

DETERMINATION OF POSITIONING ACCURACIES BY USING FINGERPRINT LOCALISATION AND ARTIFICIAL NEURAL NETWORKS

by

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Fingerprint localisation technique is an effective positioning technique to determine the object locations by using radio signal strength, values in indoors. The technique is subject to big positioning errors due to challenging environmental conditions. In this paper, initially, a fingerprint localisation technique is deployed by using classical k -nearest neighborhood method to determine the unknown object locations. Additionally, several artificial neural networks, are employed, using fingerprint data, such as single-layer feed forward neural network, multi-layer feed forward neural network, multi-layer back propagation neural network, general regression neural network, and deep neural network to determine the same unknown object locations. Fingerprint database is built by received signal strength indicator measurement signatures across the grid locations. The construction and the adapted approach of different neural networks using the fingerprint data are described. The results of them are compared with the classical k -nearest neighborhood method and it was found that deep neural network was the best neural network technique providing the maximum positioning accuracies.

Key words: received signal strength indicator, k -nearest neighborhood, artificial neural networks, single-layer feed forward neural network, multi-layer feed forward neural network, multi-layer back propagation neural network, general regression neural network, deep neural network

Introduction

Indoor position detection is an important topic to detect the positions of unknown objects [1, 2] in recent years. An ideal positioning should achieve an accurate position detection, a robust construction, fast training stage and a low price. It should give accurate positioning results under difficult environmental conditions where the received signal strength indicator (RSSI) propagation is affected by multipath components and signal noise.

Fingerprint localisation technique identifies the object location by relying on the RSSI recordings from a test region. The k number of closest RSSI values with respect to RSSI values received at object location is selected in that region and their weighted mean value of their co-ordinates is taken as the object location. Fingerprinting localisation system has two stages: training stage and localisation stage [3, 4]. During the training stage, a database of RSSI values against grid co-ordinates across the test area is obtained and stored. In the localisation stage, this

database is used to locate the unknown object co-ordinates. One of the most popular algorithms to determine the object locations is the k -nearest neighbourhood (k -NN) algorithm [5]. The RSSI values received from unknown object co-ordinates are incorporated with the RSSI values in the fingerprint database through Euclidean signal distances in this technique. The co-ordinates which give the smallest Euclidean distances are employed to calculate the unknown object locations [6].

Artificial neural networks (ANN), [7], are deployed on the fingerprint databases to predict the unknown object co-ordinates. There are several ANN techniques such as SFFNN, MFFNN [8], GRNN [9], MBPNN, [10], and DNN, [11], to calculate the unknown object positions.

Presently, positioning accuracies of physical objects are calculated by using radio frequency (RF) waves in indoor areas and several neural network (NN) techniques. In this study an overview of NN techniques are employed. Similarly, these NN techniques can also be deployed in thermal sciences [12]. Thermal data of indoor environments can be measured with the help of wireless sensor nodes and used to calculate real time object locations by employing NN. Furthermore, static and dynamic thermal problems, dynamic thermal control, prediction of thermal conductivity, and dynamic viscosity are a few examples of using NN [13].

Initially, fingerprint localisation method with k -NN is employed in this work and unknown object locations are determined. Previously mentioned NN techniques are also deployed to determine the same unknown object locations. Finally, positioning accuracies are calculated and compared among all these techniques to find the most accurate of them.

Fingerprint localisation technique

Fingerprint theory

Fingerprint localisation technique determines the unknown object locations by using a set of RSSI values at object locations and comparing them with a pre-built RSSI fingerprint map. A general map of example fingerprint area is presented in fig. 1.

Measurement points in a grid formation depending on the area topology is organized. The wireless sensor networks (WSN) transmitters stationed at several points provide RF propagation over the entire grid area. During the training stage, RSSI values are received

from all the transmitters at each grid point and recorded against the grid co-ordinates in a database.

