 12 V DC to power the pump and solenoid valves. In order to safely control the higher voltage components using 5V logic, additional electronics are required, as shown in Figure 7.5.

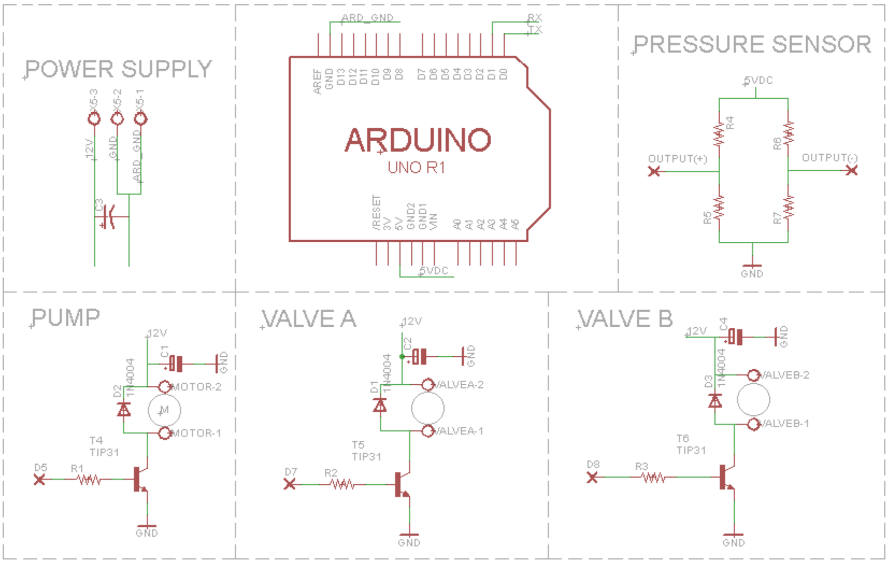

FIGURE 7.5: Custom electronic control system for controlling air flow to glove.

7.1.3 EEG Brain-Computer Interface

Electroencephalogram (EEG) was recorded from 27 Ag/AgCl electrodes placed over the sensori-motor area from positions FCz, FC1 - FC8, Cz, C1 - C8, CPz and CP1 - CP8 according to the 10/20 system of electrode placement, see Figure 7.6.

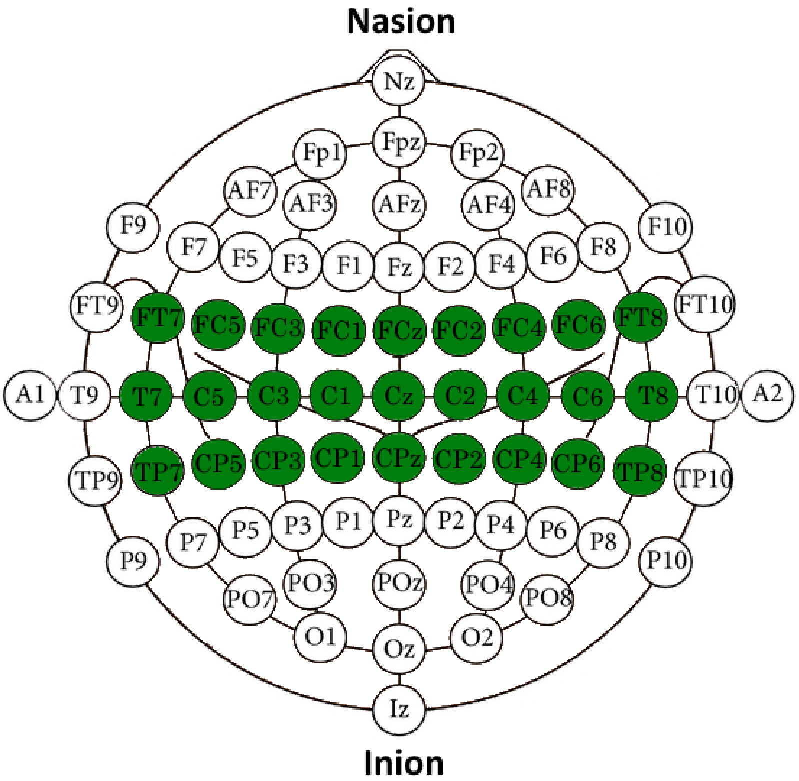

FIGURE 7.6: Electrode placement on the scalp according to 10-20 system, highlighting in green the 27 active electrodes positioned over the sensori-motor area that were used to record data for experiment.

Data was recorded using a g.USBamp system (g.tec Medical Engineering GMBH, Austria) at a sample rate of 256 samples per second. We used a modified version of g.tec software to implement a real-time two-class Common Spatial Patterns (CSP) based BCI [127], which was used to send appropriate control signals to the Arduino.

All sampled EEG was band-pass filtered in the 0.5-30 Hz frequency range and had a 50 Hz notch filter applied. EEG was further filtered to the 8-30 Hz range before the CSP stage of processing. g.tec software[1] was used to remove artifact-affected trials and noisy channels, carry out CSP analysis, produce CSP filters and train a Linear Discriminant Analysis (LDA) [414] classifier for real-time testing. During real-time testing, EEG was filtered as before, decomposed by the trained CSP filters and classified by the trained LDA classifier. The classifier output was smoothed with a moving-average filter of length 0.5 seconds. At a specific time after instruction onset (determined during BCI training), the smoothed classifier output was sampled. The control signal sent to the Arduino was based on this sample value. An overview of the entire system is presented in Figure 7.7.

[1] g.BSanalyze-Specs-Features

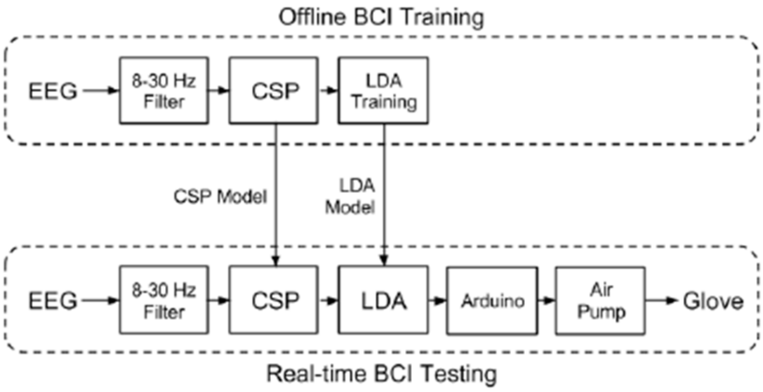

FIGURE 7.7: BCI system overview

7.1.4 System Testing and Validation

7.1.4.1 Subjects

Three healthy subjects (all male, aged 24-28), recruited from Maynooth University, participated in a system validation test. Subjects were all self-reported right handed and gave oral consent before participation.

7.1.4.2 Experimental Protocol

To demonstrate the operation and feasibility of the system, subjects participated in the training and testing of an overt movement BCI. During training and testing sessions, subjects were seated in a comfortable chair, wore the glove on their dominant hand and followed instructions presented on a PC monitor in front of them at eye level. Both the training and test procedure consisted of 40 trials, 20 rest trials and 20 active trials, which were presented in a randomized order in each session. During an active trial, the subject was instructed to perform self-paced dominant hand digit contraction and extension, as this action resembles the movement induced by glove inflation and deflation. During a rest trail, the subject was instructed to simply relax while not attempting to move their body or to imagine movement.

For the training session, each trial lasted 8 seconds. At 0 s, a fixation cross is displayed in the center of the monitor. At 2 s a warning stimulus is given in the form of a “beep”. From 3 s to 4.5 s, an instruction arrow appeared (i.e. a cue stimulus), pointing right to indicate a movement instruction or pointing left for a rest instruction. From 4.5

s to 8 s, the fixation cross remained on-screen. The subjects were instructed to perform the action (rest or movement) as soon as the arrow appeared. For each subject, the recorded EEG was analyzed separately to produce optimal CSP filters, train the linear discriminate analysis (LDA) classifier and determine the optimal delay after instruction onset to sample the smoothed classifier output.

For the test session, each event lasted 30 seconds. Instruction presentation was the same as before except that the fixation-cross remained on-screen from 4.5 s to 30 s. The additional time allocated during testing reflects the maximum duration required for the pump to fully inflate and deflate the glove. During these 25.5 s, feedback of the classifier output was also presented on-screen in the form of a bar extending to the left or right of the centre of the screen. The sign of the sampled classifier output determines the decision to inflate then deflate the glove or to let it remain deflated. A positive sample value indicates movement classification while a negative sample value indicates rest classification. As inflation and deflation of the glove takes 22 seconds, there is sufficient time per trial for full range of hand movement induced by the glove.

