International Journal of Computer Engineering and Information Technology

VOL. 11, NO. 11, November 2019, 235–242
Available online at: www.ijceit.org
E-ISSN 2412-8856 (Online)

Radial Basis Function Neural Network-Based Indoor Positioning System

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ABSTRACT

Indoor positioning system (IPS) is a useful technology for many applications such as tracking objects, finding objects, tracking persons inside a building … etc. In this study an indoor position system has been designed and implemented based on neural network. Depending on WI-FI Received Signal Strength (RSS) indoor position system has been implemented the case study building was computer engineering department fingerprint technology is used by using 32 reading for each point in the building top floor. The floor is marked with reference points 54 points with (1.16) meter distance between each point. Radial Basis Function (RBF) is another type of Neural Network that has been used in this research. RBFNN gives a training time of 69.63 sec and MSE equal to 0.00761775 and MSE for validation was 0.006856 and the MSE for the testing was 0.013331 which is considered the fastest approach to find the position. The above algorithm has been applied by using Graphical User Interface (GUI).

Keywords: *Indoor positioning, Fingerprinting, Neural network, Radial Basis Function.*

1. INTRODUCTION

The traditional algorithms for indoor positioning system are built on received signal strength indicator (RSSI), these algorithms may encounter many issues, such as incorrect positioning results, high reliance on the signal propagation path loss model, great time, and effort costs because of frail received signals, multipath interference, ecological noise, and non-line of sight propagation [1]. As the growth of Wi-Fi technology comes to be more and more advanced, the coverage of Wi-Fi is also increasing. If it is possible to use the Wi-Fi spread in an indoor environment, the inventive application of the technique will lead to great accessibility to our everyday lives. Accuracy of positioning can be achieved very precisely when both the receiving and transmitting devices broadcast on the line of sight (LOS) path. However, through experiments, most of the systems that are designed to work in an indoor ecology are non-line of sight (NLOS) propagation, and the effect of the hindrances on the indoor positioning as results of using the Wi-Fi technology cannot be disregarded [2]. The clear advantage of deploying the RSSI for indoor positioning system comes from, there is no need to develop special hardware equipment. The physical characteristics of RSSI propagation are the cause of the positioning error due to three issues which are: One, the radio wave is susceptible to loss in channel propagation as it collides many hindrances on its way. Two, the signal propagation model recently applied does not result accurate calculation. Three, the effect of the hardware of the positioning system where some of the components themselves causes physical noise, this is because of the inherent nature of some electronic elements. The Wi-Fi signal is liable to environmental interference during the propagation process, resulting in inexact location prediction. Preprocessing the received signal strength which is done recently is inefficient to solve the issue of varying RSSI. The aim is to minimize the range of this differences in RSSI so as to build a stable location fingerprints which will be the database for the next online phase.

Many algorithms have been proposed to support RSSI model for treatment of data such as neural network (ANN). In this project Radial Basis Function Neural Network (RBFNN) has been used to estimate location of user inside building. RBF is a network that utilizes radial basis functions as its activation functions. This network linearly combines the neuron parameters and the input radial basis functions. The linear combination is the output of this network. RBF networks are applied in many fields like system control function approximation and classification. The first time RBF appeared was in 1988 which was formulated in a paper written by

Broomhead and Lowe, both were researchers at Royal Signals and Radar Establishment [3].

2. FINGERPRINTING

A brief overview of the fingerprint system can be summarized as follows: to draw a relationship between the WLAN RSS network and the physical location, it is necessary to extract the discriminatory information that represents the essence of the work. Depending on Received Signal Strength (RSS), which is one of the physical characteristics of the radio signal, at every location there are distinct characteristics for the signals received from multiple fixed Access Points (APs) [4]. The APs are placed at selected locations to ensure the arrival of different signal strength values at each point. The distinct characteristics for every location are stored in a table to be used later for estimating the location [5]. A chosen study area is divided into a grid involving specified number of points at intersections of vertical and horizontal lines of the grid. These are reference points which are separated by equal distances. These are reference points which are separated by equal distances. The process of fingerprinting to estimate locations comprises two phases [6]: offl*ine* phase (data collection) [7][8] and *online* phase (positioning phase in real-time). In the offline phase, site-survey is done on the whole selected area and RSS from multiple APs at each reference point are stored in a data base. Every stored set of RSS values is mapped to the coordinates of that point at which the RSS values were recorded. The process of filling the data base up continues until the last reference point is treated.

