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Minimal Hardware Bluetooth Tracking for Long-Term At-Home Elder Supervision

Damian Kelly, Seán McLoone and Ronan Farrell

Abstract— **The ability to automatically detect the location of an elder within their own home is a significant enabler of remote elder supervision and interaction applications. This location information is typically generated via a myriad of sensors throughout the home environment. Even with high sensor redundancy, there are still situations where traditional elder monitoring systems are unable to resolve the location of the elder. This work develops a minimal infrastructure radio-frequency localisation system for long-term elder location tracking. An RFID room-labelling technique is employed and with it, the localisation system developed in this work is shown to exhibit superior performance to more traditional localisation systems in realistic long-term deployments.**

I. INTRODUCTION

Aging at-home has been highlighted as an efficient solution to the issue of population aging [1]. This means that the increasing financial and human resource requirements related to the growing elder proportion of the population can be alleviated by enabling elders to reside in their own homes instead of care homes for as long as possible. Since the population age-shift means there are relatively fewer people of a suitable age to care for these elders (referred to as the Potential Support Ratio), assistive technologies must be employed to reduce the direct contact and supervision hours necessary for an elder at home. Hence, this work develops a room localisation technique specifically for long-term reliability in typically encountered home situations with minimal installation costs.

Many home monitoring and interaction applications rely heavily on location information and would benefit from cheaper and more reliable location predictions. Examples of such applications include monitoring of activity patterns [2], provision of activities to keep the elder proactive [3], detection of safety critical conditions such as falls [4] and medication adherence promotion [5]. A significant proportion of home monitoring research uses non-identifiable sensors such as Passive Infra-Red (PIR) sensors, pressure mats and reed switches on doors to detect the location of the elder. These sensors are referred to as non-identifiable since they cannot discern between different people activating the sensor. Hence, systems which rely on these sensors to predict location experience severe performance degradation when there is more than one person present in the environment, due to visitors or pets for example. As a result, a reliable long-term solution must be able to identify the user.

For this reason, the precursor to this paper [6] relied on the identifiable Radio Frequency (RF) signals emanating from Intel's Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability (SHIMMER) health sensing platform. This ensured the system would continue to function when the occupancy of the home environment is higher than one. However, when the elder does not require the assistance of such a health monitoring platform, there is little incentive for the elder to carry the mobile device. For this reason, the localisation technique is now considered on a more general platform; a Bluetooth mobile phone. A mobile phone was chosen for three reasons; (1) a device with alternative functionality such as a communication device gives the elder more incentive to carry the device, (2) a device with a screen allows the provision of, and response to, queries about the state of the elder and (3) combinations of Bluetooth phones and body sensors are already used for home health monitoring [7], hence such devices may already be present in home monitoring scenarios. Accordingly, this platform is envisaged to enable reliable location predictions to be obtained with little extra hardware necessary.

This paper presents the theory of operation and the long-term accuracy of the localisation system as follows; Section II motivates the hardware and techniques used to validate the accuracy of the proposed localisation system over long periods of time. A brief illustration of the performance of prior localisation techniques is also presented. Section III outlines the general trial environment considered, the hardware utilised and the techniques employed to resolve room-level location. Section IV demonstrates the performance possible with the system and considers approaches to minimising deployment effort and cost.

II. HOME LOCALISATION EFFICACY

The most significant factor in the design and deployment of any localisation system is the accuracy of location predictions. The majority of prior localisation systems, both indoors and outdoors, focus on generating location estimates at the coordinate level, which represents a person's location in metres relative to some point of reference. Coordinate level predictions, however, are not as human-understandable and relevant as room-level predictions. Hence, previously employed localisation accuracy measures are not relevant to indoor environments where a prediction error as small

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D. Kelly (dkelly@eeng.nuim.ie) is a postdoctoral research fellow with Strategic Research in Advanced Geotechnologies (StratAG).
S. McLoone (smcloone@eeng.nuim.ie) is the head of the Department of Electronic Engineering, NUI Maynooth.
R. Farrell (rfarrell@eeng.nuim.ie) is a senior lecturer in the Department of Electronic Engineering, NUI Maynooth.