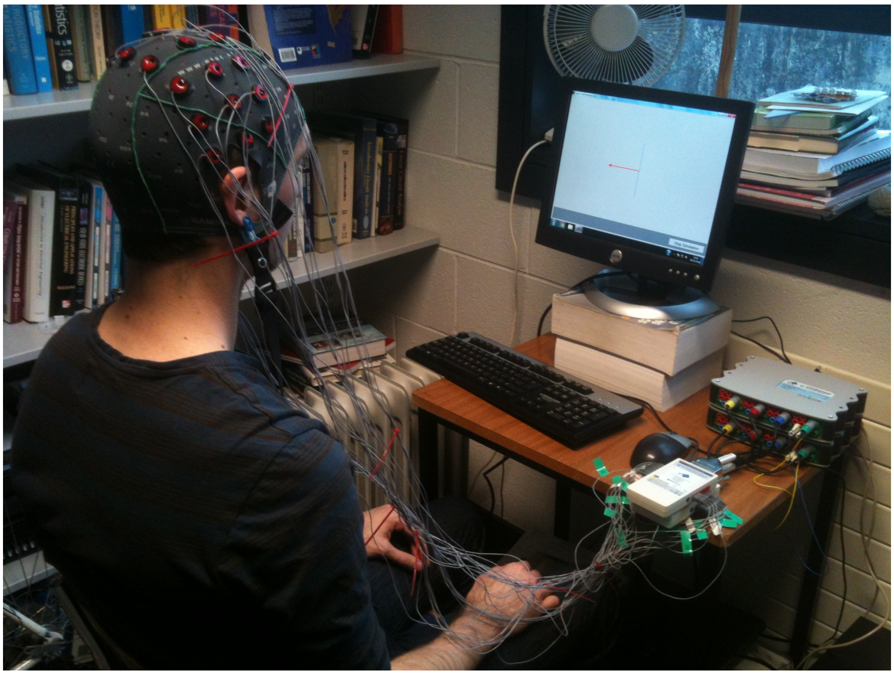

Figure 7.8: Experiment set-up showing BCI system and monitor with feedback arrow indicating activity to perform.

7.1.4.3 Results

A table of classification accuracy results of the BCI test sessions is shown in Table 7.1. Presented in Figure 7.9 is a representative section of the time course of classifier output with timings for active and rest instruction onset, classifier sample times, classifier sample points and an illustration of the changing air pressure in the glove over time as it reacts to the classifier output. The inflation time taken for the glove to move the subject hand from minimal to maximal deflection was 12 seconds. The time to deflate the glove back to its initial state was 10 seconds. Therefore, total time for inflation then deflation of the glove, producing maximal range of hand motion, was 22 seconds.

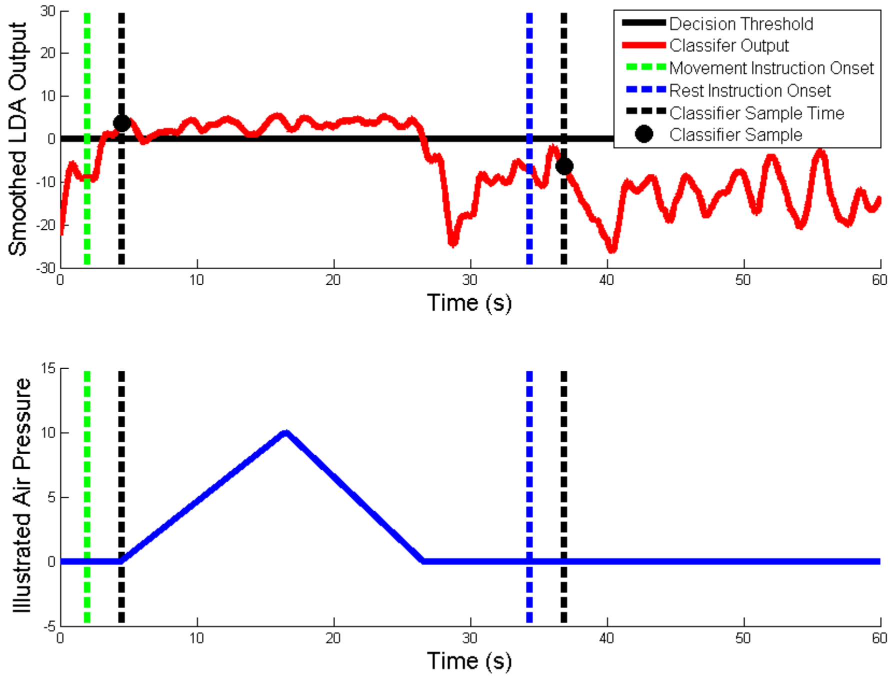

FIGURE 7.9: LDA classifier output with event timings (top) and illustrated air pressure in the glove (bottom)

TABLE 7.1: Rehabilitation BCI classification accuracy results.

Subjects	Classification Accuracy
A	92.5%
B	90.0%
C	80.0%

7.1.5 Discussion and Future Work

A system such as the one described here may be used to explore closed loop neuro-feedback rehabilitation in stroke relatively inexpensively and potentially in home environments. The main goal of this work is to report on the development of a simple, affordable and accessible neuro-rehabilitation system which could fulfil the need for home-based motor therapy with somatosensory feedback. The focus is the novelty of the system as a whole and not the results of classification as the BCI software used here is quite basic and available commercially. The system presented here uses a basic form of CSP, simple classification with LDA and a relatively easily-classifiable EEG pattern of overt movement activity. Any stage of the BCI could be replaced by a more sophisticated design and implementation. For example, there are many improvements to the CSP algorithm which could be used, a more advanced classification method such as Neural Networks or Gaussian Process classification could be utilized. Additionally, an imagined movement-based protocol could be used to explore BCI-based stroke rehabilitation methods [333, 350, 375].

Many considerations were made while developing this platform. The pneumatic glove used is comfortable to wear and uses adjustable Velcro™ straps, allowing it to fit different size hands. It is easy to don and doff therefore it is entirely possible for a family carer or even the user to use the system without technical assistance. From a safety perspective the glove is ideal as there is no electrical energy transmitted to the glove. In fact, all the materials in the glove are insulators and do not conduct electricity. In addition, the glove design inherently minimises movement restrictions placed on the user as there are no stiff mechanical parts and it is completely flaccid without air. The pneumatic control system was designed with portability in mind, weighing less than 2 kg and is housed in a compact case. The system can be used with any PC, requiring only installation of the software.

We believe that the relatively inexpensive, albeit very simple, BCI-driven haptic system described here is an example of the type of approach which may help “bootstrap” the process of creating the necessary studies which can build evidence as to the effectiveness and utility of home-based BCI rehabilitation systems. In collaboration with the Movement To Health Group of the University of Montpelier, France, a preliminary investigation involving chronic stroke patients is currently being undertaken with this device [157]. The objective of this investigation is to assess the practicality and usability of the biofeedback platform for use with chronic stroke patients and in addition, to gain insight into how the device and protocols adhered to during use, can be improved.

7.2 Machine Vision for Enhancing Facial Neuromuscular Re-education

Facial expressions play an important role in non-verbal communication, they are the primary means by which we convey social information, from the way we express ourselves to conveying our emotional state. The loss of fine facial muscle control is a serious impairment for an individual, effecting their ability to communicate effectively and often causing disfigurement which can affect the individual socially and psychologically [71, 261]. Paresis of the facial nerve after stroke causes functional and aesthetic defects, manifested by facial asymmetry with muscle impairment of the lower half of the face, drooping of the corner of the mouth, dribbling from the corner of the mouth, asymmetrical smile and a speech explicitness disorder with atonia of the lips, tongue and throat [188].

In addition, if not treated acute facial paralysis can lead to facial synkinesis, that is, unintentional movement in one area of the face produced during intentional movement in another area. Facial synkinesis is caused by aberrant facial nerve regeneration of fibers during the neural repair process [72] and therefore typically results in progressive facial asymmetry which worsens with time. This is because facial synkinesis promotes unbalanced muscular activity, unbalanced muscular hypertrophy, and unbalanced patterns of facial expression [201]. Subsequently, untreated FMS disorders can attribute to low self-esteem, have a profound impact on the quality of life and as a result may affect an individuals ability to perform ADLs.