$$r_i(\tau) = [r_{i1}, r_{i2}, r_{i3}, \dots\dots, r_{im}]^T, \tau = 1,2,3, \dots\dots, t \qquad t > 1 \tag{1}$$

The relation above describes how information of fingerprints is gathered as a vector r_i, where r_{ij} represents the RSS values which are gathered from the j^{th} AP and $r_i(\tau)$ is a fingerprint sampling at time τ from the i^{th} reference point. The well-known physical position information of a i^{th} reference point in the form of two dimensions can be expressed as [9]:

$$c_i = [x_i, y_i]^T \qquad , i = 1, \dots\dots, l \tag{2}$$

The data base of location fingerprints is called Radio Map [10]. The radio map involves a great deal of rows, each one consists of a set of RSS values for several access points at each reference location [11]. The set of RSS values at a point is called the location fingerprint of that point. Fig. 1 shows how radio map is built [12].

Once a radio map is built, it is used to improve a mapping function between RSS values and respective object location. This function is subsequently used to estimate a location of the object by given RSS values. The size of the survey site and the accuracy of the survey are factors on which time required for training depend.

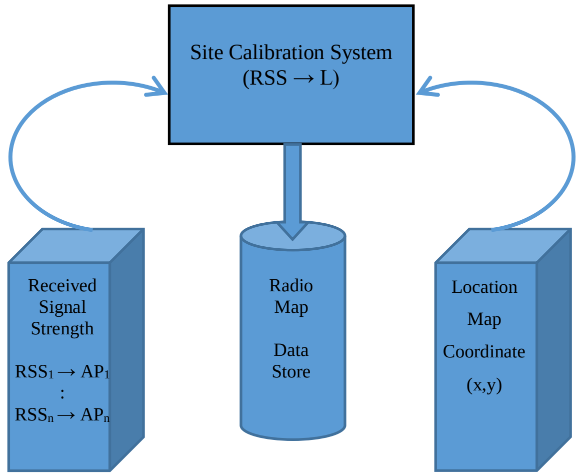

Fig. 1. Radio Map

The RSS readings are influenced by the time interval of the RSS measurements as well as the orientation of the antenna connected to the surveyor and APs devices. For each reference point, RSS readings are sampled at a regular interval and direction. The first phase of fingerprinting processed is shown in Fig. 2.

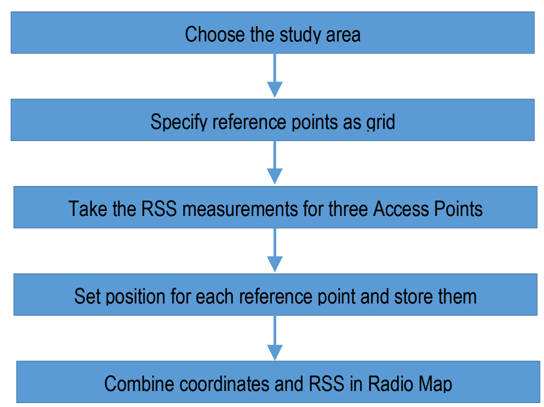

Fig. 2. Procedure of Offline Phase

The next phase is the online phase where RSS of signals received from all APs, at some point, are compared with the location fingerprints stored in the radio map and the location is estimated. Fingerprinting technology relies heavily on the number of reference points for the same intended area.

The more the reference points, the more powerful a database becomes and the more accurate results are obtained. The process of building and maintaining a high-density database is not easy. The reason is that building and maintaining a large database is time consuming and, in some cases, impossible [12]. The second phase of fingerprinting processed is shown in Fig. 3.

