Designing a Compact Wireless Network based Device-free Passive Localisation System for Indoor Environments

Philip Vance, School of Computing and Intelligent Systems, Faculty of Computing and Engineering, University of Ulster, Londonderry, UK

Girijesh Prasad, School of Computing and Intelligent Systems, Faculty of Computing and Engineering, University of Ulster, Londonderry, UK

Jim Harkin, School of Computing and Intelligent Systems, Faculty of Computing and Engineering, University of Ulster, Londonderry, UK

Kevin Curran, School of Computing and Intelligent Systems, Faculty of Computing and Engineering, University of Ulster, Londonderry, UK

ABSTRACT

Determining the location of individuals within indoor locations can be useful in various scenarios including security, gaming and ambient assisted living for the elderly. Healthcare services globally are seeking to allow people to stay in their familiar home environments longer due to the multitude of benefits associated with living in non-clinical environments and technologies to determine an individual's movements are key to ensuring that home emergencies are detected through lack of movement can be responded to promptly. This paper proposes a device-free localisation (DFL) system which would enable the individual to proceed with normal daily activities without the concern of having to wear a traceable device. The principle behind this is that the human body absorbs/reflects the radio signal being transmitted from a transmitter to one or more receiving stations. The proposed system design procedure facilitates the use of a minimum number of wireless nodes with the help of a principle component analysis (PCA) based intelligent signal processing technique. Results demonstrate that human detection and tracking are possible to within 1m resolution with a minimal hardware infrastructure.

Keywords: *Ambient Living, Device-free, Heuristics, Localisation, Neural Networks, Wireless*

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1. INTRODUCTION

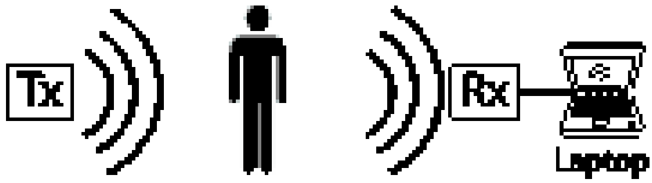
In the field of ambient assisted living for the elderly, a new technology is proposed that utilises a home wireless network to possess tracking abilities that would enable in-home activity monitoring. Home activity monitoring is a means by which a carer may give assistance to an individual remotely at a time that is convenient to them. This promotes the current desire to let the aging population remain within their home as they get older and improve their quality of life (TRIL, 2010; Mann, 2005). Determining the location or activity of an individual over time can aid in providing effective carer assistance without the overhead of regular home visits (Srivastava, 2009). Apart from the obvious emergency services applications, the context information provided may be used to monitor for irregular sleeping patterns, dietary habits, social interactions and mobility. Carers can utilise this information to provide the best care on an individual basis. Using Radio Frequency (RF) for this purpose out performs visible light (video cameras) and Infra-red (PIR sensors) as it is both non-invasive and can penetrate non-metal walls within the home (Rogers & Brown, 1997). PIR sensors also have the limitation where they only detect presence whilst there is movement. RF energy can detect presence whilst the human body is perfectly still.

There are various signal based location determination technologies that may be used for assisted living including; GPS (Vance et al., 2007; Carmien, 2003), Wi-Fi (Kelly et al., 2008, Cellular (Niemela et al., 2007) and Ultra-Wide Band (UWB). Currently, Wi-Fi is the most popular technique for in-home use as Cellular does not have a good resolution (Hightower & Borriello, 2002) and GPS generally does not operate within buildings (Shuangquan et al., 2006). UWB on the other hand can be quite effective though it is costly to implement (Yanying et al., 2009). Currently, one of the major limitations is that the user must carry a propriety device in order to be located or tracked. Such active-device indoor localisation approaches are inefficient in terms of the quality of data received and the expense of wearable device units as the user often either mislays the device, accidentally breaks it or forgets to wear it on a daily basis (Williams et al., 2010; Naditz, 2009).

This paper proposes a device-free technique for localisation which will enable the user to proceed with their daily activities without the requirement of having to wear a traceable device. The main principle behind this device-free strategy is the absorption phenomenon of the Received Signal Strength (RSS) of transmitted wireless signals as the human body crosses a transmission-receiver path (Lin et al, 2008). A number of techniques in the field of Device-free Localisation (DFL) have been proposed recently (Wilson & Patwari, 2009; Dian & Lional, 2012; Youssef et al., 2007; Patwari & Wilson, 2010; Mah, 2012) investigating technologies such as UWB, RADAR and MIMO for its use. In (Wilson & Patwari, 2009), localisation is reported to have achieved an accuracy of less than 1m though the hardware infrastructure consists of multiple nodes in excess of 20 to cover a small area. The techniques proposed in this paper aim to provide faster and more accurate and economical localisation compared to those previously reported using a minimal infrastructure.