The RSSI values at measurement points contain random behaviour due to environmental conditions. Therefore, average value of multiple RSSI measurements is deployed as the RSSI fingerprint at that point. The RSSI measurement values are received at each grid point from T_i transmitters. There are N number of transmitters. These measurement values are written in a database and

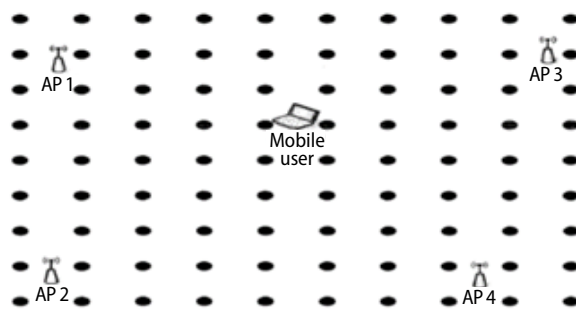


Figure 1. A test area of four transmitters, a grid of RSSI measurement points and a mobile receiver

defined as *location fingerprint RSSI vector* F_j . There are M number of grid points and F_j at j^{th} grid point is given:

$$F_j = RSS_{T_1}^j, RSS_{T_2}^j, RSS_{T_3}^j, \dots, RSS_{T_N}^j \quad (1)$$

A sample of RSSI measurements are recorded on the object receiver and identified as *sample RSSI vector* R_k . There are Z number of object points and R_k at k^{th} object point is given:

$$R_k = RSS_{T_1}^k, RSS_{T_2}^k, RSS_{T_3}^k, \dots, RSS_{T_N}^k \quad (2)$$

The difference between the *location fingerprint RSSI vector*, F_j , and *sample RSSI vector*, R_k , are used to calculate the nearest grid points to the object point. Euclidean distance, E_k , is identified as the signal distance and it is defined in eq. (3).

$$E_k = \sqrt{\sum_{j=1}^M (F_j - R_k)^2} \quad (3)$$

Euclidean distance defines the distance between two locations with respect to radio signal strengths. Therefore, weakest signal strength difference refers to the smallest physical distance between two locations [14]. Minimum Euclidean distances corresponding to minimum physical distance between grid and object locations are selected for object location calculations.

The k -NN algorithm

The k number of grid points are determined by k -NN algorithm in Euclidean database. Mean value of these grid co-ordinates are calculated to give the estimated object location.

Furthermore, a weighting scheme is introduced to increase the accuracy of object localisation with k -NN algorithm. Hence, weight functions, [15], are deployed to compensate the RSSI variations. Different weight functions can be utilized with respect to changing indoor conditions during positioning calculations.

Weights and distances are inversely proportional in many applications. Distant transmitters can have a dominant effect during localisation. Estimated positions move towards the nearest transmitter locations and the positioning errors increase. Finally, estimated object co-ordinates are calculated by using weight function, w_j , and grid co-ordinates, (x_j, y_j) , defined by k -NN algorithm, eq. (4).

$$(x, y)_{\text{estimated}} = \sum_{j=1}^k w_j (x_j, y_j) \quad (4)$$

where w_j is the weight function of the j^{th} grid point in k -NN. The selection of weight functions effects the positioning accuracy. Hence w_j is formulated to express this dependency with D_j Euclidean distances of k -NN values. Empirical weight function in eq. (5) is deployed in order to estimate the unknown object co-ordinates [16]:

$$w_j = \frac{1}{D_j^2} \quad (5)$$

$$\sum_{j=1}^k \frac{1}{D_j^2}$$

Artificial neural networks

The NN is a numerical modelling technique that mimics biological brains. A NN can initially be trained on a sample of known dataset. It determines the future similar patterns for unknown data which it has never seen before. The NN can change its structure depending on internal and external information during their flow through the network in training phase. The NN can be considered as non-statistical data modelling techniques [17, 18]. They are employed to show the relation between input and output data.

The feed-forward neural network

The FFNN is basically a straight forward network which relates the input and output functions [19]. In this technique, the signals travel through the network between input and output layers without any feedback. The performance of the NN is related to its input-output transfer function. Weights of the neurons reduce the errors between estimated and actual outputs. Sigmoid function is employed for activation during the training stage to transfer the input data to output layer [20].