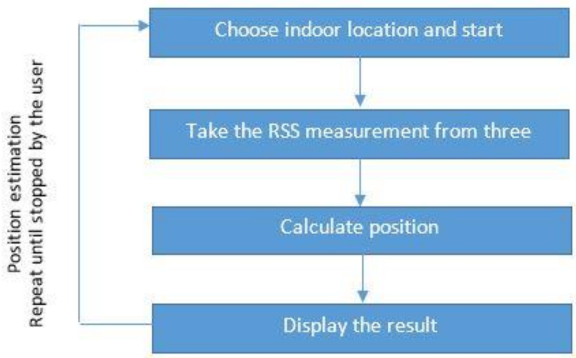

Fig. 3. Procedure of online phase

3. ARTIFICIAL NEURAL NETWORK

Researchers from many scientific disciplines have designed Artificial Neural Network (ANN) to solve a variety of problems in the fields of control and optimization, pattern recognition, and financial analysis. For instance, newly developed prototypes of ANN have been powerfully put up for recognizing patterns which are too complex or numerous for a human programmer to feature [13].

ANN is an arithmetical model which aims at realizing patterns in a database. As it is obvious from the naming it is inspired from the biological neural networks constituting the human brain [14][15], its structure is built by connecting a collection of nodes or units called artificial neurons that model the neurons in a biological brain. ANN also consists of many connections like synapses that permits a neuron, or nerve cell, to pass a chemical or electrical signal to another neuron or to the target effector cell. At the beginning the neural network had been trained on samples of known input data and corresponding locations then it was able to estimate targets via discovering similar input patterns of data later even if they had never been previously entered to the network. Usually, neural network is such a system that can adapt and change its structure depending on output or input data that the network is to deal with through the learning phase. Recent neural networks are used to solve nonlinear and statistical data and they are modeling tools that can model complex relationships between an input vector and an output vector. This feature makes it convenient to be used with fingerprinting based positioning technique. Using ANN in this field is very beneficial because when RSS values varying each time a scan is done for the same point, so it is impossible to find a mathematical relation between the input sets of data and the target coordinates (x and y) using traditional methods. When ANN was applied, it was able to obtain a best solution in a short time. Neural networks is used due to its robustness and resistance to noise and interference, which are the main factors that affect the accuracy of positioning [16]. Fig. 4 shows a diagram of a typical feed-forward neural network.

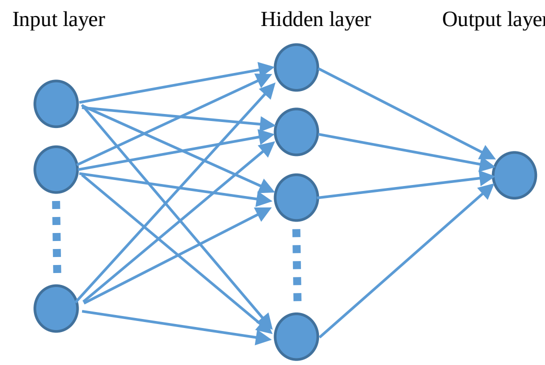

Fig. 4. Typical feed-forward Neural Network consists of 3 layers

4. RADIAL BASIS FUNCTION

Radial Basis Function (RBF) network is a special class of Artificial Neural Network (ANN) that consists of three layers, input layer, hidden layer and output layer [17]. It is usually structured as a single hidden layer with a non-linear RBF activation function and a linear output layer. RBF networks have been applied in many applications, for example system identification, nonlinear function approximation [18], adaptive control, speech recognition [19], real time approximation [20] and pattern classification [21]. RBF Network has features that make them different from other neural networks. It has been widely applied in many fields of science and engineering due to its ability of global approximation and faster learning as well as avoiding the solution of falls at local minimums.

Usually, it can be defined as a parameterized model used to estimate a random function by means of a linear combination of basis functions [22]. Training the network passes two phases: In the first phase, the algorithm determines the weights from the input layer to the hidden layer, then it determines them from hidden layer to the output layer. The construction of a fully connected RBF network is shown in Fig. 5. The input vector n is the input for all radial basis functions. *f(x)* is the output which is expressed as:

$$f(x) = \sum_{n=1}^{c} w_n \, v(\|x - c_n\|) \tag{3}$$

Where C is the number of neurons in a hidden layer, $\|x - \boldsymbol{c_n}\|$ is the Euclidean distance between x and the n-dimensional basis function center c_n, wn are the network weights.