In Section 2 of the paper an outline on the proof of concept is provided and Section 3 provides an analysis on selecting appropriate transmitter-receiver configurations. Section 4 details the novel localisation algorithms investigated and Section 5-7 present data analysis and experimental results in relation to localisation for an example indoor environment under different network configurations. Finally, Section 8 presents a concluding summary.

Figure 1. Shows LOS being intersected where attenuation will occur



2. PRINCIPLES OF DFL

Most localisation processes work on the basis that the user must carry a device for that person to be tracked. Tracking centres around using this device to broadcast a signal or transmit a scene analysis of all the Wi-Fi access points it senses (Hjelm & Kolodziej, 2006). Techniques such as Triangulation (Hightower & Borriello, 2002) or Fingerprinting may then be employed to utilise this information to provide a location estimate. DFL is a form of localisation that does not require the user to actively take part in the localisation process as no device is needed on the person being tracked. It performs on the principle that the human body, when placed close to the Line Of Sight (LOS) of a transmitter and receiver as shown in Figure 1, will affect the strength of the signal being received (Vance et al., 2007).

A number of experiments were undertaken to test whether multipath propagation of the signal had an effect on the resulting RSS information collected. In (Vance et al, 2007; Shuanguan et al, 2006), this is proven to be the case, though evidence was needed to show that the intended hardware infrastructure to be used would produce the same results. The graph depicted in Figure 2 shows our results for similar experiments to that of (Wilson & Patwari, 2009) that were carried out. As can be seen here, a person moving across the LOS has a large impact on the RSS. Each spike in the downwards direction represents an instance of a crossing.

Figure 2. Person is crossing the LOS at random intervals over the 5 min window

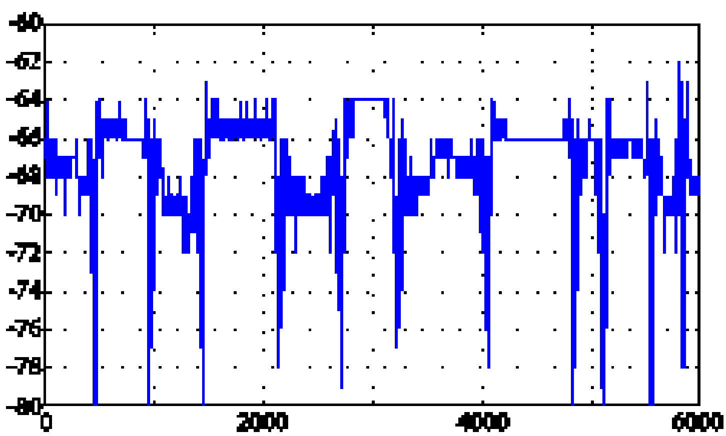
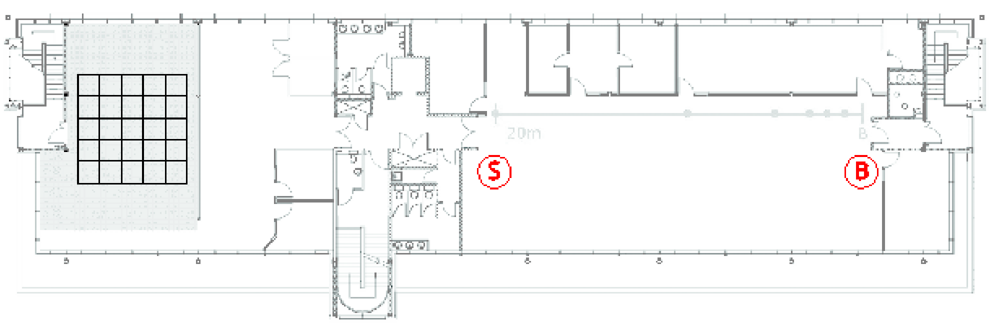


Figure 3. Top floor of the ISRC where experiments were conducted



3. MULTI Tx/Rx ANALYSIS

Experiments progressed to ascertain the limits of detection i.e. could a body be detected at a particular position within the LOS? This section outlines the experiments undertaken to ascertain the best use of the sensors to aggregate the RSS information. Investigations of the detection accuracy were explored by increasing the number of transmitter/receiver pairs in the test environment.

3.1. Experimental Infrastructure

The architecture analysis consisted of two types of wireless motes, a TelosB (crossbow, 2013) mote, configured as the base station (Rx) and a SHIMMER (Shimmer, 2012) mote as a transmitting unit (Tx). The SHIMMER is programmed to transmit a test packet every 10ms. From this packet, the TelosB may retrieve the RSS information. To aggregate the RSS information across several receivers, a Toshiba Portégé M200 laptop with Ubuntu 8.10 Linux operating system is utilised. The top floor of the Intelligent Systems Research Centre (ISRC) department of the University of Ulster, as depicted in Figure 3 was used as the test environment for the initial analysis. Further testing was completed in alternative areas of the depicted building plus two additional buildings. A sports hall was chosen to test the DFL system within an ideal environment as no obstacles or people were present whilst the experiments were conducted. The final destination was a lecture theatre in a building that has a constant influx of students at all times of the day.