Until recently there has not been much research interest in rehabilitation for facial movement dysfunction after neurological injury. This is partially due to the prioritisation of rehabilitation services, traditionally intervention efforts after stroke tend to focus on rehabilitating aspects of the central nervous system that lead to functional improvements in the activity of daily living, but also due to the lack of benefits observed from traditional approaches to facial paralysis rehabilitation, i.e. programs consisting of repetitive facial expression exercise, light massage and electrical stimulation therapy [380]. However, increasingly biofeedback interventions (e.g. mirror feedback and surface-electromyographic (sEMG) feedback) are being shown to significantly enhance facial rehabilitation when used in conjunction with a daily training regime or other interventions. Several investigators have described improvements in facial movement as an outcome of facial neuromuscular reeducation using surface EMG biofeedback or mirror feedback [22, 188, 201]. The rationale behind biofeedback for facial rehabilitation is that, unlike other skeletal muscles, facial muscles contain few if any intrinsic muscle receptors or joint receptors, i.e. the primary source of peripheral proprioceptive feedback to the central nervous system [380]. Therefore, since there is little natural feedback about facial muscle posture and movement, voluntary attempts to guide facial movements rarely result in an accurate approximation of the desired movement. The principle benefit of using biofeedback as an adjunct to facial muscle reeducation is the ability to provide accurate and immediate feedback about facial muscle activity.

From the perspective of home based therapy, mirror feedback is a particularly appealing method of delivering feedback on performance as it is easily and cheaply implemented, only requiring a standard mirror. In contrast, EMG based biofeedback is relatively burdensome, requiring additional expensive hardware (i.e an EMG acquisition unit), time consuming preparation (i.e. removal of hair and dead skin cells), and signal validity testing (i.e impedance testing, inspection of the raw EMG-baseline quality). However, the uses of a mirror for biofeedback has some disadvantages. For an individual with facial paralysis, exercising while watching oneself move with facial paralysis and the psychological distress of looking at an abnormal facial appearance may be more detrimental to recovery than beneficial [380]. Therefore developing ways to deliver visual feedback in a manner which is less disconcerting to the user and which has a positive impact on the patient's experience of the process might have value for augmenting the rehabilitation process.

7.2.1 An Intelligent Mirror for Facial Neuromuscular Re-education

Developing suitable training programs which can encourage self initiated practise of facial muscle exercises in the home is important, as the success of neuromuscular reeducation depends on attention and practice to make any long lasting improvements. Positive results have been shown in clinical practise where patients are trained to perform a couple of exercises accurately without feedback guidance, or with only an occasional need to look in the mirror to "check" that the facial expression they are attempting is correct [380].

An alternative more effective approach to generating "compassionate" visual feedback might be achieved through the application of machine vision techniques. A preliminary investigation of the use of machine vision techniques by Delannoy & Ward [84] described the use of Active Appearance Models [69] for tracking of key facial points and for the automation of facial disability scoring.

In this work we elaborate on the use of AAMs for the real-time extraction and tracking of facial landmarks, for the automatic scoring of facial function using the House Brackman scoring system, towards the development of an intelligent feedback mirror.

The purpose of the work here is to illustrate and demonstrate how AAMs can be used to manipulate an image to exaggerate or subdue facial features, a sort of feedback gain control, either to encourage further effort from the patient, or to assist slightly in completing a facial expression in an attempt to increase motivation. Subdued feedback can be considered a form of compassionate feedback, which might make it easier for the patient to focus on the feedback presented. See Figure 7.10[2] for an abstract overview of this concept.

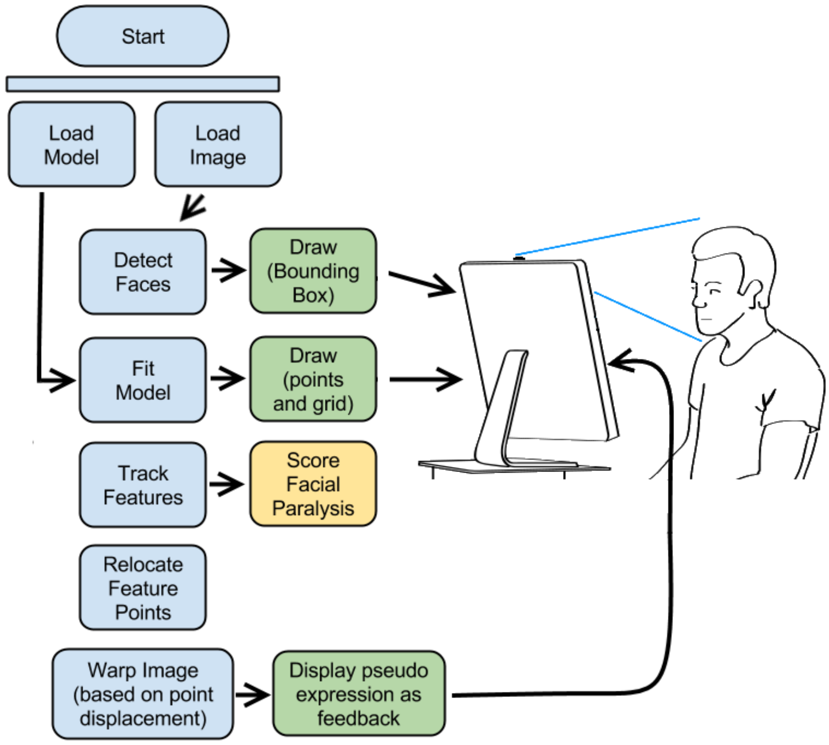

FIGURE 7.10: Abstract overview of intelligent mirror approach.

7.2.2 Active Appearance Model (AAM)

The active appearance model (AAM) was first introduced by Cootes and Taylor in [94] and is a highly flexible deformable statistical model for modelling both the shape and texture (i.e. appearance) of an image. An AAM contains a statistical model of the shape and grey-level appearance of the object of interest, built from analysing the appearance of a set of labelled examples. An AAM based location algorithm for facial feature points is divided into two procedures: face modelling and model searching. For face modelling, a training set of annotated images are required where the corresponding points have been manually marked on each example, then Procrustes analysis [85] is applied to align

[2]Source: Standing desk illustration.svg Creative Commons Attribution 3.0 Unported

the sets of points and a statistical shape model is built. After this, Eigenanalysis is applied on the texture vectors to reduce the dimensionality of the coordinates and to build a texture model, see [95] for details. Finally the correlations between shape and texture are learned to generate a combined appearance model.

In model searching, an iterative approach is constructed to adjust the model parameters, while there are two kinds of main iterative methods: the Lucas-Kanade algorithm and the inverse compositional algorithm. A new image can be interpreted by finding the best plausible match of the model to the image data. Matching the model to an image involves finding model parameters which minimise the difference between the image and a synthesised model example, projected into the image. The benefits of the AAM approach are that the model can be generalised to any valid object, only requiring the correct annotation of training images to develop new models. Expert knowledge can therefore be captured in the system in the annotation of the training examples. The models give a compact representation of allowable variation, but are specific enough not to allow arbitrary variation different from that seen in the training set. The system need make few prior assumptions about the nature of the objects being modelled, other than what it learns from the training set. With this approach, a good overall match can be obtained in a few iterations, even from poor starting estimates. Furthermore, as the model get better at matching the desired object in new images, these new matches which are essentially automatically annotated images, can be added to the training set if deemed accurate enough by the expert. Thus, while the initial process of manually annotating images can be tedious, the model can quickly start to assist in improving itself, rapidly speeding up the process of improving the model.

7.2.2.1 AAM Algorithm

In this section we outline the algorithm used to model shape and appearance as described by Tim Cootes et al. The reader is directed to the following work for further details [68, 69].

The process of developing an AAM starts with a series of annotated training images, i.e. images labelled by landmarks points which represent key features of the object to be modelled. For example, to model a face we select key facial points such as the eyes, nose, mouth and jaw line, see Figure 7.11.

