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Detection of multi-occupancy using device-free passive localisation

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Abstract: Indoor device-free passive localisation (DfPL) technology uses a received signal strength indication (RSSI)-based method to record variances of a measured signal where a person being tracked is not carrying any electronic device that can be used to estimate the location. The system monitors the changes in the RSSI measurements caused by the presence of a human body in an indoor environment. For example, it is known that the resonance frequency of water is 2.4 GHz and the human body contains >70% water. Thus, the human body attenuates the wireless signal reacting as an absorber. Wireless communication signal strengths between a number of nodes, using IEEE 802.11 or 802.15.4 standards, show that communication links covering distinct areas cannot be affected simultaneously by only one person. Thus, the authors have deployed a novel system that can identify multi-occupants in an environment using patterns of motion from those monitored areas. A pattern recognition neural network was used to identify two people in the environment. No other work based on the DfPL technique has focused on multi-occupancy.

1 Introduction

Indoor location estimation is important for many scenarios such as asset tracking, health care, games, manufacturing, logistics, shopping, security and tour guides. Indoor localisation systems can be classified into active and passive systems. Using wireless signals is an attractive and reasonably affordable option to deal with the currently unsolved problem of widespread tracking in an indoor environment. Location tracking techniques for active localisation require tracked personnel to participate actively; however, passive localisation is based on monitoring changes of characteristics dependent on people's presence in an environment. By participating actively, we mean that a person carries an electronic device which sends information to a positioning system helping it to infer that person's position. In the passive localisation case, the position is estimated based on the variance of a measured signal or video process. Thus, the tracked person is not carrying any electronic devices to infer the user's position. The implementation of multi-person tracking for active localisation systems is relatively straightforward with the aid of electronic devices such as tags or sensors. The challenge however is implementing multi-person device-free passive localisation (DfPL) systems as no devices are carried on the person to provide movement detection. Active localisation requires the tracked people to participate actively, whereas passive localisation is based on monitoring changes of characteristics dependent on human presence in an indoor environment. Active participation means that a person is required to carry electronic devices or tags which send information to a localisation system that infers that person's position. In many cases, the devices/tags used by the localisation systems can also process recorded data. The results are sent to an application server running the localisation algorithms for further processing. Passive localisation estimates the position based on the variance of a location-dependent measured signal or video process. Thus, the system is not using any electronic devices to infer the person's location.

The main focus of this paper is on solving an extremely difficult task, that is, multi-occupancy detection in a passive localisation scenario. Thus, one of the techniques used to deploy indoor passive localisation systems will be analysed. Indoor passive localisation is introduced by presenting various techniques used to deploy passive systems. Techniques such as ultra-wideband (UWB), physical contact, differential air pressure, computer vision and DfPL are used in indoor passive localisation.

One of the first techniques used to deploy passive localisation systems [1] is UWB. Through-the-wall surveillance or through-wall imaging (TWI) is often used to describe UWB passive systems [2, 3]. The UWB technique can be used for both static and motion detection. Owing to the similarities to the medical tomographic imaging, UWB localisation is considered as an extension of a technique that is called 'radio tomographic imaging'. The ability to detect and monitor objects or people through building walls is known as TWI. TWI can help law enforcement agencies discover potential risks inside a building and can have many applications in military and civil scenarios [4]. UWB is able to penetrate walls. This is an advantage compared with other techniques that do not have this ability. Various implementations of UWB technique have been proposed. A UWB system uses two main components: transmitters and receivers. A pulse generator sends short pulses via a horn antenna [5]. Echoes from various objects or people are monitored by the receivers and used to estimate location.

TileTrack is a low cost two-dimensional location system using physical contact to estimate location [6] by monitoring changes in the capacitance between transmitting and receiving electrodes (plate electrodes or wire electrodes). TileTrack uses nine floor tiles and each tile has one transmitting electrode. The tiles are 60 cm × 60 cm square-shaped made from thick chipboard and thin steel coating. Indoor airflow disruption caused by human movement was used to estimate location in the AirBus system [7], which uses a pressure sensor placed within the central heating, ventilation and air conditioning (HVAC) unit to detect pressure variations. An open or closed door can be correctly identified by AirBus in 80% of the cases with HVAC in operation and 68% with HVAC unit switched off.