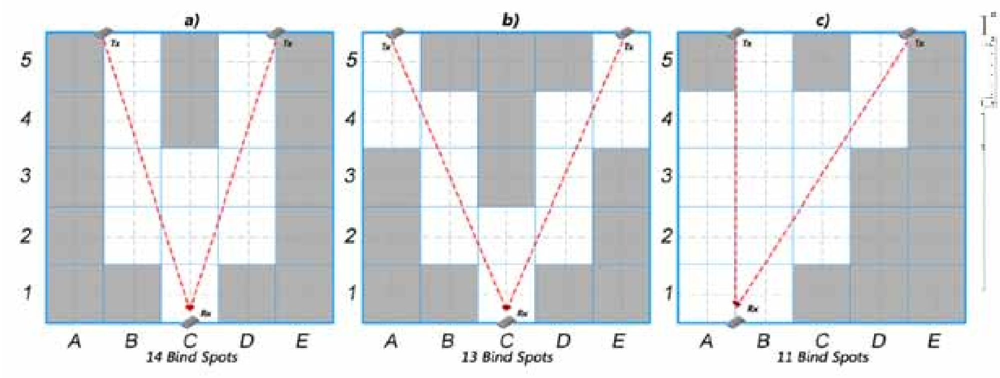
3.2. Two Nodes

Using two nodes at varying distances apart, RSS was recorded at different points along the LOS. The outcome of these tests concluded that individual patterns were possible though were difficult to discern. Unique patterns were more prominent closest to either transmitter or receiver, however, tracking of an individual required RSS signal recordings over a small area rather than LOS alone, therefore an area of $3m^2$ in the region of the test environment shown in Figure 3 was chosen. The floor in this area is divided into $60{\times}60cm^2$ squares and marked.

3.3. Three Nodes

An additional node was introduced as a transmitter and physically placed so as to form a triangular configuration as depicted in Figure 4. The orientation of the sensors was decided upon by

Figure 4. Figure showing the blind spots encountered during trials of different node placements within the defined area

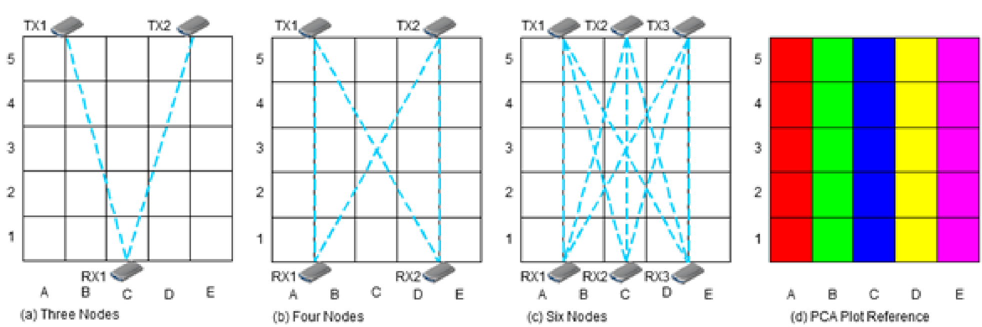


running various experimental setups to ascertain the best coverage by observing the number of blind spots (areas of the grid with no RSS signature) encountered as shown in Figure 4.

The RSS information was recorded for each grid location spanning a five minute window including whilst nobody was present. During each phase of the recordings, the individual held the same posture and faced the same direction to negate any other possible influences on the data. All tests were carried out whilst the labs were empty, in the evenings and weekends. Findings showed that the area close to the LOS of both transmitters and within the triangular formation all showed signs of achieving unique patterns to identify each grid location. Data recordings outside the LOS, at the two corners nearest to Rx for instance, showed no discernible difference to data taken whilst no one was present.

This was explored further by running additional tests to experiment with the range of the LOS perpendicular to its travelled path. As explained in (Shuangquan et al., 2006), the signal can be affected at various angles emanating from Tx, though a custom made transmitter was used in this case. Similar tests were carried out in the lab to find that the signal was affected at angles ranging from 15 to 20 degrees from the LOS but were not always consistent. This would cause blind spots which were void of all signals and therefore impossible to use for localisation.

Figure 5. Small area of $3m^2$ encompassed by various node setups with (a) showing the three node triangular matrix, (b) showing the hour glass shape of the four node setup and (c) displaying the six node setup. (d) is used as reference for coloured plots shown later



Following this analysis, it was apparent that the use of 3 nodes was not sufficient to localise a human body at all desired positions within the grid.