The FFNN consist of neurons which are constructed in layers. It generally has one input layer, one output layer. Neurons in the input layers are defined as input data and neurons in the output layer are defined as output data. Hidden layers, between the input and output layers, transform the input data to generate the target output data. The NN calculate the error derivative of the weights and back-propagation algorithm, [21], is the best method to derive these error derivatives.

A description of the back-propagation multilayer network can be given in fig. 2. There are m layers in the multilayer network. The K_j is the number of neurons in j^{th} layer. Network has P number of patterns of training set with K_0 dimensional X inputs. The K_m dimensional T targets are used in training of the network. The network O output response to the input and target training patterns is given:

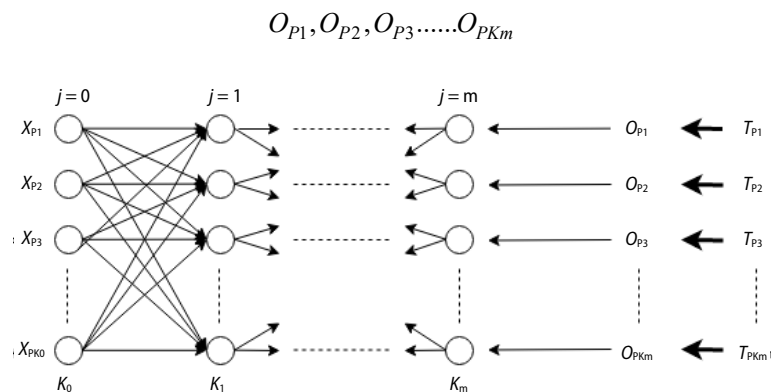


Figure 2. General feed forward and back propagation NN

Finally, different NN techniques are employed, and the most accurate technique is determined. Firstly, SFFNN technique is used. Its NN structures is shown in fig. 3. The neurons in the input and output layers represent the input and output data, respectively. The hidden layer between input and output layer carries out the transformation of input data to generate the target output data.

Target output data is the (x, y) position co-ordinates of grid points across the test area. There are j fingerprint signatures which are defined as the RSSI values received from j transmit-

ters at each grid location. Each neuron in a layer is connected to all the neurons in the next layer. Each of these connections is related by its weight, w_{ij}^k , where index i is the neuron number of the $(k - 1)$ layer and j is the neuron number of k^{th} layers. The output value of a neuron is multiplied by the related weight and added to the signal value of the neuron in the next layer. Generally, the number of neurons in hidden layer is less than or equal to the size of the input layer and more than the size of the output layer. In this study, the size of hidden layer is taken as equal to the size of input layer as shown in fig. 3. Discrete

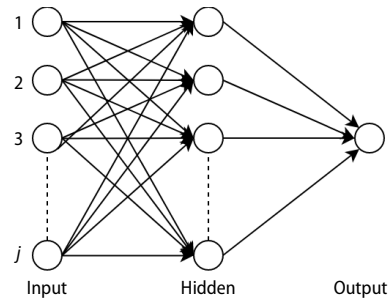


Figure 3. The SFFNN architecture

back-propagation algorithm can be applied to SFFNN if required. It is deployed to determine the weights and adjust them for each neuron in the hidden layer. This is a supervised learning method. The weights are adjusted several times in each epoch during the training.

Secondly, MFNN, multi-layer feed-forward artificial neural network technique is deployed. It includes one input layer, one output layer and several hidden layers as shown in fig. 4. The MFNN technique is like SFFNN with the exception that the number of hidden layers is more than 1.

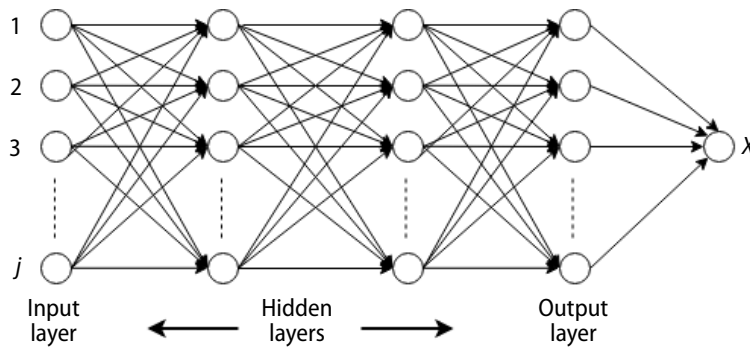


Figure 4. The MFNN architecture

Thirdly, back propagation method, MBPNN, can also be employed between hidden layers. This is identified as multiple back propagation neural network technique.