A passive localisation system tracks people that are not carrying any electronic devices or tags. Computer vision can be considered as passive localisation [8]. A computer vision-based system ‘EasyLiving’ [9] transforms any environment into a smart environment that uses location information. Application examples include switching on/off devices near a specific location, monitoring human behaviour and many others. The system uses two Triclops colour stereo cameras and three personal computers (PCs). Each camera is connected to one PC. The third PC runs the person tracker application. Each person is separated and tracked by means of video processing algorithms. EasyLiving has been tested with a maximum of three people in the environment. The possibility of obstructions is higher if the number of people increases.

DfPL [10, 11] identifies human presence by monitoring variances in the signal strength of wireless networks. DfPL is based on the fact that human body contains about 70% water and it is known that the water resonance frequency is 2.4 GHz. Most common wireless networks use the 2.4 GHZ frequency, thus the human body behaves as an absorber attenuating the wireless signal [2, 4, 12–15]. The focus of our research and the remainder of the paper are based on DfPL using wireless sensor networks (WSNs).

The paper is organised as follows: Section 2 expands on non-human factors affecting wireless signals, Section 3 introduces the functionality of a pattern recognition neural network (PRNN), Section 4 presents the test bed and the results obtained from a PRNN. Section 5 present future works and Section 6 concludes the paper.

2 Non-human factors affecting wireless signals

Errors in location estimation can be caused by many factors. Various error sources such as multipath, non-line-of-sight (NLOS), interferences and shadowing effects have been identified in [16]. These can affect received signal strength indication (RSSI) localisation systems. Other error sources that were found to affect systems based on radiofrequency (RF) technologies are clock synchronisation, multipath, variable atmospheric conditions, differences in the conducting and reflecting properties of materials, direction of antennas, geometry, possible attacks and unavailability of base stations. This section will discuss some of the most common source of errors in the RF-based localisation systems.

NLOS is radio transmission using a path that is obstructed, usually because of a physical object and could affect a location estimation [17]. The best example here is GPS which is based on the line-of-sight (LOS) with the satellites. Permanent availability of the LOS is ideal, but because of many factors this cannot be achieved. Thus, measurements errors will affect the accuracy and precision of the localisation system. However, dead reckoning, has been used successfully with GPS and other technologies to improve the accuracy when exact measurements are temporarily unavailable. Location estimation using dead reckoning is based on previous information about the location of the tracked device, direction and speed. Indoors, WiFi-based systems, for example, could be affected by the NLOS. NLOS is usually caused by low amplitude of the signal transmitted between two terminals or the signal is completely blocked by obstacles, known as occlusion. Owing to very low amplitude, the signal cannot be differentiated from the background noise. Thus, the system’s accuracy and precision will decrease.

Multipath refers to a transmitted signal that arrives at a receiver by two or more paths [18]. This is caused by the obstacle that might exist in an environment. The multipath effect can cause distortions of the amplitude and phase of the signal. In the case of NLOS, the probability of multipath increases. This is usually a common problem faced in most cases by radio waves in indoor environments. Indoors, multipath is present because of reflections, diffractions, scattering from walls, ceilings or floor surfaces. Multipath is avoided by considering only the strongest signal that arrives at the receiver. However, this does not take into account the path of the signal, thus it is likely that the strongest signal does not arrive at the receiver on the shortest path.

If the case of two terminals with WiFi capabilities, one mobile and the second one placed in a fixed location, the amplitude of the signal strength decreases with the increase of the distance between the two terminals [8]. Signal strength attenuation has been used as a technique to estimate the distance between two terminals. However, indoors, signal strength measurements used with other location estimation techniques might be affected because of signal attenuation caused by obstacles such as walls, furniture or human presence. Attenuation is one of the main reasons of NLOS where LOS is a requirement. In wireless communications, the concept of fading represents a deviation of the attenuation. It can be caused by multipath propagation or by shadowing from various obstacles. Both scattering and reflection occur and overlap. The main factor that differentiates them is the size of the particle. Scattering appears for particles smaller than the light wavelength, and reflection for larger particles.