3.4. Four Nodes

To account for the blind spots, a new set-up was planned containing 4 nodes setup in a fashion to maximise coverage. In the configuration with two Txs and two Rxs, there would be 4 streams of data within the grid creating the shape of an hour glass as shown in Figure 5b. Exact placement of nodes was reviewed and the setup shown in Figure 5b was the best performing configuration. When placed too far apart, blind spots were created in the centre areas of the grid, whilst too close together created blind spots on the outer edges of the grid.

A number of datasets were collected, each spanning a 5 min window for every position within the grid. For ease of reference, each grid position was also numbered from A1 to E5. The majority of positions within the grid indicated a unique repeatable pattern, however, patterns were quite close and sometimes difficult to distinguish. Examples of these patterns are explained further in the next section.

3.5. Six Nodes

With further experimentation using four nodes, it became apparent that the error rate for pattern classification for each position may become quite high, as will be explained in the results section, despite the various methods used for data filtration. To address this, the number of nodes was increased, to six in total. The formation of the nodes was based on the four-node configuration in such a way to maximise coverage as depicted in Figure 5c. This now gave nine streams of data to work with compared to the previous four.

Using the same guidelines as laid out formerly, another compilation of datasets was collected and analysed. The findings showed a more consistent method of attaining repeatability of individual pattern classifications for each position within the grid. The next step in the process required the development of an algorithm to recognise these patterns and produce a position estimation of a person standing within the test environment.

4. ALGORITHMS FOR LOCALISATION

In this section, a number of algorithms used in the DFL process are discussed. Principal component analysis is also highlighted as an analytical technique used to find relationships within the data.

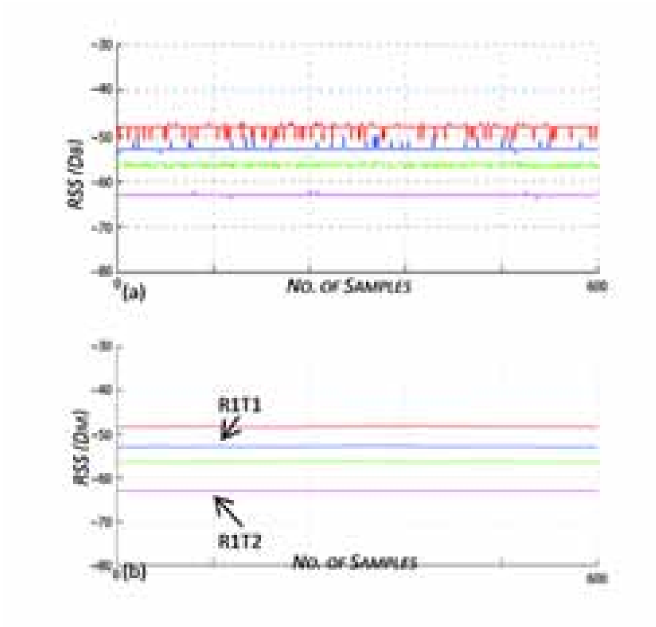
4.1. Max/Min Heuristic Threshold Algorithm

A preliminary algorithm was transcribed with multiple thresholds, stemming from the original intrusion detection work. Setting the thresholds required subtracting the RSS whilst no one was present away from the RSS received whilst a human body was present at a particular location within the grid.

With the raw RSS being very erratic in some cases due to multipath effects, see Figure 6a for example, a Savitzky–Golay (SGolay) filter (Manfred et al., 1981) was employed. This also helped reduce the number of false detections that would otherwise be problematic with the tendency of RSS to spike at irregular intervals [24].

The SGolay smoothing filter works in a similar fashion to performing a local polynomial regression on a series of values. It preserves the features of the data such as the maxima and

Figure 6. RSS data from a sample location with (a) showing the raw data and (b) showing the SGolay filtered data



minima and width, which are usually lost with other techniques such as the moving average. As shown by Figure 6b, the data has lost its irregularity but has kept its key RSS level. This figure represents half the dataset collected from two transmitters (T1 and T2) for one position within the grid from the perspective of one receiver (R1). Of the four streams depicted, two are whilst no one was within the grid (Red and Green lines, referred to here as 'zero lines') and the other two are whilst a person was standing at a particular location (referred to as 'active lines').

$$\text{Threshold}\left(\text{T}_{\text{m}}\right) = \sum_{\text{n}=1}^{N_S}\left(\text{X}_{\text{n}}^{\text{m}}\text{Active} - \text{Y}_{\text{n}}\text{Zero}\right)$$