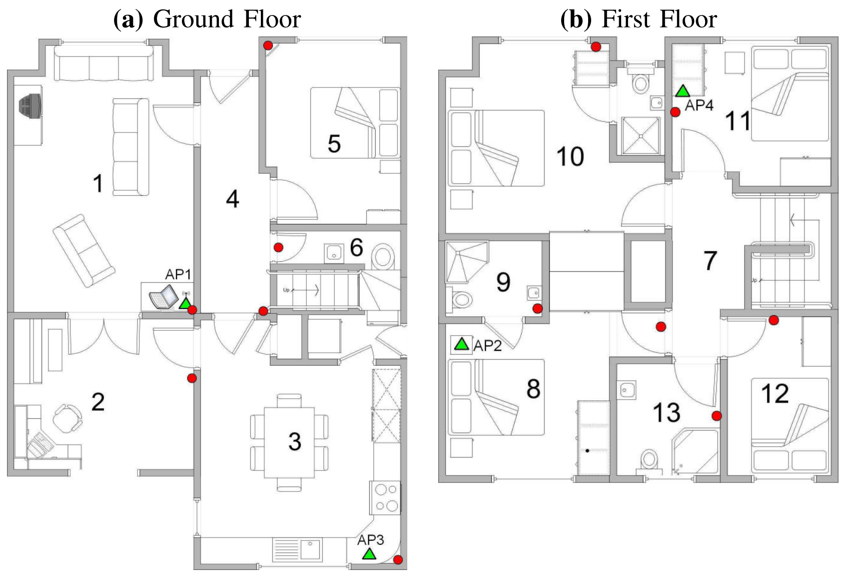

Fig. 1. Experimental home environment. Dots indicate PIR locations and triangles indicate Bluetooth access point/beacon locations.

as a metre, for example, could equate to an incorrect room prediction.

Furthermore, almost all previous localisation work has only focused on the localisation accuracy for short periods of time due to the high effort involved in providing location labels for data over long periods of time, such as days or even weeks. Accuracy over such short periods of time cannot be assumed to reliably predict the long-term performance of the system. These issues are addressed in this work by employing alternate localisation technologies to generate accurate room-level location labels automatically.

A. *Location Sensor Redundancy*

PIR is a technology commonly employed in elder home monitoring systems (e.g. [5] and [8]) since it does not have the inconvenience of requiring the elder to carry a mobile device. It simply approximates the location of the elder to be the last room in which a PIR sensor detected motion. This has the obvious implication that when there is more than one person in the environment the identity of each person in each room cannot be resolved, hence, individual location predictions will be unreliable.

For the long-term experiments in this paper, a PIR localisation system is deployed to allow a comparison of the accuracy of typically utilised elder-monitoring technology and the Bluetooth localisation system which will be presented in this paper. To determine true location, an RFID room labelling technique is also employed whereby the user scans an RFID tag on a doorway every time they transition between rooms.

B. *Long-Term Prediction Accuracy Metrics*

Since room-level location prediction in a home environment has not been the focus of previous localisation work, it is necessary to explore an accuracy metric more appropriate to the room-level localisation problem. Coordinate localisation accuracy measures are not relevant to room-level localisation systems since a large error distance in a large room may not be as incorrect as a large error in a small room. Conversely, a small error distance near a wall may translate to an incorrect room prediction; an effect not highlighted in prior localisation work. Hence, we develop an accuracy measure which will indicate the ability of a system to correctly detect the room-level location of the user over extended periods of time.

To understand the movement patterns of an individual in their home environment, the localisation system was deployed in a private home environment, illustrated in Figure 1. There are 13 rooms in the environment and the figure indicates the number labels each room is given. Seven consecutive days of movement data was acquired for a resident of the house between the hours of 10am and 8pm. This represents a significant period of time over which to evaluate the system's performance. It should be noted that the phone was always carried by the experimenter during these tests. In a realistic deployment, the phone's accelerometers can be employed to detect if the phone has been left down.

If equal time was spent in each room over the experiment period then the overall accuracy would be the unweighted mean of the recognition rates of each room. However, upon considering the relative frequency of room occupation over the period of a week (Figure 2) it is apparent that there is an uneven distribution of time spent in each room. Hence, the overall accuracy is approximated by the weighted mean of individual room recognition rates as follows;

$$\hat{a} = \sum_{k=1}^{K} a_k . w_k, \tag{1}$$

where k is the room number, a_k is the recognition rate for room k and w_k is the corresponding weighting, derived from the relative frequency of occupation. This accuracy measure,

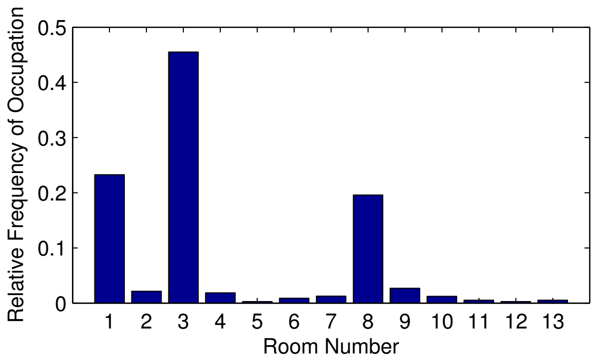

Fig. 2. Relative frequency of occupation of rooms in Figure 1.