3 Pattern recognition neural network

Pattern recognition networks are feedforward networks which can classify input vectors based on target classes [19]. The feedforward networks are also known as multilayer perceptron (MLP) networks. MLP are very popular because of their flexibility and regardless of the complexity of the patterns, the network can be trained to assume the shape of the patterns in the input vectors. MLP networks are called

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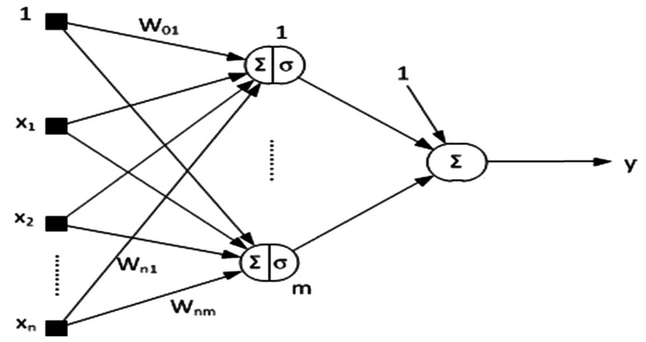

Fig. 1 *Pattern recognition network layout*

universal approximators as they can approximate any non-linear input–output relationships between inputs and outputs.

Fig. 1 presents the layout of a MLP network with an input layer, a hidden layer and an output layer. The hidden layer is responsible for the transformation of the input weights and it may consist of one or many linear or non-linear neurons depending on the problem to be solved. The hidden neurons sum the corresponding weights of the inputs and pass this sum through a transfer function, denoted by σ. The output layer is fed with the output of the hidden neurons through the hidden output neuron connections. The outputs are obtained by computing the weighted sum which is then passed through a linear or non-linear function.

The power of neural networks derives from the processing in the hidden units also known as hidden neurons. The n inputs, $x_1, \ldots, x_n$ are fed to the hidden unit and processed by various activation functions. In the pattern recognition network case, the function maps the minimum and maximum values of the input vectors to the interval $[-1, 1]$. The activation function is given by

$$y = \frac{(y_{\max} - y_{\min})(\boldsymbol{x} - x_{\min})}{(x_{\max} - x_{\min})} + y_{\min} \tag{1}$$

where $y_{\min} = 1$ (default value), $y_{\max} = 1$ (default value), $\boldsymbol{x}$ is the input vector, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values from the input vector. The outputs generated by the hidden neurons are then fed as inputs to the output layer where an identical activation function is used to generate the output of the pattern recognition network. We implement a PRNN (Section 4) to identify multi-occupancy patterns specific for indoor wireless environments. The network uses supervised learning and learns from input–output pairs during the training process. Thus, the main reason to use PRNN is the fact that the network can learn patterns and we are identifying patterns of motion in an environment.

4 Evaluation

The number of smart sensor nodes available on the market is increasing. The nodes are equipped with a processor, memory, a radio, batteries for power supply and one or more sensors, for example, thermal, optical, magnetic, accelerometers, biological, humidity and barometric pressure. There are a large variety of sensors that are able to measure different properties of the environment and make the nodes suitable for applications in many areas.

4.1 Test bed devices

We have deployed a WSN using Sun Small Programmable Object Technology (SunSPOT) hardware platform. The configuration of the SunSPOT platform uses Java Virtual Machine Squawk and the wireless communication between the nodes is IEEE 802.15.4 compliant. The SunSPOT development kits include one base station and two free-range SunSPOT nodes.

A SunSPOT node has four components: (i) sunroof; (ii) sensor board including a 2G/6G three-axis accelerometer, temperature sensor, eight LEDs, light sensor, two programmable switches, I/O connector; (iii) a processor board running a 180 MHz 32 bit ARM920T core with 512 K RAM/4M Flash; (iv) an internal 3.7 V 720 mAh LI-ION (lithium-ion) rechargeable battery (zennaro2008 experimental, Sun2012). The radio communication of a SunSPOT node is based on an integrated TI CC2420 (Texas Instruments) radio chip which is IEEE 802.15.4 compliant and works in the 2.4–2.4835 GHz ISM band. The TI CC2420 uses a 2.4 GHz transmitter/receiver with digital direct sequence spread spectrum baseband modem with MAC support. Other features that were important for this project include RSSI with 100 dB sensitivity, transmit power between −24 and 0 dBm, 250 kbps bit rate and 2000 kChips/s chip rate and a minimum receiver sensitivity of −90 dBm [20].

Fig. 2 presents a testbed with ten nodes separated in two halves. The first half, N1–N5, broadcast messages on port 42 and listens for broadcasts on port 43, whereas the second half, N6–N10, send messages on port 43 and receive messages from neighbour nodes on port 42. This testbed was deployed in order to avoid congestion when the number of nodes increases. Without this separation, the number of node-to-node links would have been equal to 90. Thus, there is a high possibility of delays caused by congestion. Using different broadcast ports, we have reduced the number of links to 50. Two UDP ports, one for each half, are used to speed up data collection. The base station, connected to a host PC, is responsible for selecting the nodes to record values from.