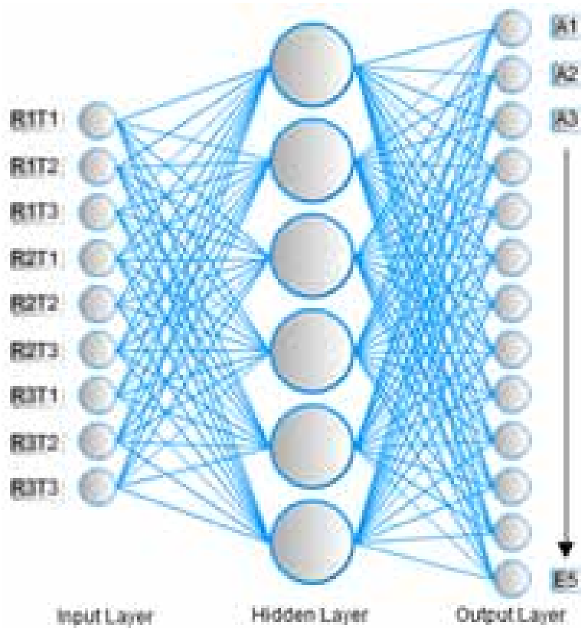
$1 \geq \text{m} \geq 25$

Threshold values (T) were set for this location by subtracting the 'zero line' (Y1) away from the 'active line' (X1) with 'n' representing the particular threshold being set and N_s being

Table 1. Example values for 3 positions

Position	R1T1	R1T2	R2T1	R2T2	Total
A1	8.68	-3.24	0.98	0.3	13.2
A2	7.02	1.26	0.01	0.2	8.49
A3	5.67	-0.06	-2.27	-0.14	8.14

Figure 7. Shows a NN taking in nine features as inputs using 6 node setup



the number of nodes. The 'zero lines' remain the same for all datasets, therefore repeating these steps for all datasets created a table of threshold values with each position having four values. An example of this format may be viewed in table 1.

The four node model as shown in Figure 5b is used here to explain the principles of this elementary algorithm. All four values are labelled in respect to the receivers 'R1' and 'R2'. The 'Total' attribute is used as an indication the total change in RSS for that particular location. A large value means that the position shows good signs of attenuation in the signal due to someone's presence. New incoming data had the zero line data pre-subtracted before being compared with the table of values. For there to be a match with new data, all four values had to compare to one of the entries within the table. If no closely aligned set was apparent, the closest comparable set was chosen as the predicted location.

$$Position\ P = \min_{1 \le n \le 25} \left(Tn - I \right)$$

Comparison was made through subtracting the values obtained from incoming data (I) away from every entry (T) in the table and using the entry with values now closest to zero as the estimated location.

4.2. Intelligent Systems Approach

Using intelligent techniques such as Neural Networks (NNs) to account for the variability within the signal is a promising solution. A number of feed forward NNs and training algorithms were reviewed and the Levenberg-Marquardt based back propagation was found to be the best performing algorithm for this particular problem. As shown in Figure 7, the network was trained by

Table 2. Results for heuristic approach

Data Sample	Train/Test	New Data
Accurate 0.5m	72%	53%

passing all the features simultaneously into the input layer of the network. There are 25 nodes in the hidden layer and 25 nodes in the output layer, one for each position (A1 - E5).

With each stream of data being passed, 2 seconds worth of data was processed at a time. We also tried increasing this amount to a max of 5 seconds though the difference in results proved to be negligible when compared with the trade-off of a faster process.

5. INITIAL PERFORMANCE

In this section, the results taken from each algorithm analysis using the four node setup will be discussed.

5.1. Heuristic

The following table shows the results achieved using the most successful heuristic approach that was tested which was the max/min technique. The values shown are the result of using several sets of data, recorded over a week long period to assess the algorithms effectiveness.

Results from two different type tests are shown. ‘Train/Test’ data represents the averaged data of several sets which was used to manually set the thresholds. A return of 72% shows that some of the thresholds set were too close together and with the small variance within each RSS signal, the algorithm was unable to correctly identify each position. The ‘New Data’ represents a completely different dataset, unseen by the algorithm and recorded on a separate occasion. Again, with the variability of RSS due to environmental factors such as movement of furniture and humidity conditions (Pahtma et al., 2009; Boano et al., 2009), the algorithm provides a low level of detection, i.e. it can only detect a users presence at the correct location 53% of the time.