TABLE I
THEORETICAL MINIMUM ACCURACY AND PRACTICALLY DETERMINED ACCURACY FOR PIR LOCALISATION IN BOTH SINGLE AND MULTIPLE OCCUPANCY SCENARIOS.

	Theoretical	Actual
Single Occupancy	100%	78%
Multiple Occupancy	45%	53%

which shall be referred to as Empirical Accuracy (EA), allows an estimate of the frequency of correct room predictions over the period of a week based on the recognition rates of the individual rooms.

Before this accuracy measure is applied to PIR localisation in a realistic deployment, the theoretical PIR accuracy should be considered. During the tests in this home environment the occupancy levels varied between one, two and three people. In a single occupancy scenario the location prediction accuracy of the PIR should, in theory, be 100%. When two people are present, the ability to correctly predict the location of the person of interest can be as low as 50% and when three people are present the tracking accuracy could be as low as 33% due to multiple sensors firing in different rooms. Based on the fact that multiple occupancy occurs with 2 people 68% of the time and with 3 people 32% of the time, Table I summarises the theoretical accuracy for the PIR localisation system in both single and multiple occupancy scenarios.

To determine the actual PIR accuracy, PIR sensors are installed in the locations indicated by the dots in Figure 1 and PIR data was collected while room labels were obtained using the RFID technique. It can be observed from Table I that the single occupancy PIR performance is perfect in theory and acceptable in practice. The lower accuracy in practice is mainly due to the effects of interference from moving curtains and doors after the user leaves the room. The multiple occupancy accuracy, both in theory and in practice, is significantly lower than the single occupancy accuracy. This confirms that PIR is not suitable for elder localisation when there is a likelihood of occupants besides the monitored elder present. Since PIR localisation suffers from such poor performance, the RFID labelling technique is necessary to generate significant periods of labelled motion data to validate the long-term performance of the Bluetooth

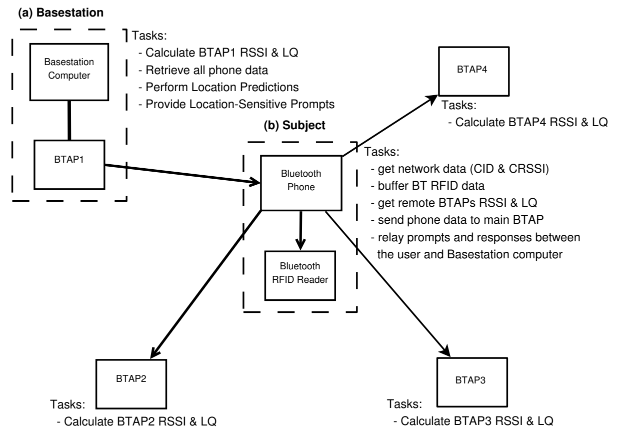

Fig. 3. The connection topology for the BMMS system. Each arrow represents a Bluetooth connection. The start of each arrow indicates the connection master and the end of each arrow represents the slave.

Movement Monitoring System (BMMS) developed in this work.

III. BLUETOOTH MOVEMENT MONITORING SYSTEM

A. Deployed Hardware Platform

To overcome the fundamental limitations of non-identifiable signal localisation techniques such as PIR, an RF localisation technique is utilised. To increase the convenience of the mobile device, making it a more attractive device to the user, a Bluetooth mobile phone was chosen as the mobile device. A Nokia N95 was chosen due to its high levels of functionality and programmability. A number of Blueradios BR-SC30N Bluetooth Access Points (APs) are used to generate the location indicative signals. Figure 3 illustrates the novel configuration of the Bluetooth Movement Monitoring System (BMMS). Arrows indicate Bluetooth connections.

The main components in Figure 3 are (a) the Basestation computer and (b) the subject. The Bluetooth computer is responsible for collecting the location indicative signals, predicting elder location and producing location-sensitive prompts, interactions and services. The subject carries a Bluetooth phone and a connected Bluetooth RFID reader. In a realistic deployment the RFID reader is not necessary; it is only used to acquire room labels for these experiments.