The i^{th} neuron output in k^{th} layer in the network can be determined:

$$y_i^k = g\left(\sum_{i=1}^{n_{k-1}} w_{ij}^k y_i^{k-1} + T_i^k\right) \quad (6)$$

where g is the sigmoid activation function. It is used to model the non-linear relationship between input and output layers. The T_i^k is the threshold value added to the input.

The MBPNN is used to calculate the final weights of neurons in the network. The error, calculated in the output layer neurons, is than back propagated to hidden layers by deploying the Gradient Descent method [22]. This minimizes the squared-error cost function in neurons. The sum of the squared-errors of cost function is given:

$$E_p = \frac{1}{2} \sum_{k=1}^m (h_{kp} - O_{kp})^2 \quad (7)$$

where p is the number of training pattern, O – the actual output, and h – the predicted value with size m .

Similarly, j number of RSSI signatures is collected from j number of transmitters at each grid point. These signatures are employed as the input to the training network. The outputs of the network are defined as the (x, y) co-ordinates of the grid points and they are used as the two targets during the training. Once the training phase is completed, any j numbers of RSSI signatures received from an unknown object location are applied as input to MFFNN and the output (x, y) co-ordinates are calculated. The prediction errors between the actual object co-ordinates and the calculated object co-ordinates are determined with different ANN techniques. Average error calculations between the ANN techniques are carried out to find the most accurate technique.

The general regression neural network

The GRNN has a one pass learning algorithm, [23]. The regression equation is considered a parallel NN like structure. If the joint probability density function (pdf) of x and y is known and z co-ordinate is omitted, the conditional pdf and the expected value can be computed. Parameters of structures can be determined from examples rather than iteratively. The structure learns and starts to generalize. It can estimate y values for any new x value during the propagation time. Suppose that $f(x, y)$ represents the joint continuous pdf of a vector random variable x and scalar random variable y . The regression of y on x or conditional mean of y given x is defined:

$$R(y|x) = \frac{\int_{-\infty}^{\infty} y f(x, y) dy}{\int_{-\infty}^{\infty} f(x, y) dy} \quad (8)$$

When $f(x, y)$ is unknown, it can be estimated from a sample of x and y data. A class of consistent estimators is proposed by Parzen, in [24], which can be applicable in the multi-dimensional case. The probability estimator $f(x, y)$ is based on sample values of x^i and y^i of random variables of x and y and can be estimated from the training set by using the Parzen estimator:

$$f(x, y) = \frac{1}{(2\pi)^{(p+1)/2} \sigma^{(p+1)}} \frac{1}{n} \sum_{i=1}^n \exp\left[-\frac{(x-x^i)^T(x-x^i)}{2\sigma^2}\right] \exp\left[-\frac{(y-y^i)^2}{2\sigma^2}\right] \quad (9)$$

where n is the number of sample observations and p is the dimension of the vector variable x . The $f(x, y)$ assigns a sample probability of width σ for each sample of x^i and y^i . Probability estimate becomes the total sum of these sample probabilities. Placing the joint probability estimate $f(x, y)$ into conditional mean in eq. (8) generates the desired conditional mean y for given x , eq. (10):

$$y(x) = \frac{\sum_{i=1}^n \exp\left[-\frac{(x-x^i)^T(x-x^i)}{2\sigma^2}\right] \int_{-\infty}^{\infty} y \exp\left[-\frac{(y-y^i)^2}{2\sigma^2}\right] dy}{\sum_{i=1}^n \exp\left[-\frac{(x-x^i)^T(x-x^i)}{2\sigma^2}\right] \int_{-\infty}^{\infty} \exp\left[-\frac{(y-y^i)^2}{2\sigma^2}\right] dy} \quad (10)$$

The term $(x-x^i)^T(x-x^i)$ in eq. (10) can be defined as a scalar function, w_i^2 , and eq. (10) becomes:

$$y(x) = \frac{\sum_{i=1}^n y^i \exp\left(-\frac{w_i^2}{2\sigma^2}\right)}{\sum_{i=1}^n \exp\left(-\frac{w_i^2}{2\sigma^2}\right)} \quad (11)$$

The resulting regression in eq. (11) deals with the summations of the observations. The estimate $y(x)$ can be considered as the weighted average of observed values, y^i . Each observed value is exponentially weighted according to its Euclidean distance from x .