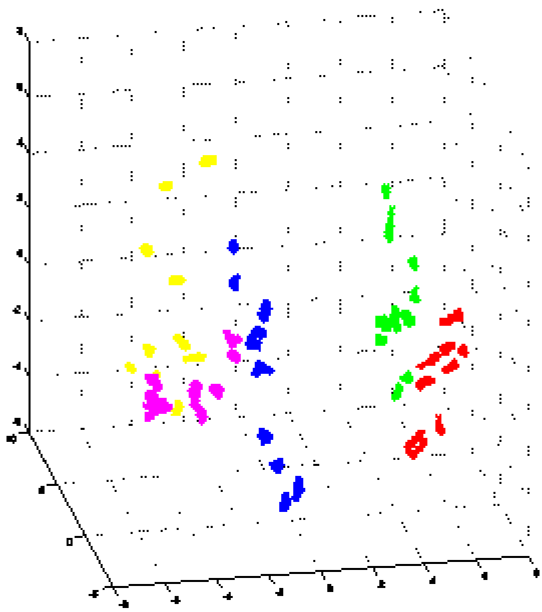
5.2. Neural Networks

Table 3 shows some of the results taken from the Neural Network experiments. The ‘Train/Test’ datasets were divided in two, with half for training/validation and half for testing. ‘New Data’ is from a separate dataset recorded on a different occasion. The NN performed well on the ‘Train/Test’ sets though performance reduced when presented with new data.

Table 3. Results for NN approach

Data Sample	Train/Test	New Data
Accurate 1.5m	98%	84%
Accurate 1m	96%	68%
Accurate 0.5m	96%	59%

Figure 8. Union of two Datasets with PCA applied



At 1.5m resolution, the NN correctly identified all positions where a person was standing 84% of the time over 100 trials. Although this is a satisfactory result for localisation, it is believed that this result may be improved upon by further understanding the relationship within the data. These results show a trend that needs to be explored further in order to increase the accuracy at 0.5m resolution.

6. ANALYSIS OF INITIAL PERFORMANCE DATA

Whilst the NN's proved successful in achieving a moderately high percentage of data classifications, there was still an unacceptable margin of error. The reason behind the error is difficult to perceive visually when simply plotting the RSS values versus time for each position. To account for this obscurity, Principle Component Analysis (PCA) (Prasad, 2007) was utilised. PCA is a feature reduction technique that transforms a number of correlated variables into a smaller set of uncorrelated variables called principle components (Prasad, 2007). In this case, PCA works by reducing the number of data streams or features which in turn allows visualisation of the data more efficiently. Figure 8 shows union of two datasets with PCA applied.

Using Figure 5d as reference, it can be shown that positions A1 through C5 have good separability. This can be concluded from the way in which the red, green and blue plots within Figure 8 can be linearly separated with a single line. Problems encountered with previous methods mainly occurred with positions in the region of columns D and E (yellow and pink markers) which is reinforced by the representation of the data shown in Figure 8.

The clusters between these two columns are intermingled and therefore difficult to disseminate. There are two possible reasons for this to occur; first being a fault within the hardware setup given that the nodes are of the same type, the pattern within the clusters should be somewhat symmetrical. The second being that the environment itself may have be causing this imbalance

Figure 9. PCA of two consecutive tests performed in an ideal location with minimal environmental factors