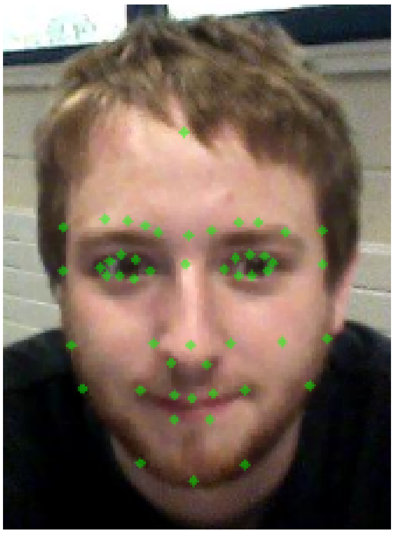

FIGURE 7.11: Example of face image labelled with 54 landmarks

Annotating the images results in a series of images each labelled with a set of points p_i, where $p_i = (x_i, y_i)$. Assuming all the sets of landmark points are in a common co-ordinate frame, each set of points can be represented by a vector, x. The resulting vectors form a distribution of points in $2n$ dimensional space. To reduce the modelling complexity of the resulting data set, principal component analysis (PCA) [363] is applied to the data. An approximation of the shape x in any of the training sets is then given by Equation (7.1).

$$x \approx \overline{x} + P_s b_s \tag{7.1}$$

where $\overline{x}$ is the mean shape, P_s is a matrix of t eigenvectors of the covariance matrix of the training set and b_s is a set of shape parameters. Since the eigenvectors which form P are linearly independent it is possible to rearrange Equation (7.1) to extract the shape parameters, b_s:

$$b = P^T(x - \overline{x}) \tag{7.2}$$

The vector, b defines a set of parameters of a deformable shape model. By varying the elements of b we can vary the shape of x. Therefore, it is possible to approximate any plausible face shape by choosing values of b, within limits derived from the training set.

To model the grey-level appearance g, a shape-normalised image is developed by warping each of the training images so its control points p_i match the mean shape $\overline{x}$.

The grey-level information g_{im} is then sampled for the shape-normalised image over the area covered by the mean shape. To minimise the effects of environmental lighting variations, the samples are normalised by applying a scaling factor α and an offset β.

$$g = \frac{g_{im} - \beta}{\alpha} \tag{7.3}$$

The goal is then to chose values for α and β which best match the vector to the normalised mean. Letting $\overline{g}$ be the mean of the normalised data, both scaled and offset so that the sum of elements is zero and the variance of elements is unity α and β can therefore given by

$$\begin{aligned} \alpha &= g_{im} \cdot \overline{g} \\ \beta &= \frac{g_{im} \cdot 1}{n} \end{aligned} \tag{7.4}$$

where n is the number of elements in the vectors, i.e the number of landmark points.

By applying PCA to the normalised data we obtain a linear model for grey-level appearance:

$$g = \overline{g} + P_g b_g \tag{7.5}$$

where $\overline{g}$ is the mean normalised grey-level vector, P_g is a matrix of t eigenvectors of the covariance matrix of the training set and b_g is a set of grey-level parameters.

The shape and appearance of any example can thus be summarised by the vectors b_s and b_g. Finally, since there are correlations between the shape and grey-level variations, a further PCA is applied to the concatenated vectors to obtain a combined model of the form:

$$\begin{aligned} x &= \overline{x} + Q_s c \\ g &= \overline{g} + Q_g c \end{aligned} \tag{7.6}$$

where c is a vector of appearance parameters controlling both the shape and grey-levels of the model, and Q_s and Q_g map the values of c to change the shape and shape-normalised grey-level data. A face can be synthesized for a given c by generating the shape-free grey-level image from the vector g and warping it using the control points described by x.

7.2.2.2 Model Fitting

Matching the appearance model to a face in a new image is a two part operation. No prior knowledge is assumed about where the face may be in an images or it's scale and orientation. Instead, a simple eigen-face model is used for initial face detection. A correlation score S, between the eigen-face representation of the image data M, and the image itself I, can be calculated at various scales, positions and orientations:

$$S = |I - M|^2 \tag{7.7}$$

In principle the image could be searched exhaustively, however a much more efficient process is to use a stochastic approach. Therefore, both the image and the model are sub-sampled to calculate a correlation score using only a small fraction of the models sample points.

After finding a good starting approximation of the face, the model parameters b can then be adjusted to best fit the model to the new image. The objective of the search algorithm is therefore to minimise the difference between a real face image and one synthesised by the appearance model.

A difference vector δI can be defined as:

$$\delta I = I_i - I_m \tag{7.8}$$

where I_i is the vector of grey-level values in the image, and I_m is the vector of grey-level values for the current model parameter.

To locate the best match between model and image, we wish to minimise the magnitude of the difference vector:

$$\Delta = |\delta I|^2 \tag{7.9}$$

This can be achieved by varying the model parameters c. Since there are typically a large number of parameters involved this becomes a difficult optimisation problem. However, to overcome this problem some priori knowledge of how to adjust the model parameters during search leads to an efficient run-time algorithm.

Therefore, there are two parts to the problem: learning the relationship between δI and the error in the model parameter δc and using this information in an iterative algorithm to minimise Δ.

The simplest model that could be chosen is linear:

$$\delta c = A\delta I \tag{7.10}$$

This turns out to be a good approximation to provide decent results. Finding A involves performing multiple multivariate linear regression on a large sample of known model displacements δc and the corresponding difference images δI.

7.2.3 Setup

7.2.3.1 Hardware Description

The following section describes the hardware and software systems used in this work as well as the environmental setup used.

Harware

PC:

- 3.4GhZ (Intel i7 processor)
- 6Gb ram
- 1Gb Ati Radeon HD 6800 graphics card
- 1TB Harddrive

Logitech Quick Cam Deluxe

- Resolution: Up to 1.3 megapixel
- Frame rate: Up to 30 frames per second
- Image Format: 640x480

Software:

- Ubuntu 10.04 LTS
- QT4

– OpenCv 1.1.0

– AAM Library

The camera was positioned on top of a 17" monitor screen. Images were taken approximately 1/4 of a metre away from the subject, who was seated in a chair, with the camera's focus aligned with the centre of the subjects face. The room was moderately lit with one ceiling light (a fluorescent beam) directly above the subject. In addition, a large window to the left of the subject also let in natural light. No attempt was made to normalise this light as it did not cause any complications during preliminary testing.

7.2.3.2 Software Description

A cross platform application (supporting both Windows and Linux) was developed using the Qt Framework (software development framework with graphical user interfaces support), in conjunction with the OpenCv[3] library (Open Source Computer Vision Library) and the AAM library developed by Tim Cootes (Active Appearance Model Library).

Images are acquired and displayed to screen using OpenCv. Some initial preprocessing is then done to locate any faces in the captured image, as the AAM library requires a starting point for searching. This is accomplished using a Haar feature-based cascade classifier, an effective object detection method proposed by Paul Viola and Michael Jones [381]. The OpenCV library comes with many pre-trained classifiers for detecting faces, eyes, smiles etc.

7.2.4 Building Models

To build a statistical model of appearance we require a set of annotated "training" images which contain different examples of the object to be modelled, in this case a face. Before annotating the image we must first decide upon a set of suitable landmarks, i.e. points of interest, which describe the shape of the object we wish to model. It is important that the chosen points of interest are evident in every training image.

Choosing appropriate landmarks is important, good choices include distinct, easily recognisable points such as points of high curvature or junctions (e.g corners and boundaries). However, when modelling an object there is typically not enough well defined

[3]BSD-3-Clause

points to give more than a basic description of the objects shape, therefore some additional lesser points are often added, for example intersecting points which lie between strong landmark points. See Figure 7.12 for illustration.

FIGURE 7.12: Image articulating landmark points: blue points illustrate strong landmarks while red points illustrate weaker supplementary points.

7.2.4.1 Annotation

Images were manually annotated with a custom devised 54 points model shown in Figure 7.13. The mark-up scheme is as follow:

Legend:

L - Left

R - Right

C - Center

LOC - Left Of Center

ROC - Right Of Center

Points:

1. C Forehead
2. L Lower Temple

3. L Temple
4. L Cheek Bone
5. L Jaw Bone
6. LOC Chin
7. C Chin
8. ROC Chin
9. R Jaw Bone
10. R Cheek Bone
11. R Lower Temple
12. R Upper Temple
13. R Outer Eyebrow
14. R ROC Eyebrow
15. R LOC Eyebrow
16. R Inner Eyebrow
17. Supraglabella
18. Glabella
19. L Inner Eyebrow
20. L ROC Eyebrow
21. L LOC Eyebrow
22. L Outer Eyebrow
23. L Outer eye
24. L LOC Upper eye
25. L C Upper eye
26. L ROC Upper eye
27. L Inner eye
28. L ROC Lower eye

29. L C Lower eye
30. L LOC Lower eye
31. R Outer eye
32. R LOC Upper eye
33. R C Upper eye
34. R ROC Upper eye
35. R Inner eye
36. R ROC Lower eye
37. R C Lower eye
38. R LOC Lower eye
39. LOC Nose
40. C Nose
41. ROC Nose
42. R Nostril
43. L Nostril
44. L Outer Mouth
45. LOC Upper Mouth
46. LOC Lower Mouth
47. C Upper Mouth
48. ROC Upper Mouth
49. R Outer Mouth
50. ROC Lower Mouth
51. L Lower Cheek
52. L Upper Cheek
53. R Lower Cheek
54. R Upper Cheek

7.2.4.2 Model Generation

The AAM model used in this work was developed using Tim Cootes software kit (aam_tools). The models were generated using a set of 60 images; 10 images (taken at slightly varying angles focused at the centre of the face) of 6 different people (included 2 women and 4 men). The images were manually annotated using the 54 point system described in 7.2.4.1.