The Basestation computer must acquire the location indicative signals; Received Signal Strength Intensity (RSSI) and (Link Quality) for every connection in the system. The relatively inexpensive Bluetooth chips employed in mobile phones are generally unable to provide these readings for connected devices. Instead it is necessary for the phone to connect to the Bluetooth APs in the environment and remotely query their RSSI and LQ readings. It then relays these readings back to the Basestation computer. This is an inexpensive technique of generating several location indicative signals at one Basestation computer since the APs do not require a Basestation computer or wired network to the main computer, as is necessary in prior RF localisation work.

This leads to a relatively cheap but accurate solution to localisation in environments with multiple occupants since fewer APs are necessary than PIR sensors. The use of a mobile phone also allows the acquisition of cellular signal strength (CRSSI) and cellular Basestation ID (CID) signals which have also previously been shown to vary as a function of location [9].

B. Location Prediction Algorithms

Since we are interested in generating room-level location predictions from the available location indicative signals, a number of classifiers can be employed by using the available signals as location dependent input features. As with any classification problem a training phase is necessary where classification models for each class, or room, are generated. Then in the online classification phase, these models are used to generate room predictions. The 5 classifiers considered here are:

1) k-Nearest Neighbour (kNN)
2) Naive Bayes Classifier (NBC)
3) Linear Discriminant Analysis (LDA)
4) Quadratic Discriminant Analysis (QDA)
5) Gaussian Mixture Models (GMMs)

kNN is a non-parametric classifier which predicts the class based on a majority vote of the classes of the k most similar training samples. As such, it is flexible but prohibitively computationally intensive. The remaining classifiers are efficient maximum probability classifiers. NBC treats each RF signal input feature independently, leading to the most efficient location computations. LDA and QDA model the input features as covariate features, producing linear and quadratic discriminant borders respectively. GMM approximates the features as a mixture of Gaussians, leading to the most flexible feature representation. More information on these classifiers and their tradeoffs can be found in [10].

IV. Localisation Performance

To assess the long-term performance of the localisation system, the RFID labelling technique was used to obtain two days of labelled movement data. The first day was used for training of the classifiers and the second was used for testing. Then the second day was used for training and the first for testing. Then the mean of both experiments was noted. The first column in Table II shows the mean EA for each location classification technique outlined above. It can be seen that the highest accuracy is the result of the kNN algorithm. Since kNN is a non-parametric classifier, it takes a significant length of time to calculate the Euclidean distance between every training sample and every test sample. Hence, the probabilistic classifiers are favoured for efficient execution. It can be observed that LDA and QDA both achieve the highest levels of accuracy amongst the probabilistic classifiers, closely followed by GMM. NBC has relatively poor localisation performance. It is important to note that these accuracies were achieved with realistically varying occupancy levels, yet are still higher than the single occupancy PIR localisation accuracy in Table I.

TABLE II
Mean EA for localisation with all available signals, Bluetooth RSSI and Bluetooth LQ only.

	All Signals	RSSI Only	LQ Only
kNN	0.85	0.62	0.78
NBC	0.66	0.57	0.57
LDA	0.80	0.51	0.58
QDA	0.80	0.61	0.69
GMM	0.78	0.78	0.73

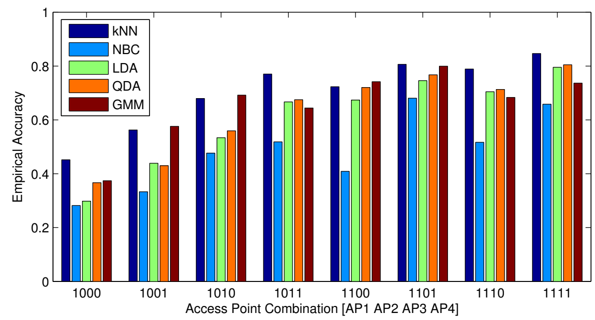

Fig. 4. The effect of the subset of available APs on the EA.

A. Signal Redundancy

Prior RF localisation work only utilises either RSSI or LQ readings from each access point, assuming that the other available signals do not provide any extra information. We, however, utilise all available Bluetooth readings along with the cellular signals available on the phone to predict location. Columns 2 and 3 in Table II indicate that lower accuracies are the result of adopting the previously accepted approach of using one available signal. Hence, the BMMS achieves improved localisation performance by using these secondary signals.