It is worth noting that this was an experimental testbed using Java SunSPOT nodes which are low cost. The wireless nodes currently on the market are even lower in cost and the DfPL technique only requires the mainboard

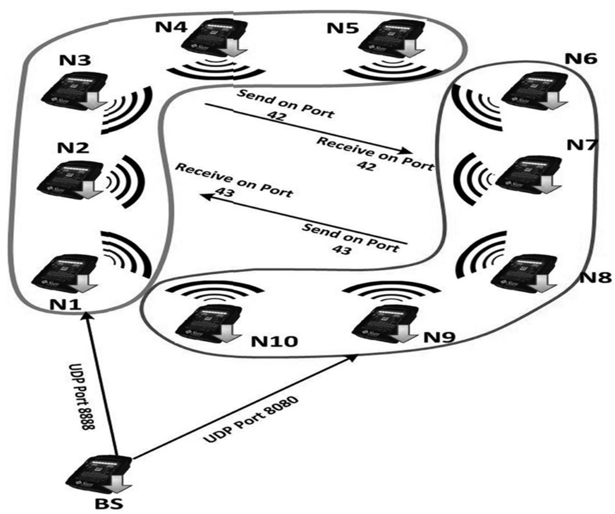

Fig. 2 *WSN testbed with ten Java SunSPOT nodes*

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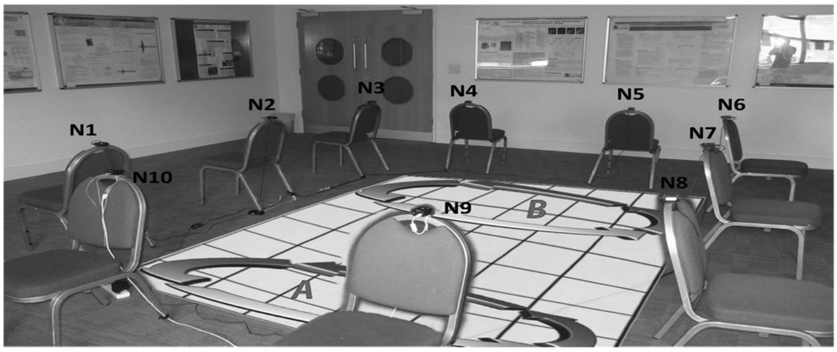

Fig. 3 *Testbed with bidirectional links*

and wireless radio, thus custom boards can be designed. The localisation accuracy is higher if there are a higher number of nodes. However, the technique presented can also be applied in 802.11-based networks not only in WSN networks. This means that any device with WiFi communication can be used as nodes, thus there is no extra cost as most buildings have wireless networks deployed.

To collect data from the nodes we can use either TCP or UDP. The test we performed showed that UDP is faster and has a better throughput. Using a 'hello command' the base station scans for available nodes setting the order used for data collection. An important aspect before collecting RSSI measurements is synchronising the nodes with the host (PC). This helps us to accurately record the timestamp from a node forwarding measurements recorded from neighbour nodes.

4.2 Test bed physical environment

The MS020 room in the Intelligent Systems Research Centre, University of Ulster (see Fig. 3), is a large indoor room without too many obstructions. This room has a size of 7.8 m × 10.6 m. However, we use only a part of the room, 3.8 m × 2.8 m, where we deployed the proposed WSN using ten chairs. The idea was to use a room where there are not too many obstacles such as furniture. The testbed was deployed using approximately half of the room's size with no people in the area. The main focus is to use two areas, A and B, in the testbed in order to identify multi-occupancy.

The tests were conducted by monitoring the RSSI in the deployed testbed. The data recorded by each link contains seven parts, four parts of silence with no people separating the periods that people are causing variances in the wireless communication (see Fig. 4).