After annotation, the aam_tools were used to generate a base shape model and shape variation model. The following AAM model resulted from this process, see Figures 7.13 and 7.14.

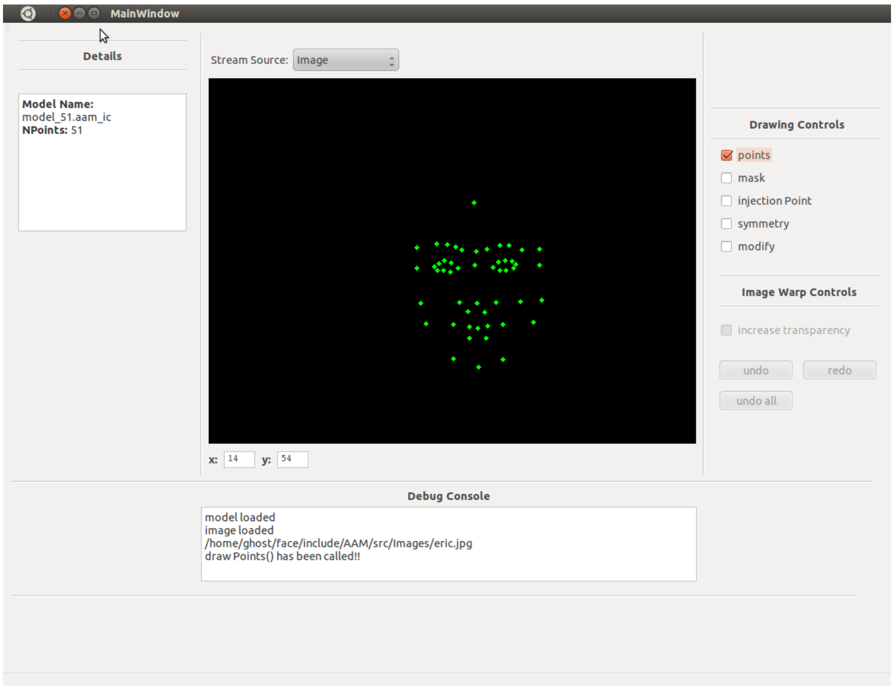

FIGURE 7.13: Base shape showing annotation points.

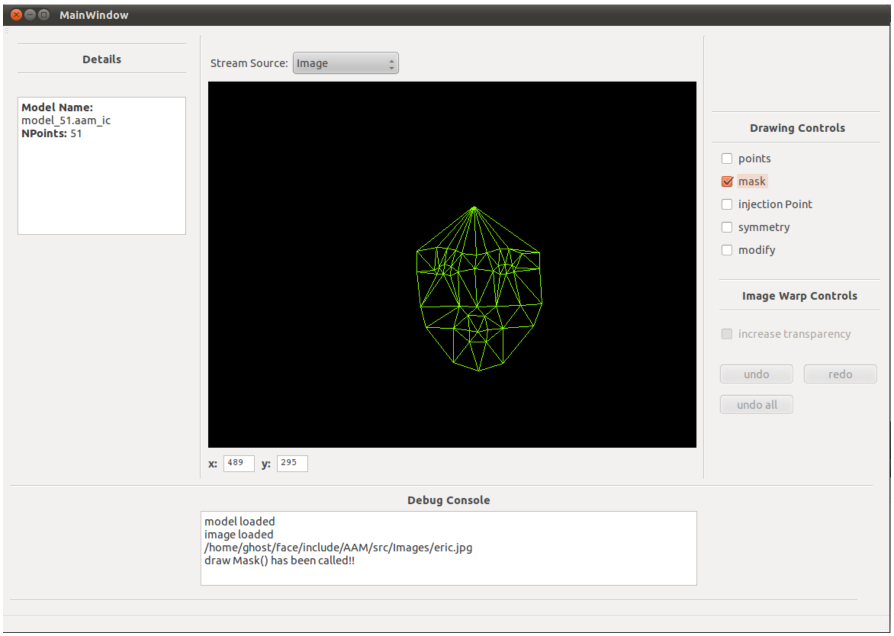

Figure 7.14: Base shape showing triangulated mesh.

7.2.4.3 Model Fitting

Fitting an AAM to an image consists of minimizing the error between the input image and the closest model instance, i.e. model parameters are found that maximize the match between the model instance and the input image, see 7.2.2.2 for details on the model fitting process. However, the AAM fitting procedure is computationally expensive and tends to fail when the initial position of AAM model is far away from a face in an image. See Figure 7.15.

Figure 7.15: Image showing the misclassification of a face by an AAM after 50 steps.

Therefore in order to reduce the fitting time and to improve the performance of the model, a good initial approximation of the location of the face is required. This can be achieved through a face detection algorithm [413]. There are many methods which can be used for this purpose, however one of the most robust and often used facial detection approaches is the Haar cascade classifier, described previously. The Haar classifier method is a machine learning based approach that uses statistical characteristics of facial features to train a cascade function from a series of positive images (i.e. images containing faces) and negative images (images which do not contain faces). The resulting Haar classifier is then used to detect faces in new images, not unlike an AAM.

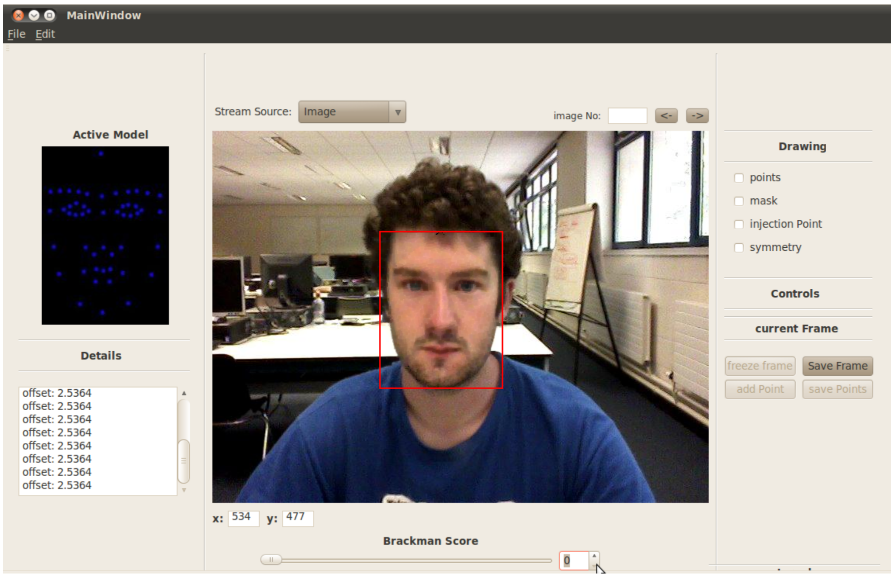

FIGURE 7.16: Initial detection and localisation of face in image using Haar cascade classifier. Red bounding box identifies location of face.

After a face has been detected using the Haar Classifier the AAM model is then applied and can then be fit much more accurately and quickly than before, see Figure 7.17.

