Methods of pattern classification for the design of a NIRS-based brain computer interface

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Abstract. A Brain-Computer Interface (BCI) is a communication system that offers the possibility to act upon the surrounding environment without using our nervous system's efferent pathways. One of the most important parts of a BCI is the pattern classification system which allows to translate mental activities into commands for an external device. This work aims at providing new pattern classification methods for the development of a Brain Computer Interface based on Near Infrared Spectroscopy. To do so, a thorough study of machine learning techniques used for developing BCIs has been conducted.

Keywords: Brain-Computer Interfaces, Near Infrared Spectroscopy, Pattern Classification, Machine Learning.

1 Introduction

In order to produce different motor or cognitive tasks, human brain generates different activity patterns that can be monitored by a BCI and translated directly into commands for a computer without using nervous system's efferent pathways. There are two types of brain activities that can be used for a BCI: electrophysiological and hemodynamic [1]. The majority of BCIs developed so far are based on Electroencephalography (EEG). EEG is a non-invasive technology that measures electric brain activity through electrodes placed on the scalp. This technology has many drawbacks such as the very poor quality of signals, the sensitivity to many sources of noise and the use of many electrodes to monitor signals which make its use outside research context impossible. As an alternative to EEG technology, Near

Infrared Spectroscopy (NIRS) presents itself as an attractive method for developing a BCI that can be used in daily life [2]. NIRS is an optical spectroscopy method that measures task-induced blood oxygen level dependent (BOLD) response. NIRS-based BCIs have many benefits like robustness to noise, good spatial resolution and portability. But this technology is still in its maturation phase and further research works are to be conducted to make it reliable for a usage outside the lab.

2 Brain-Computer Interfaces general architecture

Designing a BCI is a hard task that requires several skills including neurosciences, biomedical engineering, computer science, etc. The main functions of a BCI are signal acquisition, feature extraction and pattern classification, translation into commands and sometimes feedback is required for online paradigms (Fig. 1):

- Signal acquisition: different types of sensors are used for monitoring brain signals depending on the technology employed. In case of NIRS-based BCIs, a near-infrared light emitting source like a laser or a diode and a light detector like a photodiode are used.
- Feature extraction: relevant features are extracted from raw signals. Different signal processing techniques are used for this issue.
- Pattern classification: features are mapped into different classes corresponding to different mental states. This task is done by automatic machine learning algorithms called classifiers.
- Translation into commands: a specific command is associated to each class in order to control or communicate with an external device.
- Feedback: sometimes real-time feedback is necessary for increasing users's performances.

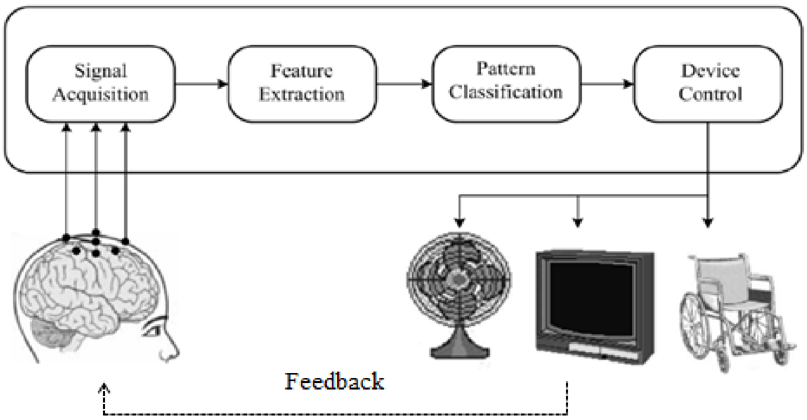

Fig.1. Brain computer Interface architecture [3]

3 Pattern classification in NIRS-based BCIs

During the last years, many pilot studies have been conducted to solve problems related to NIRS-based BCIs and enhance their efficiency. Most of these studies focused on the signal acquisition [2] or the feature selection [4] parts of a BCI, and few ones addressed problems related to the pattern classification component of NIRS-based BCIs. The possibility of classifying different motor or cognitive tasks using NIRS-based BCI technology has been proved by many research groups [5], [6], but simple experimental protocols were used and common classification techniques were applied. The use of enhanced machine learning techniques was crucial for the development of EEG-based BCI technology. These techniques addressed the problems of long-time calibration sessions before the use of a BCI system and high variability of monitored signals [3], [7]. Nowadays, NIRS-based BCI technology faces the same problems and the use of adaptive and robust machine learning techniques is necessary to introduce it in a daily-life context. The high variability of brain signals makes the mapping of activation patterns from different sessions and different users to disjoint classes by an individual classifier impossible.

Different combination schemes of classifiers and online adaptation of classifiers seem to be promising methods for NIRS signals classification. Many studies showed that the use of multiple classifier systems is crucial for modeling very complex systems because there is no single classifier that solves all problems [8]. In the context of EEG-based BCI design, there are some papers highlighting the importance of using dynamic combination of classifiers to attain good classification rates in the context of transfer learning (transfer models between subjects and between sessions) [3], [7], [9], [10]. But, in our knowledge, there is no studies related to ensemble learning in the context of a NIRS-based BCI design. Fig. 2 illustrates a multiple classifier framework: different classifiers can be built by diversifying input data or diversifying models and the merging process can be a majority voting, a weighting average mean, a linear or non-linear function [11].

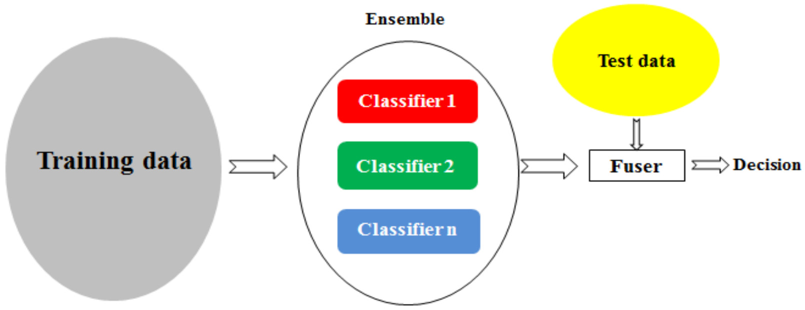

Fig. 2. Multiple classifier system

4 Conclusion

In this work, we highlight the need of developing adaptive and robust pattern classification techniques in order to make NIRS-based Brain Computer Interfaces more reliable. Many studies showed that there is no single classifier that can model all systems and usually a set of classifiers is more powerful than individual ones when dealing with complex systems. In a recent pilot study, we have investigated the detection of attention deficits through hemodynamic activity of the brain by applying usual pattern classification techniques on signals monitored by a NIRS system [12]. In next steps we will try to design more advanced techniques suitable for this type of signals.

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