The messages sent by each node contain the following parameters: RSSI, node ID, battery voltage and battery level. Initially, the battery voltage and the battery level were considered as necessary because of the fact that wireless communication could be affected if the node's battery is running low. The tests were set up with the nodes plugged in to powered USB hubs. The USB hubs ensure that the communication will not be affected by batteries running low. The first testbeds used unidirectional wireless communications. In the first case, the two nodes send packages directly to the base station. In the second testbed, two of the nodes are the transmitters whereas the receivers are the other two nodes. The receivers collect the packets from the transmitters, adding the signal strengths (RSSI) between transmitters and receivers to the messages, and forward them to the base station. The nodes are placed 1.5 m away from the base station with a distance of 1.5 m separating the nodes and a 1 m height for the case with the two nodes. In the case of four nodes, the distance between the four nodes is 1.5 m and the base station does not require a specific location anymore. To deploy an application using WSNs, it is necessary to take into account the design and resources constraints which are specific to WSN nodes. It is important to consider specific limitations of WSNs, such as short communication range, bandwidth, processing power and storage space. The next step towards deploying the testbeds used to identify multi-occupancy was to modify the wireless communication from unidirectional to bidirectional communication. The main reason was to obtain a higher number of links between the nodes that could be affected by human presence. Other important features had to be considered, such as time synchronisation between nodes. Thus, a function that synchronises all the nodes with the host PC has been implemented. Further, data collection is developed using multi-threading. Multiple threads allow the collection of values from all the nodes at the same time. The data collected is stored in a PostgreSQL database using multiple connections to the database, one connection for each thread reading data from nodes.

Fast fading is one of the multipath effects and this can be overcome by using the fingerprint localisation technique. Fast fading refers to the signal's high frequency deviation of attenuation and can be eliminated by averaging the RSS

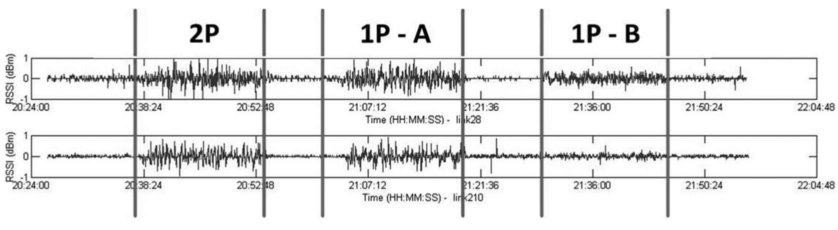

Fig. 4 *Normalised RSSI from nodes N2–N8, N10*

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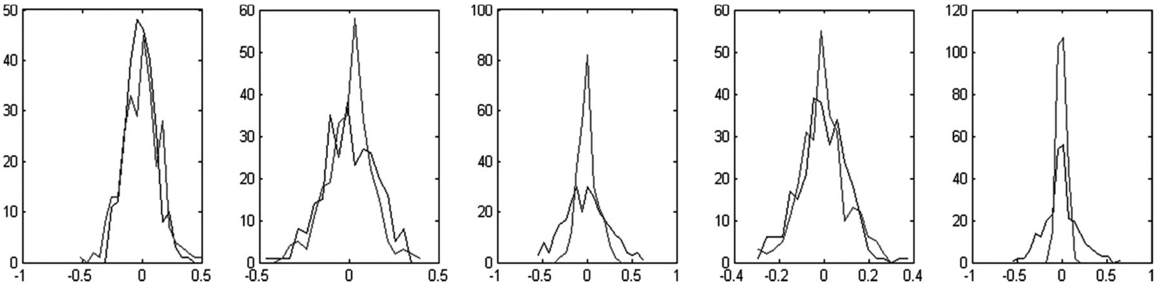

Fig. 5 *Histograms of the links from nodes N2 to N6–N10*

values over a certain period of time for each location fingerprint [17]. Fingerprinting and RSS averaging are both used here.

4.3 Data dimensionality reduction

We have discovered that not all the 50 links covering the monitored environment can be used to identify multi-occupancy. Principal component analysis was used to identify the principal components of the RSSI dataset. We calculate the percentage of variance that each links introduces. It can be noted that the first 10 links account for ∼56% of the variance in the dataset whereas the first 25 links account for ∼90% of the variance. Thus, we can do a dimension reduction of the dataset to the first 25 links. This means that we can actually use unidirectional node-to-node communication because of the identification of the 25 links that are used by one half of the nodes. However, because of bidirectional communication usage, we reduce the dimension of the dataset using an approach that is called histogram-based class separability. For example, the set of five plots in Fig. 5 presents the class separability for two out of the three defined classes. The first class contains RSSI values that define the motion of one person in area A whereas the second class is defined by RSSI values recorded for one person in area B. The classification process has a number of three classes.