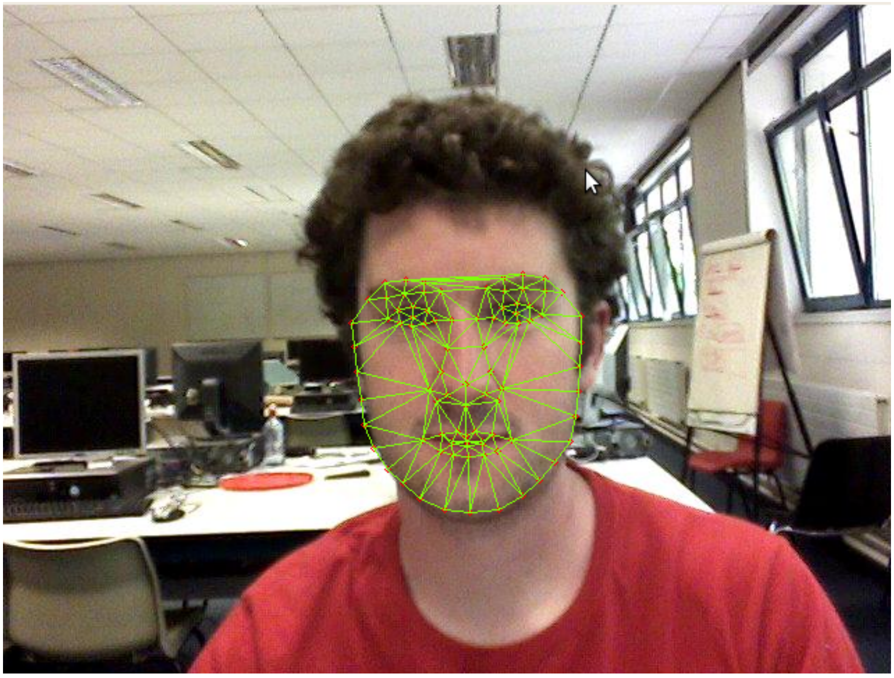

FIGURE 7.17: Successful detection and classification of face in 6 steps, using Haar Cascade Classifier to constrain search space.

7.2.5 Automatic Facial Paralysis Scoring

After a face has been located with OpenCv and surrounded by a bounding box, the AAM model described in Section 7.2.4 is applied to find and track specific facial features. Initially it may take a couple of seconds for the model to find and fit a face in the image, however afterwards subsequent tracking is smooth and relatively seamless. Once the model is fit we can then focus on key points of the AAM model which are related to facial feature points unused to calculate the HB score, i.e. for facial paralysis of the right side, points (13-15) and (48-50) and for facial paralysis of the left side, points (20-22) and (44-46).

A HB based score can easily be generated by comparing the difference between the facial feature points on the normal side of the face to that of the paralysed side.

7.2.5.1 House-Brackmann Scoring

The House-Brackmann (HB) facial nerve grading system [151] is a standardised grading system developed to objectively quantify and describe facial nerve damage. The HB score is calculated by measuring the upwards (superior) movement of the mid-portion of the top of the eyebrow, and the outwards (lateral) movement of the angle of the mouth. A score of one point is associated with each 0.25 cm movement, up to a maximum of 1 cm. A total score is then added up to give a number out of 8, see Table 7.2.

Table 7.2: House-Brackmann Scoring System.

Grade	Description	Measurment	Function %	Estimated function %
I	Normal	8/8	100	100
II	Slight	7/8	76-99	80
III	Moderate	(5/8)-(6/8)	51-75	60
IV	Moderately severe	(3/8)-(4-8)	26-50	40
V	Severe	(1/8)-(2-8)	1-25	20
VI	Total	0/8	0	0

7.2.6 Facial Feature Warping

Due to the lack of publicly available datasets containing images of individuals with various levels of FMS damage we instead illustrate the reverse process which the intelligent mirror will apply, that being the synthesis of images with facial paralysis, starting with images of healthy subjects. First the AAM model is fitted to an image of a healthy subject, with a normalised facial expression. Then the points pertaining to the corner of the mouth and eyebrow are shifted laterally to cause asymmetrical facial expressions and the image is then re-rendered, see Figure 7.18.

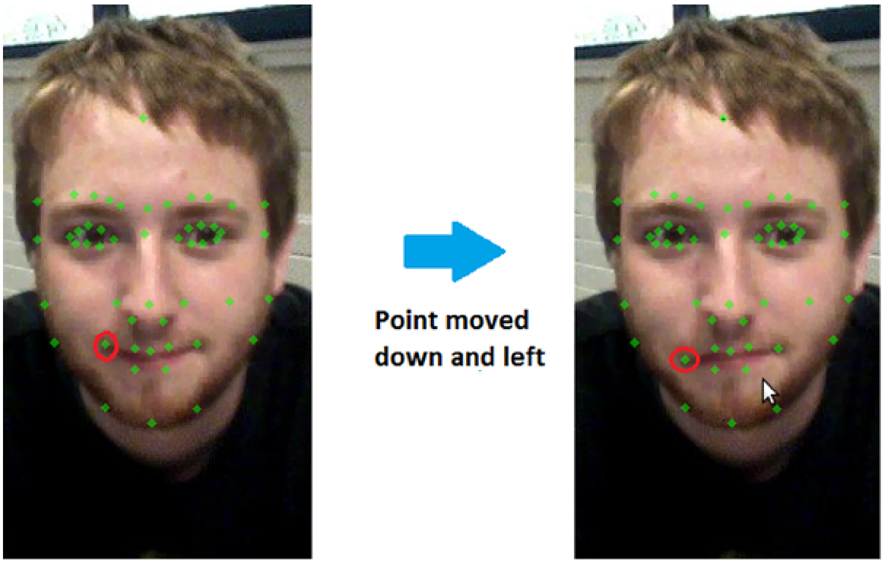

FIGURE 7.18: Illustration of relocating key facial points to synthesis FMS paralysis.

In practise, the intelligent mirror would apply the process described in reverse, first fitting a model to an image of a patient with facial paralysis, estimating the level of facial paralysis according to the asymmetry of key facial features and finally shifting the relevant facial feature points in an attempt to generate a feedback image with more symmetrical facial features.

7.2.7 Results

7.2.7.1 Facial Feature Tracking

The resulting AAM model described above was tested on 50 new images, i.e. images not contained in the original training group but which did include some images of the original 6 subjects, as well as new unused subjects.

The accuracy of the classifier was visually inspected and reported on after automatic classification of these images. The classifier achieved an accuracy of 46 correctly fit AAMs, an accuracy of 92%. Two of the unclassified images were due to false negative by the Haar Classifier, (i.e. no face was detected in these images and thus the fitting of the AAM was not attempted). The other two misclassification resulted from poorly fitted AAMs, which despite being in the correct region bounded by the Haar classifier, the resulting model was skewed and stretched.

While this image set is quite small, it was intended to be used as a proof of concept for tracking interesting facial features, towards the automatic scoring of facial paralysis and the development of the proposed intelligent mirror.

7.2.7.2 Synthesising FMS paralysis

Figures 7.19 and 7.20 illustrate the function described in Section 7.2.6 to systematically generate images with various degrees of paralysis according to the HB scoring system. The point displacement used for each consecutive image is based on the HB scoring system described in Section 7.2.5.1.

(I)
(II)
(III)
(IV)
(V)

FIGURE 7.19: Image sequence showing generation of progressive HB scored facial paralysis; (I) Normal, (II) Slight, (III) Moderate, (IV) Moderately severe, (V) Severe.

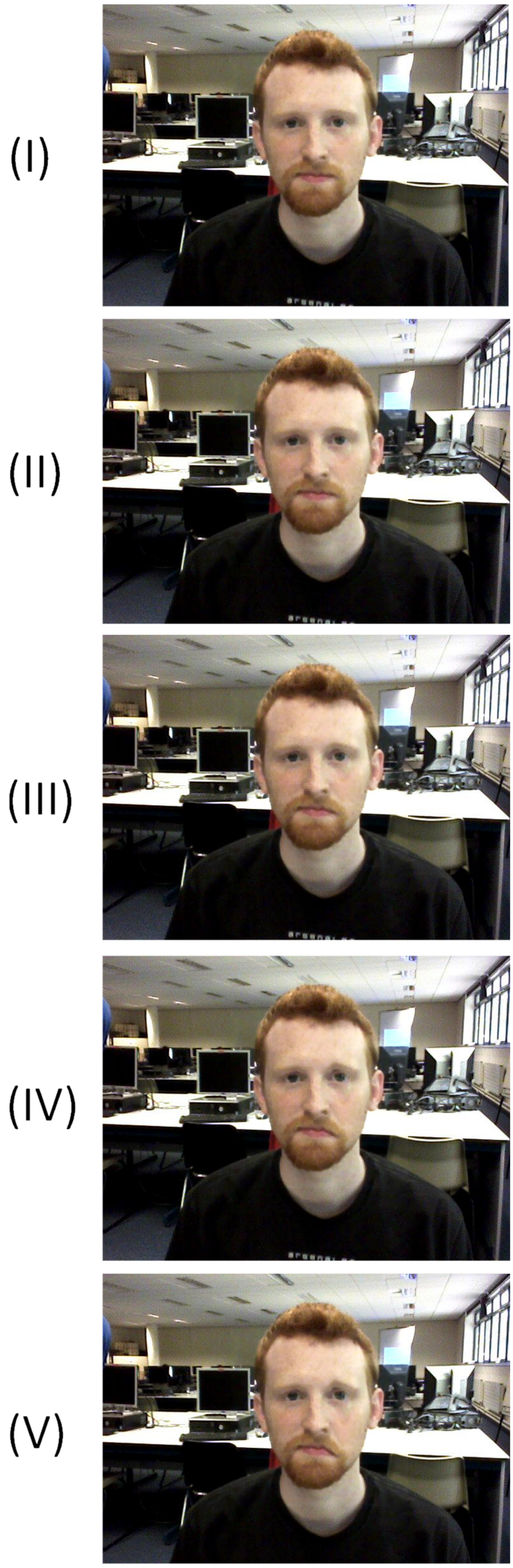

FIGURE 7.20: Image sequence showing generation of progressive HB scored facial paralysis; (I) Normal, (II) Slight, (III) Moderate, (IV) Moderately severe, (V) Severe.