The deep neural network

A DNN, is an ANN with multiple hidden layers between input and output layers, [25]. The DNN is a feed forward network. Data flows from input layer to output layer without looping back. Deep learning methods target at learning feature hierarchies by using features from higher level hierarchy formed by the lower level features. They have learning methods of deep architectures with NN of many hidden layers.

There are two important issues with training DNN. These are overfitting and computation time. Overfitting takes place due to added layers of abstraction which allow to model simple dependences in the training data. Large number of data is used in DNN and computation time is longer compared to shallow ANN. The DNN use training parameters such as network size, learning rate and initial weights.

The most important advantage of deep learning is replacing handmade features with efficient algorithms for unsupervised or semi-supervised feature learning and hierarchical feature extraction. In this study 20 hidden layers with one input and one output layers are employed for DNN. Similarly, RSSI values received at grid points are used as the inputs and the grid point co-ordinates are the outputs of the NN for training. *Neural Designer* software is deployed for DNN work.

Experiments

Fingerprint localisation

Fingerprint dataset which are used in this study is recorded in a sports hall with dimensions of 20 meters by 10 meters and a grid space of 1 meter. Eight RFCODE manufactured wireless sensor nodes are used as transmitters at the corners and the boundaries of the hall. An RFCODE wireless sensor receiver is employed to collect RSSI data by placing it at each grid point during training stage.

The collection of 8 RSSI values in dB form at each grid point is recorded in a dataset identified as fingerprint map in a server computer. There are total 200 fingerprint points and 1600 single recordings of RSSI values in the fingerprint map. Fingerprint map is extended by obtaining 100 sets of eight RSSI recordings totalling 800 RSSI values at each grid point. Hence, fingerprint map contains 160000 RSSI values. A sample data set of single RSSI values with respect to (x, y) grid co-ordinates are presented for the reader in tab. 1. Similarly, 800 RSSI values received at each unknown object location are also recorded across the test area as the target RSSI values during localisation stage. They are used to calculate the unknown object location co-ordinates by deploying the trained NN.

Initially, classical fingerprint localisation technique is employed by using Euclidean distances between RSSI values at grid points and unknown object points. The k number of minimum Euclidean distances are selected by using k -NN algorithm. Weighting mechanism in

Table 1. A sample of recorded single RSSI values in decibel form from eight transmitters against grid co-ordinates (x, y)

(X,Y)	(0,0)	(1,0)	(2,0)	(3,0)	(4,0)	(5,0)	(6,0)	(7,0)	(8,0)	(9,0)	10,0)	(11,0)	(12,0)	(13,0)
A	-59	-63	-45	-58	-59	-63	-45	-58	-55	-47	-60	-62	-44	-41
B	-59	-63	-46	-55	-57	-61	-48	-56	-54	-49	-56	-58	-45	-40
C	-58	-61	-50	-54	-56	-62	-49	-58	-54	-50	-56	54-	-46	-45
D	-57	-59	-49	-53	-57	-61	-47	-55	-52	-53	58-	-55	-45	-42
E	-58	-58	-47	-55	-58	-64	-42	-56	-54	-56	-59	-54	-47	-43
F	-59	-57	-44	-56	-59	-62	-44	-57	-58	-54	-56	-53	-48	-44
G	-57	-55	-45	-55	-58	-63	-47	-59	-57	-55	-57	-54	-49	-43
H	-59	-63	-47	-54	-59	-60	-45	-58	-57	-56	-58	-55	-48	-41

eq. (6) is applied with the grid co-ordinates corresponding to k number of Euclidean distances. Finally, eq. (5) is used to determine the final unknown object location co-ordinates. Error distance values are calculated between the actual and the estimated object co-ordinates. A sample of k -NN localisation results is tabulated in tab. 2. Average error distance with k -NN localisation is approximately equal to 1 grid space.