We analyse the separability of the first two classes defined for areas A and B. The third class is defined by two people, one in A and a second one in B. To classify values as belonging to the third class, the classification process will consider simultaneous variances of the signal defining A and B together. Based on the histograms, we have calculated the differences between the maximum peaks of the histograms and selected all the links that had a difference >25. We have observed that the links with a difference >25 provide the best class separability. Based on this analysis we have selected 23 links. Furthermore, using the selected links, we have selected only parts of the recorded data as follows: 2P – two persons, one in area A and the other in area B, 1P-A – one person in area A, and 1P-B – one person in area B. Fig. 4 shows the selected links for node N2.

4.4 Neural network pattern recognition

The neural network pattern recognition tool in Matlab solves pattern recognition classification problems and uses a two-layer feedforward neural network with sigmoid output neurons that can be created in Matlab using the ‘patternnet’ function.

We have used ‘nprtool’ to create and train a PRNN. This is a GUI providing step-by-step instructions, in a wizard style, allowing you to select the data to be used in the classification process. The tool provides all the steps in order to train and classify the data. A selection of the percentage of data that will be used for training, validation and testing can be chosen. Furthermore, we set the number of neurons in the hidden layer. Afterwards, the network is created and we can begin the training. The training is a supervised training in that each input value has a corresponding output. A good training result is usually obtained after a number of retraining trials until you achieve a good fit. The main reason for retraining is that the learning process starts from a random value and tries to learn based on the examples provided, pairs of values and the classes the values belong to. Owing to a random selection of the initial weights, the initial error would be large.

At the start of the training process, an information window is shown providing information about the neural network architecture, the algorithms used, the progress of the training process and various plots such as performance, training state, error, confusion matrices and receiver operating characteristic (ROC). The RSSI data were split as follows: 75% of the data for training, 15% for validation and 15% for test. We have used a network with a number