7.2.7.3 Software Bench Testing

The entire process used to manipulate and re-rendering an image, (once the user has selected the points they wish to move and has released the right mouse button) takes approximately 1/4 of a second.

TABLE 7.3: AAM fitting and image warping timings

Operation	Time (ms)
Model Fitting	55
Warp Image	131
Re-draw Image	6
Total	192

This means the image can be transformed approximately 5 times a second. This software was designed with the intention of manipulating still images, however with some tweaks to the software base and by utilizing more advanced computer vision techniques this frame rate could easily be increased to real time (25-30) frames per second (FPS) allowing the user to manipulate live video stream.

7.2.8 Discussion

The goal of the work described here is to demonstrate how one could develop an ambient (mirror) technology that can be incorporated for the purposes of home based rehabilitation of motor facial paralysis. The results described here illustrate how machine learning techniques such as active appearance models can be used to locate and track key facial features for the automatic scoring of FMS paralysis and for the synthesis of distorted facial expressions. While in the demonstration of the latter process, images of healthy subjects were morphed to synthesize facial paralysis, in practise the reverse process would be applied to normalise the appearance of facial paralysis in an image. Subsequently, this image would then be presented to the individual as a form of "compassionate" feedback during training.

Our preliminary bench testing results demonstrate that with the current set-up a distorted image can be rendered 5 times a second. While this rate is much lower than that required to present fluid, real-time feedback (approximately 30 FPS), the work described here is intended as a proof of concept only. No effort was made to optimise the efficiency of the AAMs used or any other aspect of the solution. Subsequently, there is plenty of work which can be done in the future to increase the rate at which images can be manipulated using the technique described. In this work a standard unoptimised AAM was used. Much effort has already been made to optimise the efficiency of the AAM fitting procedure, [318, 374, 413]. Furthermore, more efficient facial detection algorithms could be used instead of the expensive Haar Classifier. In addition, while the computer used in this project was relatively powerful at the time, no effort was made to take advantage of its multi-core architecture or to offload any visual processing to its external graphics card. The author is confident that innovations here could drastically increase the resulting frame rate achieved.

It is hoped that the technology described here will contribute towards ultimately developing a low cost, intelligent mirror which can provide real-time feedback, suitable for augmenting facial motor paralysis rehabilitation training in the home setting.

7.3 Summary

This chapter described efforts to utilise aspects of machine learning for closed loop neurofeedback rehabilitation, with emphasis on developing low cost systems suitable for deployment in the home setting.

The first section of this chapter focuses on describing the design, implementation and test of an inexpensive and portable BCI-controlled hand therapy device, which provides haptic feedback to the user using a lightweight inflatable glove. The device works by classifying patterns of brain activity using a machine learning technique (i.e. a CSP classifier) to detect efferent motor activity relating to a specific class of movement activity. The chosen activity in this case is the intentional tapping of the fingers of the dominant hand. Correct classification of this movement subsequently triggers our custom designed pneumatic pump system which controls the inflation and deflation of a glove, thereby delivering somatosensory (i.e. afferent) feedback to the user and closing the motor control loop. System tests demonstrate that glove control can be successfully driven by a real-time BCI.

The second section of this chapter illustrates how a particular machine vision method called Active Appearance Models (AAM) can be used to develop an intelligent mirror for the provision of biofeedback for facial muscle system rehabilitation. We describe the use of AAM for automating a standard facial disability scoring procedure, the House Brackmann system, and for distorting images to generate subdued visual feedback during practise of facial motor exercises.

Although currently in their infancy, we believe that systems like those described here are preliminary examples of the promising applications of machine learning techniques, which in the future may help acutely improve the effectiveness of unsupervised exercise training and subsequently the efficacy of home-based rehabilitation.

Chapter 8

Conclusion

8.0.1 Summary and Discussion

As global ageing converges with technology and globalization, new challenges as well as opportunities emerge. Challenges arise as social and economic structures attempt to adjust to the shifting age demographic, that is the diminishing population of youth and the rising population of elders. An ageing population inevitably leads to a rise in the number of people living with chronic illness and disability while at the same time reduces the proportion of young healthy people able to support them. With healthcare systems worldwide already struggling to cope with current demands for healthcare services, there is a drastic and immediate need to confront this problem now and to prepare for the future. Reducing severe disability from stroke and increasing the independence of those affected are key to holding down healthcare costs. However, to do this, effort needs to be made to alleviate the stress on healthcare services. This might be achieved by moving away from conventional rehabilitation services and towards more community supported, home-based rehabilitation programs. To accomplish this, cost effective healthcare tools, suitable for deployment in the home-setting are required, which can with some effect automate, enhance and support the ongoing rehabilitation process. However, to be successful, the efficacy of the resulting rehabilitation service needs to be at the very least comparable to that of clinical programs, if not better, while also being cheaper.

Currently there is a dearth of such tools for this purpose and subsequently a major disadvantage of home-based rehabilitation programs is the lack of affordable specialized equipment and insufficient data as to their efficacy. Unfortunately this lack of data makes it difficult for companies which might provide systems to justify the investment required to make this technology widely available. This, in turn, makes collection of the required evidential data even less likely to happen. Subsequently, there is a serious need to improve on the development of affordable and accessible technology for enhancing conventional rehabilitation and towards improving the efficacy of home based rehabilitation.

Recently innovations in computer and communication technology have resulted in the ubiquity of computer systems and as a result there is an unprecedented amount of readily available, cost effective technology at our disposal. From the perspective of healthcare, there is great utility in the application of such technology for augmenting rehabilitation efforts. A key aspiration of this thesis has been to contribute toward increasing the availability of such technology for healthcare purposes, as well as to demonstrate the tenable potential of such technology for improving home-based rehabilitation after stroke. This goal has been achieved through the development of novel, low cost technology, with emphasis on enabling further research in the area of motor intervention and towards improving the efficacy of home-based rehabilitation. It is further supported through the presentation and demonstration of novel applications which utilise the technology.

To summarise, the contributions of this thesis are as follows.

After introducing the necessary physiological background information in Chapter 2, a literature review identifying various challenges and opportunities for advancement in technology-assisted rehabilitation was presented in Chapter 3. In particular, this chapter found that while there is currently some commercial technology available for stroke rehabilitative purposes, there is little technology which has been demonstrated to be practical, inexpensive and effective for the home.

Chapter 4 introduced the design of a novel sensor glove system for finger tracking and hand gesture recognition. The ambition of this work was to demonstrate how wearable and mobile technology can produce inexpensive technology which may be suitable for use in a home-based rehabilitation setting. In a preliminary test using healthy subjects, we demonstrate the ability of this glove system to control a TV through the use of therapeutic hand gestures, resembling those practised in therapist driven rehabilitation therapy.

Chapter 5 explores the application of game theory and agent based modelling for studying patient-therapist interaction dynamics, with a view to designing more efficient and effective controllers for automated therapeutic intervention in motor rehabilitation. Chapter 3 identified that although exhaustive effort has been afforded to advancing the mechanical design of robot devices for motor rehabilitation, little work has been done on improving the high-level control systems which ultimately provoke neuroplasticity and as a result such devices are struggling to make a difference in clinical trials. While the work described in Chapter 5 is purely conceptual, it demonstrates the sort of innovative thinking which is likely required to advance the current state of high-level control strategies. We contend that designing suitable assistive controllers for automating movement-based rehabilitation therapy requires an understanding of the interaction between patient and therapist. We propose that a better understanding can be accomplished through framing the interaction as a problem in game theory. In this work, we advocate the use of such agent based models for analysing patient-therapist interactions. We demonstrate in a simplified implementation the effectiveness of this approach through simulating known behavioral patterns observed in real patient-therapist interactions, such as learned dependency.