Table 2. Samples of k -NN, SFFNN, and MFFNN localisation results

Unknown object co-ordinates [m]		k -NN estimated object co-ordinates [m]			SFFNN estimated object co-ordinates [m]			MFFNN estimated object co-ordinates [m]				
X_0	Y_0	X_E	Y_E	Error	X_E	Y_E	Error	X_E	Y_E	Error		
2	2	2.9	2.8	1.20	2.7	2.7	0.99	2.6	2.5	0.78		
2	8	2.8	8.7	1.06	2.6	8.5	0.78	2.5	8.7	0.86		
3	4	3.7	4.9	1.14	3.5	4.5	0.71	3.6	4.4	0.72		
5	7	5.8	7.7	1.06	5.4	7.6	0.72	5.5	7.4	0.64		
6	3	6.7	3.8	1.06	6.5	3.6	0.78	6.4	3.7	0.81		
8	5	8.9	5.9	1.27	8.6	5.6	0.85	8.6	5.5	0.78		
12	3	12.7	3.6	0.92	12.5	3.6	0.78	12.6	3.7	0.92		
14	8	14.8	8.7	1.06	14.6	8.5	0.78	14.5	8.6	0.78		
16	5	16.9	5.5	1.02	16.6	5.9	1.08	16.4	5.9	0.98		
18	7	18.6	7.9	1.08	18.5	7.7	0.86	18.6	7.5	0.78		
Average error [m]				1.08	Average error [m]			0.83	Average error [m]			0.81

The SFFNN localisation

The SFFNN model is employed to determine the unknown object locations. The RSSI values arriving from eight transmitters are recorded at each grid point and stored in a database. There are 100 RSSI values coming from each transmitter resulting a total of 800 RSSI values at each grid point.

Hence these recordings for 200 grid points are used to train the NN. The NN is an adaptive network system. It can change its structure depending on external and internal information which flows through the network during the training phase. In SFFNN, the signals travel from input to output without any feedback [26]. Once the NN has been trained on samples of the known fingerprint database it will be able to predict the similar unknown patterns of future input RSSI data. The behaviour of the NN depends on the input-output transfer function. During the learning process, sigmoid activation function is employed to translate input signal to output signal, fig. 5.

Training model during learning process will have 100 sets of 8 RSSI data, 2 outputs of grid (x, y) co-ordinates and 1 hidden layer of 8 neurons. Figure 3 displays the architecture of SFFNN. Once the NN training is completed, 8 RSSI values received from unknown object location are applied at the inputs of the NN and the output co-ordinates will be obtained as the target object co-ordinates.

The 100 sets of 8 RSSI values are applied at the 8 inputs and 100 target co-ordinates are applied at the output of SFFNN. The network is trained with these values. In localisation stage, 8 unknown RSSI values are applied to the input of the trained network. Unknown object co-ordinates of (x, y) is generated at the network output. A sample of results is tabulated in tab. 2.

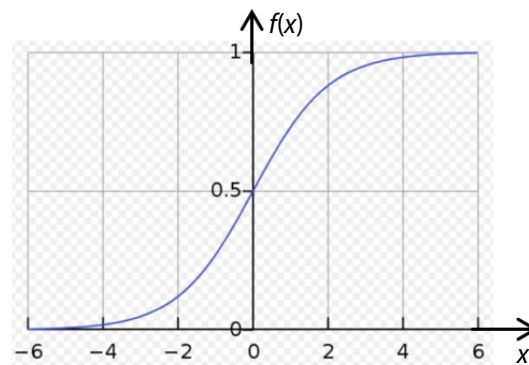


Figure 5. Sigmoid activation function

The MFFNN localisation

The MFFNN model is similar to SFFNN with the exception that it has multiple hidden layers between input and output layers, [27]. Input signal moves to output through several hidden layers. In this study 8 inputs, 5 hidden layers of 8 neurons each, and 2 outputs of (x, y) co-ordinates are deployed for MFFNN localisations. Similar training process is completed where 100 sets of 8 RSSI values are applied as inputs and (x, y) co-ordinates of each grid point are given as 2 outputs. Input RSSI values passed through 5 hidden layers and ended at 2 outputs corresponding to grid co-ordinates. Same sigmoid activation function is used during the learning process to translate input signals to output signals. Eight RSSI values arriving from unknown object locations are applied to trained network inputs and target output co-ordinates are generated at the network outputs. A sample of MFFNN localisation results are given in tab. 2. It was observed that there is not much error distance difference between SFFNN and MFFNN.