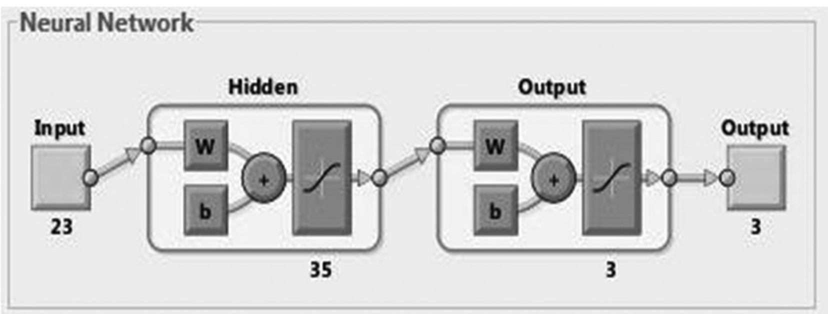

Fig. 6 *Neural network pattern recognition architecture*

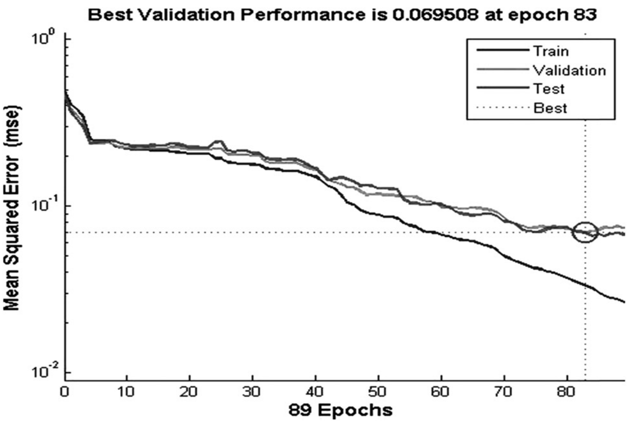

Fig. 7 *Neural network pattern recognition – best validation performance*

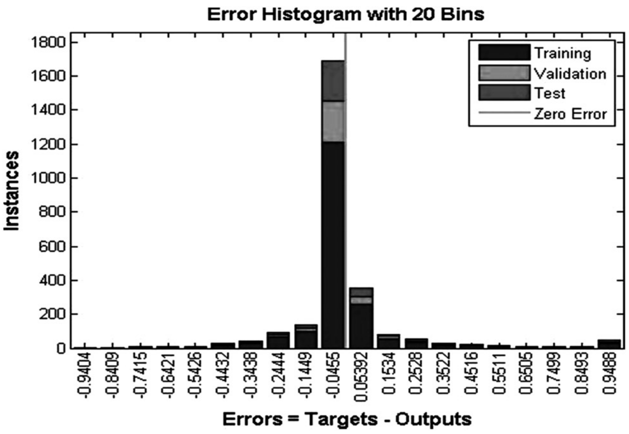

Fig. 8 *Neural network pattern recognition – error histogram*

of 35 neurons in the hidden layer (see Fig. 6). We have modified the number of neurons in the hidden layer which has been increased from 10 to 35 neurons. However, using the advanced script and changing the defaults values for the number of epochs, performance goal, learning rate, minimum gradient and validation checks parameters, we were able to obtain an accuracy percentage of above or ~80% for new data on the majority of training sessions. The classification accuracy for the training data was above or ~93% and for validation above or ~85%. The parameter values for the advanced script are as follows: 10 000 epochs, performance goal is equal to 10^8, learning rate is equal to 0.001, validation checks equal to 10 and minimum gradient is equal to 10^8.

In the case of the results presented, we use the default parameters as follows: 1000 epochs, performance goal equal to 0.00, learning rate equal to 0.001, validation checks equal to 6 and minimum gradient equal to 10^6. The only parameters that were modified were the number of neurons in the hidden layer that was increased to 35 neurons.

Fig. 7 shows that the best validation performance was achieved at epoch 83 and after six validation failures the training stopped at epoch 89. Fig. 8 shows the error histogram. It can be noted that the majority of the instances are nearby to the zero error mark.

Mean square error (MSE) is the most used error indicator in neural networks. MSE creates an error surface based on the combination of each weights generated for the inputs. The training process tries to find the lowest point in the error surface and that is based on the optimum weights. Thus, the process searches for the weights that will return the lowest error for the whole training set. The gradient in neural networks defines the variance or the slope of the error surface. An efficient method to find the lowest point in an error surface is the gradient descent approach. However, the neural network pattern recognition uses an alternative for gradient descent that is called conjugate gradient. The speed of convergence of the conjugate gradient uses a more