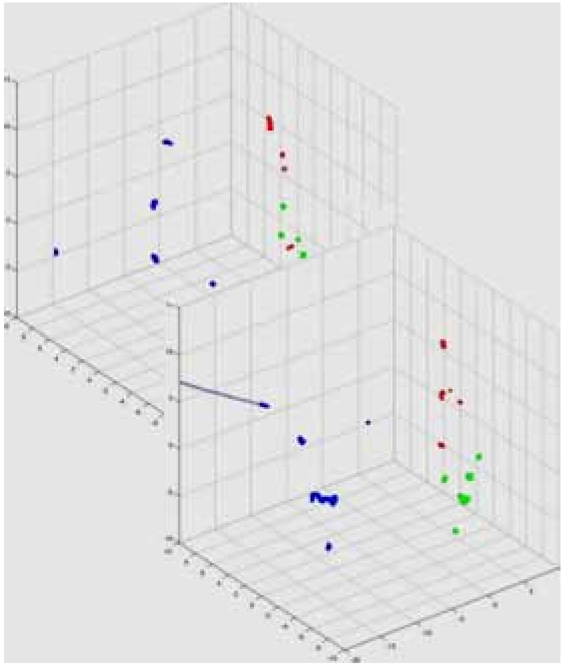


Figure 10. Example of a signature graph for position A1 in the grid

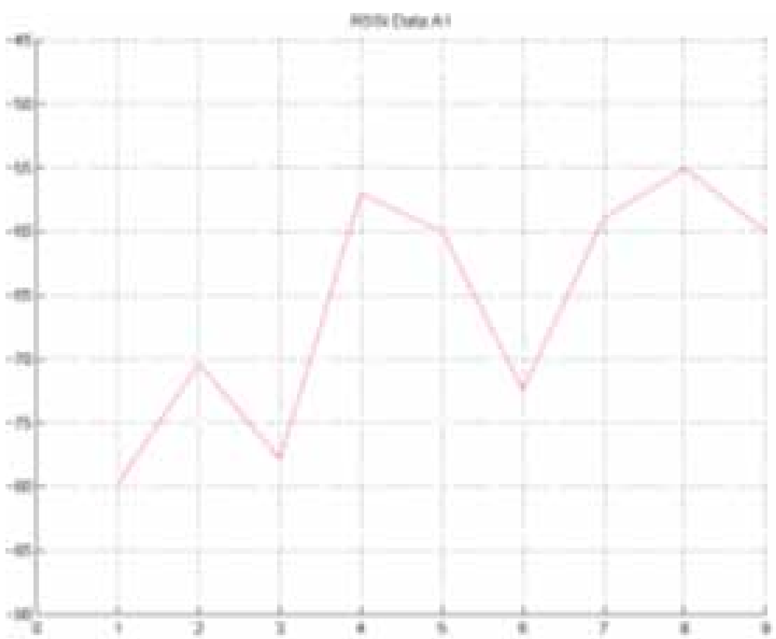


Table 4. Results for six node setup

Data Sets	A	B	C
Accurate 0.5m	92%	92%	88%

from factors such as temperature, humidity or objects within the room having moved position since the last experiment. These theories were resolved by further testing in an environment with very little noise from people and obstacles. The findings showed that the patterns within the four node setup were sufficient enough to produce independent patterns for classification per position, though on the repeat experiment, slight movement of the person being tracked had larger repercussions for the pattern recognition algorithm. Shown in the following diagram (Figure 9) are the PCA outputs for a single experiment and its repeat encompassing half of the usual test area.

Although the data points within each graph are closely aligned to the same areas, the slight change of position, i.e. the person being tracked was not standing in the exact same position as previously tested, have skewed the data in some areas. The resulting cause is misclassification for some positions within the grid. A further test to confirm this theory was carried out using a set of tests with no one present. The results from these tests showed the points collected at the same position within the graph in both cases. As these results confirmed this hypothesis, it was decided that a further two nodes were needed to provide more information (visibility in the environment) for classification to be more successful.

6. IMPROVED LOCALISATION RESULTS

Due to there being 3 receivers in the hardware setup, each collecting information from 3 separate transmitters, the total number of data streams increased to nine. This made it difficult to reuse the PCA method to view the data effectively therefore a new technique was to be used to allow the comparison of data sets. This comparison was through the use of a graphical comparison. Each of the nine streams per position were averaged to give nine single values and used to plot out a new graph which became known as a 'signature graph' (SG) as shown in Figure 10.

Each of the graphs appeared unique and visually discernible from all other graphs. The test data was processed in the same way with a signature graph being created for every two seconds worth of data per position. When compared with the initial set, each graph within the test set could be visually matched with the correct position. Each point may not have occupied the same space though the general shape of the graph still held. The results in table 4 show the total for three different test sets obtained at different times when using the SG method for classification.

The SG method here differed slightly in that the averaged values of the signature graph were used for the comparison basis and not the difference between the active and zero lines as described previously. Each classification was based on the lowest sum squared error from the results of the subtraction of test values from each of the signature values. Each of the test sets were also collected on a separate occasion using the same environmental setup.

The results from this method proved very successful, achieving an accuracy between 88 and 92 percent. When reviewing the data more carefully, it was discovered that all positions could be visually matched with the only impairing factor being that one particular value was offsetting the result due to a particularly large error difference.

Table 5. Analysis of the proposed DFL system in comparison to alternative techniques

	LWOS	Through Wall	Nuzzer	Commercial Systems	DFL
Measured Signal	Changes in RSS	RSS Attenuation	Changes in RSS	Reflection and Scattering	Patterns in RSS
Number of Nodes	Few	Many	Few	Few	Few
Number of Streams	4	756+	6	N/A	9
Accuracy	Moderate	High	Moderate	Very High	High
Multiple Users	Limited to number of strips	Yes	Ongoing Work	Yes	Designed for one user

7. DISCUSSION

The Signature Graph (SG) method using Six nodes has provided the most accurate results to date giving an accuracy of localisation to $0.5m^2$ 92% of the time. This implies that increasing the number of nodes will increase the accuracy of the results though there should be a trade-off of cost versus performance. It is believed that adding any more nodes to the current coverage area would be too costly whilst a reasonable accuracy may be achieved with the current six. The performance the NN's were comparable to that of the SG method, therefore the SG method prevailed due to the lower computational cost. In comparison to other methods for proposed in (Wilson & Patwari, 2009; Mah, 2012; Seifeldin & Yousseff, 2009), the approach described within this paper demonstrates a higher level of accuracy in regards to (Seifeldin & Yousseff, 2009) whilst maintaining a minimal hardware framework.