B. Bluetooth AP Redundancy

Intuitively, larger numbers of installed APs leads to higher EA due to higher location dependent signal diversity for each location. There is, however, increased system deployment effort for this increased performance. For this reason an investigation is conducted of which subset of available APs results in the best localisation performance. Figure 4 illustrates the EA for all classifiers for all combinations of APs. Each combination of APs is denoted by the binary string corresponding to [AP1 AP2 AP3 AP4], where a '1' represents available, and a '0' represents not available. AP1 is always available since it is the Basestation computer AP.

As expected, the highest accuracy is possible when all APs are utilised. However, when AP3 is not included in the location predictions, the accuracy is approximately similar to when all APs are available for the kNN, LDA, QDA and NBC classifiers. Surprisingly, GMM accuracy is slightly higher with less APs, which can be attributed to shifts in clusters of data between days, leading to certain mixtures accidentally specialising on classification regions which are more important. However, when AP4 is unavailable instead

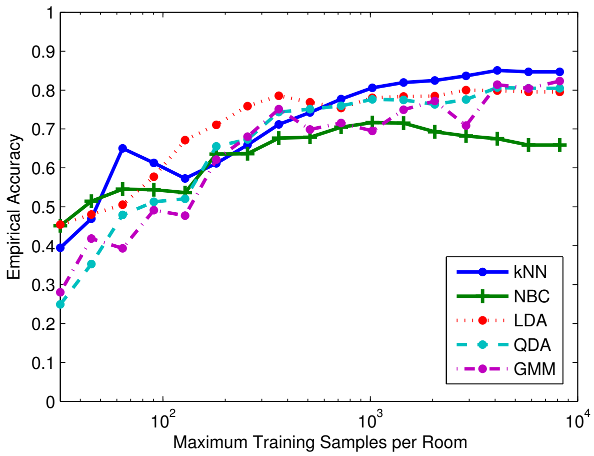

Fig. 5. EA as a function of training dataset size.

of AP3, the location predictions are lower for all classifiers. This indicates that EA is highly dependent on which subset of AP locations are used. It is difficult to predict which deployment locations are important to long-term accuracy since AP3 is in a commonly inhabited location and would be assumed to significantly contribute to localisation accuracy. Hence, the only way to select the relevant AP locations is to empirically evaluate each AP's contribution. However, by that stage the deployment effort has already been expended and there is little point in removing the relatively cheap APs.

C. Training Dataset Size

The results presented thus far are achieved using a day of training data. If the automatic RFID room labelling technique is not available, a day of training data would be prohibitively difficult to obtain. Hence, it is necessary to explore if similar levels of accuracy are possible with fewer training samples available for each room. The BMMS hardware can produce signal samples at a rate of 0.5Hz. Depending on the length of time spent in each room during a day, some rooms only have 100 training samples available from these experiments. A limit on the number of training samples available in each room is imposed and the EA for each classifier as a function of the maximum permitted training samples in each room is recorded. Figure 5 illustrates that the EA for all classifiers is highly sensitive to the maximum quantity of available training data. In fact there needs to be a maximum of at least 10^3 samples permitted per location for acceptable localisation performance.

Highest localisation performance occurs with the most available training data. At high levels of available training samples, there is significant imbalance in the quantity of samples per location, with a high proportion of samples available from more commonly inhabited rooms. Hence, using a quantity of training data representative of the proportion of time a person spends in each location, leads to the highest long-term localisation accuracy by exploiting classifier bias towards more commonly inhabited rooms. Accordingly, using an automatic room labelling technique is imperative to the acquisition of sufficient levels of training data and, as a result, achieving highly accurate movement detection.

V. Conclusions

This paper has presented work on an affordable and long-term reliable home monitoring technology for the elderly. It has been demonstrated that higher accuracy is possible by assuming the user is carrying a device which emits identifiable signals, such as a mobile phone. The perceived inconvenience of the system is reduced by ensuring the device has alternative functionality such as a mobile phone and a user prompting device, rather than a passive monitoring device. This technique has been shown to enable improved localisation performance over the PIR localisation technique typically employed in previous elder monitoring research.

Previous RF localisation work has been unable to demonstrate long-term localisation accuracy because sufficient location sensor redundancy has not been available. By using an RFID labelling technique, the importance of RF signal redundancy, RF AP redundancy and training dataset size on long-term localisation performance has been demonstrated. Future work seeks to validate these results over significantly longer periods of time and investigate the effect of location-sensitive interactions with the elder on the elder's behaviour and movement patterns.

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