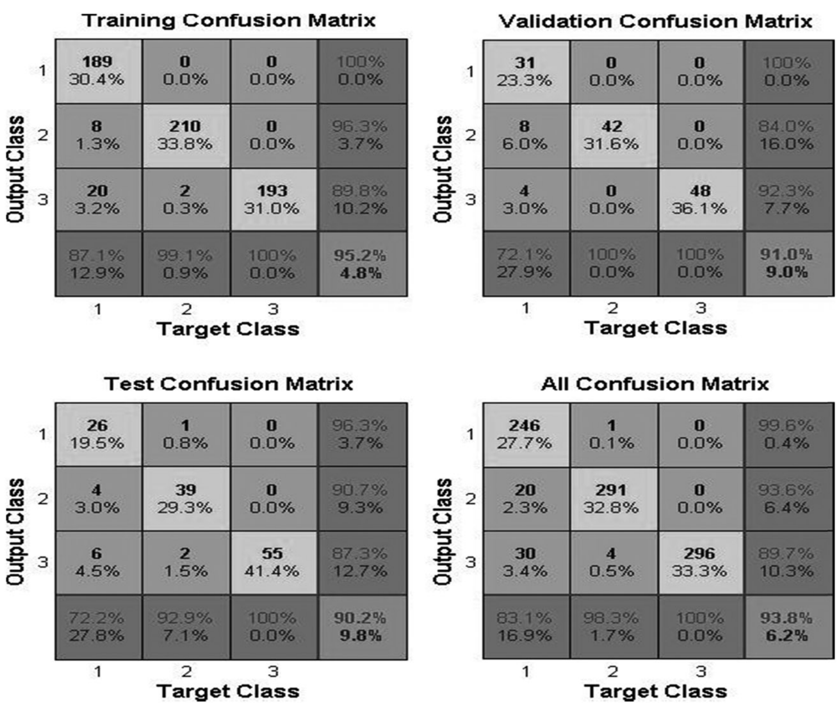

Fig. 9 *Confusion matrices*

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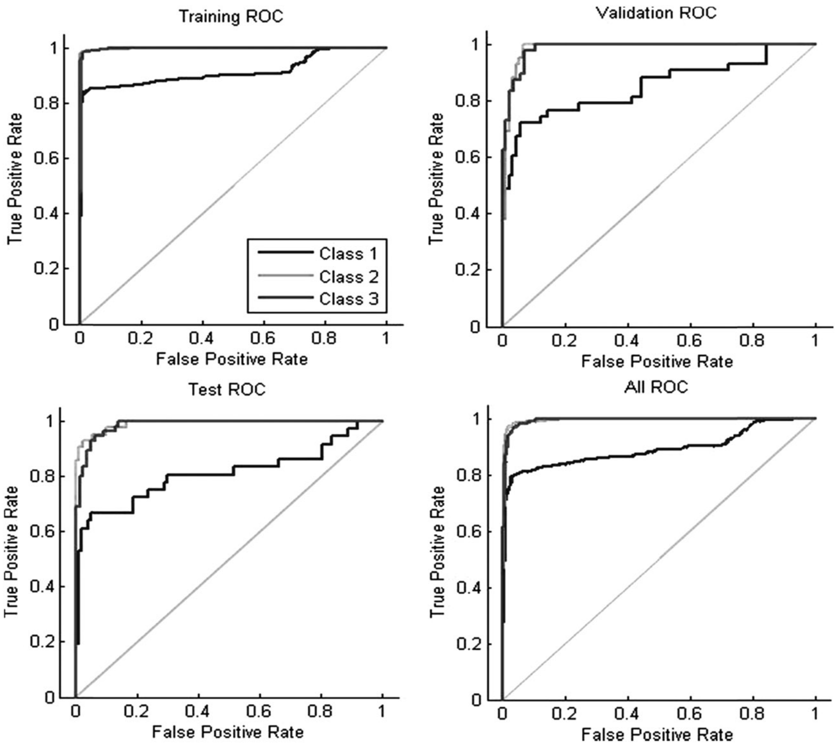

Fig. 10 *Receiver operating characteristic*

complex dependence to the eigenvalues compared with the gradient descent and can use preconditions.

Fig. 9 shows the overall confusion matrix. We have obtained an accuracy of 95.2% for the training data, 91% for the validation data and 90.2% for new data. Thus, the overall accuracy is equal to 93.8%.

Fig. 10 presents the ROC curves for the RSSI dataset used for classification. ‘Class 1’ represents the class for one person in area A, ‘Class 2’ is for one person in B and ‘Class 3’ is for two people, one in A and the other in B. ROC is used in signal detection theory to illustrate the performance of a classifier. It is computed as the ratio between true positive rate (TPR) and false positive rate (FPR). TPR is known as sensitivity and FPR is one minus specificity. The ROC graphs are sometimes called the sensitivity against (1 ‘specificity’) plots.

5 Future work

The Internet of Things (IoT) is an emerging paradigm where physical objects with embedded sensors will communicate with an e-infrastructure to send and analyse data using the Internet. IoT envisions a future in which digital and physical entities can be linked, through their unique identifier and by means of appropriate information and communication technologies. In the future, we aim to build upon our DfPL research in order to deliver a robust field-trial ready human detection system for disaster situations in conjunction with the IoT public infrastructure of sensors. Challenges still remain in using the public IoT for emergency response teams as they need to quickly assess any diasters where people may be trapped. The primary problem is to ascertain who is trapped and where. This can be aided by the integrated wireless sensors and artificial intelligence techniques. Innovative methods are required to improve accuracy levels and to allow positioning to be achieved for a reasonable cost in terms of time and infrastructure and this proposal aims to build such a system.

As previously touched upon, in an indoor environment, radio signals change in intensity as they travel through an object. RF signals bounce all over the place and factors such as furniture, people and/or temperature can all affect the way a signal travels indoors. It also happens that the human body interferes with wireless signals such as originating from a household access point. It has been discovered that detection of human movement can be achieved by using a combination of a mobile phone lying static while connected to a commercial household access point. The detection of movement in the vicinity of a mobile phone can serve a number of mobile applications. A combination of RSSIs and mathematical techniques is used to obtain a relative measurement of the received signal strength at the device. Intelligent filters attempt to overcome the uncertainty in the measurement by use of probabilistic smoothing and prediction techniques.We have a patent pending in this area [21], which we are currently commercialising and hoping to licence in the near future.

6 Conclusion

We have presented the results from a controlled environmental set up using ten nodes Java-based WSN. A PRNN was used to identify motion patterns and identify specific multi-occupancy patterns. The results showed the possibility of using pattern recognition networks to detect multi-occupancy using DfPL considering the timestamps and links affected by human presence. A person cannot affect wireless links covering distinct areas in the environment at the same time. Histogram-based class separability measures were used to select the links that provide the best class separability.

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