The MBPNN localisation

The MBPNN is a combination of several NN models, [28]. It has multiple hidden layers between input and output layers. Feed-forward networks are straight forward network that relates the inputs and outputs. In order to make the NN suitable in specific tasks, the connections between neurons must be chosen carefully and the weights on the connections must be selected properly. The signals, reaching to output layer, are back propagated to input layer. This forward and backward propagation between input and output layers several times helps to correct the weights between neurons. This way the error between the desired output and the real output will be reduced. The network must determine that how the error changes as the weight changes. Hence back propagation algorithm is the most widely used algorithm to calculate the error derivative of weights. Figure 2 illustrates the back-propagation model NN. Learning process is carried out similarly by training the network with input RSSI values and the output grid co-ordinates. The RSSI values arriving from unknown object location are applied as input and the output target co-ordinates are derived. A sample of MBPNN localisation results are given in tab 3.

Table 3. Samples of MBPNN, GRNN, and DNN localisation results

Unknown object co-ordinates [m]		MBPNN estimated object co-ordinates [m]			GRNN estimated object co-ordinates [m]			DNN estimated object co-ordinates [m]				
X_0	Y_0	X_E	Y_E	Error	X_E	Y_E	Error	X_E	Y_E	Error		
2	2	2.4	2.5	0.64	2.4	2.6	0.72	2.4	2.4	0.57		
2	8	2.5	8.6	0.78	2.4	8.4	0.56	2.5	8.4	0.64		
3	4	3.6	4.5	0.78	3.5	4.5	0.70	3.5	4.4	0.64		
5	7	5.4	7.6	0.72	5.4	7.5	0.64	5.4	7.4	0.57		
6	3	6.4	3.5	0.64	6.4	3.5	0.64	6.3	3.5	0.58		
8	5	8.5	5.4	0.64	8.4	5.5	0.64	8.3	5.5	0.58		
12	3	12.5	3.6	0.78	12.4	3.4	0.57	12.2	3.5	0.54		
14	8	14.5	8.4	0.64	14.4	8.5	0.64	14.3	8.5	0.58		
16	5	16.4	5.7	0.81	16.5	5.5	0.70	16.3	5.4	0.5		
18	7	18.5	7.4	0.64	18.4	7.6	0.72	18.3	7.5	0.58		
Average error [m]				0.71	Average error [m]			0.65	Average error [m]			0.58

The GRNN localisation

This localisation depends on the joint probability density function of x and y position co-ordinates given the RSSI training dataset [29]. Estimated value is the most probable value of y represented by eq. (8). Basic statistics of the input variables and the target variables which are used in eq. (10) are given in tab. 4.

Table 4. Overall statistical values of input dataset for each transmitter across the fingerprint map

Tx/RSSI	Min [dB]	Max [dB]	Mean [dB]	Std σ
A	-92	-59	-60	4.64
B	-90	-57	-61	4.59
C	-94	-62	-65	4.37
D	-91	-62	-65	4.32
E	-96	-45	-52	7.17
F	-94	-45	-49	6.90
G	-90	-58	-62	7.21
H	-88	-58	-62	7.11

The GRNN toolbox of MATLAB is used to generate the GRNN model and carry out the training on input dataset. A sample of GRNN localisation results are presented in tab. 3.

The DNN localisation

In this study, DNN is considered as a feed-forward NN. It has large number of hidden layers, 20 of them, with 8 neurons each. The 1 input layer of 8 neurons and 1 output layers of 2 neurons are also deployed. Neural designer software has employed to determine the unknown object co-ordinates. A sample of DNN localisation results is presented in tab. 3.