Chapter 6 discusses the issue of adherence to unsupervised exercise training in the home setting and explores the application of extrinsic feedback for enhancing unsupervised motor learning. We propose the development of automatic rehabilitation systems for the home setting which can help improve patient engagement during unsupervised training. For this purpose we investigate the use of obfuscated extrinsic feedback on motor performance, the provision of which has been shown to enhance motor learning, positively influence motivation and improve patient self-efficacy during conventional physical therapy interventions. Towards this goal we introduce the design of two novel systems. First, a low cost digital hand dynamo-meter which can record and process (filter, plot etc.) grip strength in real time. Second, we present a low cost open source EMG acquisition system for monitoring muscle activity and for extracting features of muscle dynamics. We demonstrate the systems ability to record and extract interesting muscle dynamics, in the form of an indication of peripheral muscle fatigue using mean frequency analysis.

Chapter 7 investigates the potential application of machine learning to stroke rehabilitation, through two distinct applications for the provision of biofeedback during exercise training. The first section of this chapter describes a portable and inexpensive BCI-controlled hand therapy device for delivering neural activated haptic feedback using a light-weight inflatable glove. The second section of this chapter focuses on the application of active appearance models (AAMs), a machine vision technique for detecting and tracking key facial features. We describe the use of AAMs to both track facial features for the automatic scoring of facial paralysis based on the House Brackmann system, and for synthesizing new facial expressions of a subject given their current appearance and the displacement of key facial points. We demonstrate this ability by generating images of progressive paralysis, according to the HB scoring system, from base images of healthy subjects. We then discuss how such techniques could be used to develop an intelligent mirror for the provision of subdued feedback during facial muscle system rehabilitation.

8.0.2 Concluding Remarks

This thesis describes many novel technology derived solutions for the enhancement of motor intervention post stroke. Emphasis has been placed on the development of inexpensive, open source technology for improving the capacity of home-based rehabilitation programs. The author hopes that the work described in this thesis is thought-provoking and that the affordable technology described therein will help bootstrap the process of creating the necessary studies which can build evidence as to the effectiveness and utility of such approaches for improving the efficacy of home-based rehabilitation. Towards this goal, the author advocates the replication of any of the systems describe here, in the hopes that it might help reduce the ever increasing cost of healthcare and assist in the alleviation of suffering in stroke survivors.

Appendix A

Recorded Demonstrations of Tools

The following appendix contains links to video demonstrations of the various tools developed for this thesis.

A.0.1 Sensor Glove Videos

Title: Sensor glove and Ogre 3D.
Url: https://www.youtube.com/watch?v=4hqJqB1ZNxg&feature=youtu.be&a
Brief: This video shows off the sensor glove ability to capture hand motion in real time and to animate a 3D hand in a virtual sandbox using custom designed visualisation software.

Title: LEAP motion controlling 3D hand Demo
Url: https://www.youtube.com/watch?v=diusooUZH_E
Brief: This video demonstrates the depth camera (LEAP motion controller) aspect of the sensor glove project. The videos illustrates the systems ability to track the hand's spatial location and orientation, as well as its integration into the custom designed visualisation software.

Title: Sensor Glove controlling a simple robotic hand interface device
Url: https://www.youtube.com/watch?v=5H3GHXqE6go
Brief: This video shows the sensor glove driving a novel robotic hand which was also developed by the author of this thesis but not described therein. This system was developed as part of an university open day demonstration and as a potential device for demonstrating the ability of the sensor glove to control a suitable hand interface device.

A.0.2 Custom Hand Dynamometer and EMG system Videos

Title: Early test of the grip strength and muscle assessment rig.
Url: https://www.youtube.com/watch?v=WvqCSHOCIR0
Brief: This video shows an early demonstration of the real-time capture and streaming of grip strength measured through the custom designed hand dynamometer and EMG acquisition system, described in chapter 6. At this stage the EMG signal has not been filtered or de-trended, hence the noise and weakness of the signal. In addition, the graphing software is zoomed in and therefore plotting at a reduced sampling rate. Also, it might be noted that the hand dyamometer signal is clipped as it approaches the upper plotting boundary, this was an early bug which was promptly fixed by adjustment of the hardware.

A.0.3 Pneumatic Glove Videos

Title: Original Romover Pneumatic Glove system
Url: https://www.youtube.com/watch?v=IimjNGtmcnY
Brief: This video shows off the original unmodified Romover glove system and its Analog pump system.

Title: Description of Custom designed digital pump system
Url: https://www.youtube.com/watch?t=1&v=hEjZlYD5Cvw
Brief: This video details a short description of the custom designed electronics/pneumatic control system used in the pneumatic glove system.

Title: Demonstration of the glove inflating and deflating
Url: https://www.youtube.com/watch?t=1&v=ymlxQsNCbDM
Brief: This video demonstrate one of the early tests of the custom digital pump system ability to inflate and deflate the pneumatic glove on command.

Appendix B

Addition resources

Data-sheets and Schematics for ModularEEG system

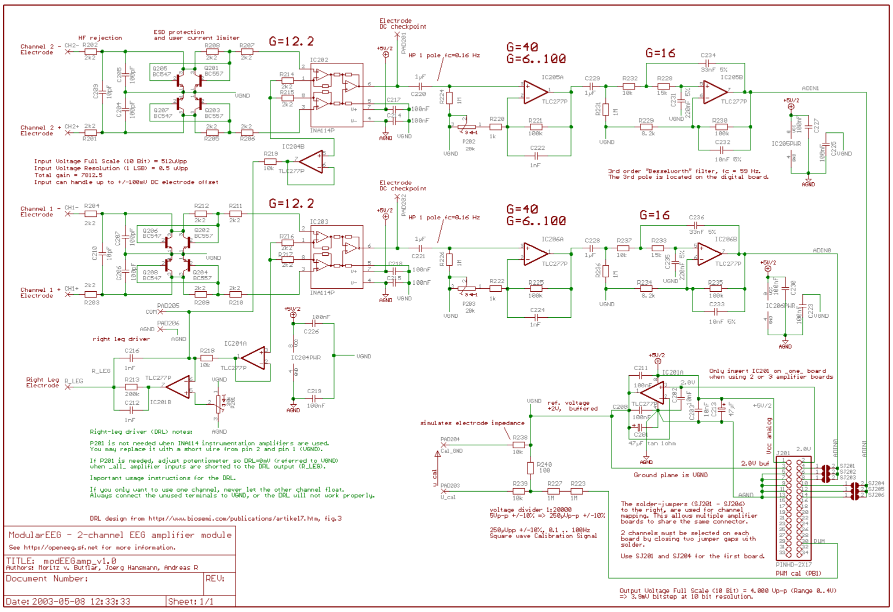

Figure B.1: Analog Schematics

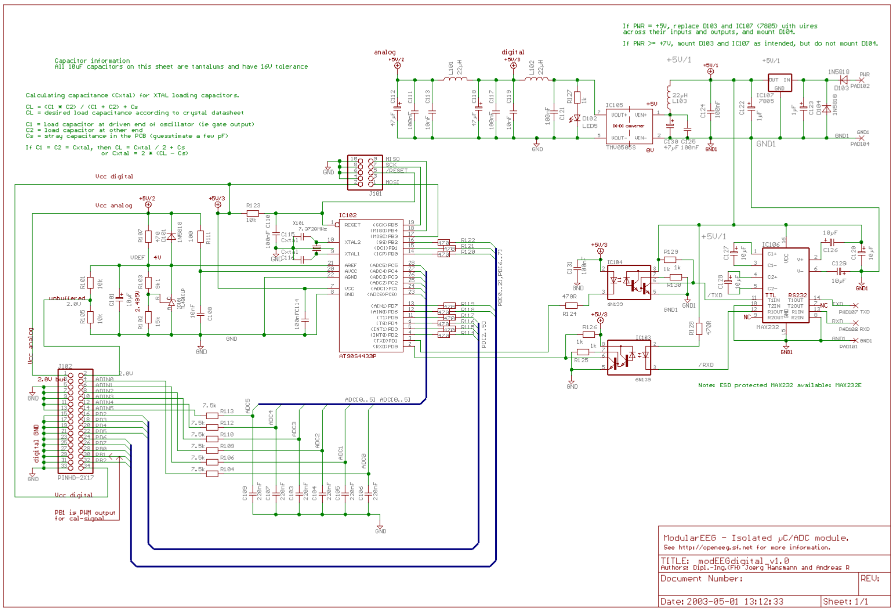

Figure B.2: Digital Schematics

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