As shown in table 5, the proposed DFL system compares well to the other technologies listed. The LWOS system is moderately accurate though detection is limited to the number of strips incorporated into the design. The shielding device used to directionalise the signal (Shuangquan et al., 2006) also reduces its detection scope and therefore it is a limiting factor. Specialised hardware is required for this design which would increase overall costs of the system. Through Wall (Wilson & Patwari, 2009) offers better resolution in regards to accuracy but the trade-off is the number of nodes required. It uses the attenuation of individual signals to detect presence and with 756 or more streams; the system can track multiple entities within the detection space. This however is based on LoS therefore accuracy will degrade as multipath increases. To overcome this, additional nodes are introduced but as with LWOS, adding additional nodes would increase overheads. Commercially available systems have close to pinpoint accuracy at short range but the major issue here is the extremely high costs involved in the acquisition of the devices. Nuzzer (Seifeldin & Youssef, 2009), which looks at changes within RSS rather than being solely dependent on LoS attenuation offers a simpler and more cost effective approach. It uses common equipment such as laptops, desktops and wireless routers which would suggest fewer overheads provided that this equipment was readily available. In an elderly persons home however, this is not likely to be the case. Its accuracy is derived using two separate approaches from which the deterministic technique is best providing a distance error of 8.98m 75% of the time. A higher level of accuracy has been reported at 1.2m though at a lower success rate of 25%. DFL however, as shown in table 4, achieves the same distance error of 1.2m 94.6% of the time and at 1.8m 100% of the time. This is because DFL looks for patterns within the RSS rather than changes within individual signals meaning that each pattern may be composed of multipath effects as well as the original signal. The equipment being used is somewhat uncommon but readily available at the equivalent cost of using multiple computers and has the added advantage of blending into the environment easily due to the size of the nodes.

8. CONCLUSION

In this paper, a new Device-Free technique for indoor localisation has been proposed. Research has shown that there is a need for DFL and this work addresses this requirement by providing a cost effective method for healthcare systems to actively monitor elderly persons remotely. DFL focuses primarily on a single user being tracked. Multiple users have yet to be explored and may be possible in future with the addition of extra sensors. Our approach currently relies on the use of wireless motes working on the 2.4Ghz bandwidth though it is easily transferable to any Wi-Fi network working on the same frequencies.

An overview of the work undertaken in the approach to realising our DFL system is given and problems encountered along the way are discussed. We have improved upon our tracking capabilities provides 92% accuracy at a resolution of less than 1m. Further work will involve exploring new techniques of data manipulation to increase the location classifications closer to 100%.

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Philip Vance received a BEng (Hons) in Electronics and Computing from Ulster University, UK in 2006 and a PhD in Engineering from Ulster University in 2011. He is currently a research associate in the School of Computing and Intelligent Systems at Ulster University working on computational modelling. His other research interests include multi-robot systems, ambient assisted living and intelligent systems.

Girijesh Prasad holds the post of professor of Intelligent Systems in the School of Computing and Intelligent Systems. He is an executive member of the Intelligent Systems Research Centre (ISRC) and leads the Brain-Computer Interface and Assistive Technology (BCIAT) research team. Girijesh obtained a BTech degree in Electrical Engineering from REC Calicut (now NIT, Calicut, India) and an MTech degree in Computer Science and Technology from the University of Roorkee (now, IIT, Roorkee, India). He obtained his PhD degree from the Queen's University of Belfast. He is a Chartered Engineer and a Fellow of Institute of Engineering and Technology (FIET) and a Senior Member of IEEE. He is a founder member of IEEE Systems, Man, and Cybernetics society's Technical Committee on Brain-Machine Interface Systems. His R&D work is focussed on self-organising hybrid intelligent systems for addressing problems associated with industrial as well as biological systems having complex non-stationary characteristics. His specific areas of research interests include computational intelligence, adaptive predictive modelling and control, ICA, EEG/MEG based Brain-Computer Interface, Brain Modelling, Rehabilitation and Assistive Robotics, Biometrics, and Industrial Process Control. He has published over 180 research papers in journals, books, and international conference proceedings.

Jim Harkin received the BTech degree in electronic engineering, the MSc degree in electronics and signal processing, and the PhD degree from the University of Ulster, Derry, Northern Ireland, U.K., in 1996, 1997, and 2001, respectively. He is a Senior Lecturer with the School of Computing and Intelligent Systems, University of Ulster, Derry. He has published over 80 articles in peer-reviewed journals and conferences. His research focuses on the design of intelligent embedded systems to support self-repairing capabilities and the hardware/software implementation of spiking neural networks. Dr. Harkin is a member of the Institution of Engineering and Technology (IET) and is the recipient of the Distinguished Learning Support Fellowship in 2006 from the University.

Kevin Curran is a reader in Computer Science and group leader for the Ambient Intelligence Research Group. Dr Curran has made significant contributions to advancing the knowledge of computer networking evidenced by over 800 published works. He is a regular contributor to BBC radio & TV news in the UK and quoted in trade and consumer IT magazines on a regular basis. He is an IEEE Technical Expert for Security and a member of the EPSRC Peer Review College.