Results

Fingerprint database is built across a test area and it is used as training data for various NN models. This paper has presented a measurement and NN simulation-based localisation study. A summary of localisation accuracies is presented in tab. 5.

Initially classical weighted fingerprint localisation technique is implemented. Positioning accuracy of a grid distance is calculated between the actual and estimated object positions.

Table 5. Summary of average localisation accuracies

Average localisation accuracies					
k -NN	SFFNN	MFNN	MBPNN	GRNN	DNN
1 m	0.83 m	0.81 m	0.71 m	0.65 m	0.58 m

There are 200 training points across the test area with 1 metre distances between them. Unknown object locations are estimated using the learned network with these

training points. There are 8 anchor points where the RF transmitters are located. As a result, there are 8 RSSI values recorded at each training grid point. In this study, large numbers of unknown object locations are tested to estimate their positions.

Overview of several NN models such as SFFNN, MFFNN, MBPNN, GRNN, and DNN are presented for the application of fingerprint localisation. Each model has generated its own localisation accuracies. It was observed that as the number of hidden layers is increased the localisation accuracies are also increased. Graphical representation of target object co-ordinates and the estimated target object co-ordinates with different NN techniques are given in fig. 6.

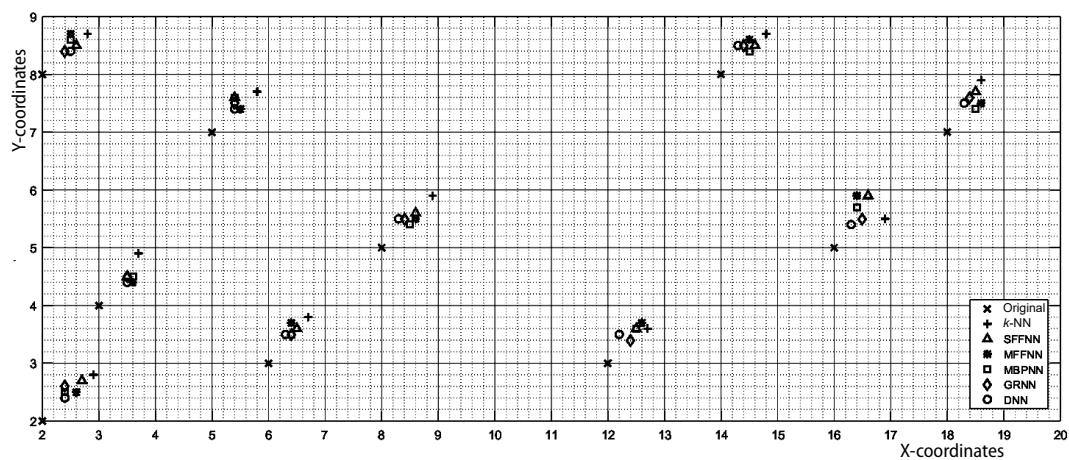


Figure 6. Graphical view of sample target co-ordinates and estimated target co-ordinates with different NN techniques

The SFFNN and MFFNN models did not show large accuracy difference between them. On the other hand, MBPNN and GRNN models have displayed considerable localisation accuracy, around 30% more, compared to classical k -NN technique. The best NN model was found to be DNN model. Large number of hidden layers is employed in this model. The localisation accuracies with DNN model increased %50 relative to k -NN model.

The RSSI based NN simulations have shown that localisation accuracies are drastically improved compared to classical k -NN technique. A fair size database of 200 points is sufficient enough to achieve good localisation accuracies. Future work will consist of advance DNN studies with different number of hidden layers and introduction of back propagation between these layers using different applications.

Acronyms

ANN	– artificial neural networks	NN	– neural network
DNN	– deep neural network	pdf	– probability density function
GRNN	– general regression neural network	RF	– radio frequency
k -NN	– k -nearest neighborhood	RSSI	– received signal strength indicator
MBPNN	– multi-layer back propagation neural network	SFFNN	– single-layer feed forward neural network
MFFNN	– multi-layer feed forward neural network	WSN	– wireless sensor networks

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