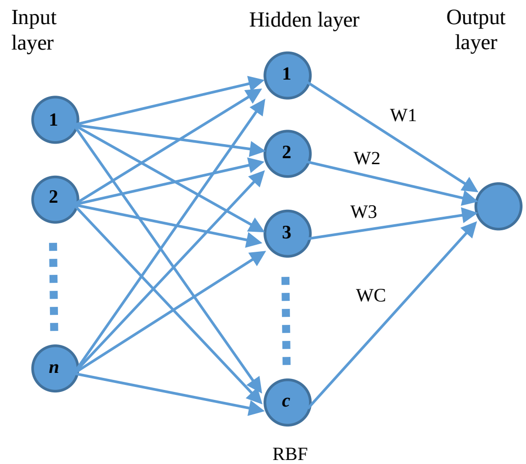

Fig. 5. Typical Radial Basis Function Network consists of 3 layers.

Generally, the function that has been used is Gaussian radial basis, it means $\boldsymbol{\tau}(\|\boldsymbol{x}-\boldsymbol{c}\|) = \boldsymbol{exp}(-\boldsymbol{\beta}\|\boldsymbol{x}-\boldsymbol{c}\|^2)$. RBF networks can be used to approximate any continuous function by fitting the values of the function $f(x_i) = b_i, i = 1, \dots, C$ at known points x_i. In equation (3), the centers of the basis functions are set equal to x_i and then the weights are determined by employing b_i and solving the system of linear equations. Fig. 5 illustrates a single dimension RBF approximation example [23]. RBF network is classified as a kernel function network. The inputs to the model in these kernel function networks pass through kernel functions that limit the response of the network to a local region of the input space for each kernel or basis function. To produce the output of the network, an output of each basis function is weighted. Table 1 below lists some of the common basis functions.

Table 1: Basic Functions

Function	**Expression**	
Gaussian	$\varphi(x) = exp(-x^2/2\sigma)$	$\sigma > 0$
Multi-Quadric	$\varphi(x) = exp(x^2 + \sigma^2)^{1/2}$	$\sigma > 0$
Generalized Multi-Quadric	$\varphi(x) = exp(x^2 + \sigma^2)^{\beta}$	$\sigma > 0, 0 < \beta < 1$
Inverse Multi-Quadric	$\varphi(x) = exp(x^2 + \sigma^2)^{-1/2}$	$\sigma > 0$
Generalized Inversed Multi-Quadric Functions	$\varphi(x) = exp(x^2 + \sigma^2)^{-\alpha}$	$\sigma > 0, \alpha > 0$

Radial basis function has been used with fingerprinting in indoor localization. The input layer represents the received signal strength (RSS) measurements from three access points. In the second layer, the number of neurons is determined according to the requirements of the actual application. Gaussian function was utilized in the Wi-Fi positioning project due to positive definite function in any dimensional space and has a single solution. The formula of the Gaussian *h(x)* is as follows:

$$h(x) = exp\left(-\frac{(x-c)^2}{r^2}\right) \tag{4}$$

In the output layer there are two outputs (x and y) represent the location of user inside the building. Fig. 6 illustrates flow chart for RBF Neural Network (RBFNN). RBFNN has been greatly used to achieve indoor positioning systems. It can be trained to reduce the localized generalization error and is adopted to estimate locations based on RSS values. Comparing to other types of ANNs the advantage of RBFNN is that they are simple to be structured, fast to learn and they can estimate locations with less error. RBFNN is a neural network structured of three consequently connected layers: an input, a hidden, and an output layer. It should be identified by defining the number of hidden neurons, center vector and width value which defines the Gaussian activation of each hidden neuron, and the connection weights between the hidden and the output neurons.
The gathered RSS values in the database are loaded to the network which are received by the input layer. The number of neurons in hidden layer is N and 2 neurons in the output layer represent the estimated coordinates x and y. RBF is a function whose value is affected by the distance from a certain point, in this context a signal sample point. RBFs are triggered in the second layer, i.e. the hidden layer, to calculate the distance between the input vector and the weights. In the summation layer, a summation operation is done for the hidden output values of each class and their connection weights are created instantly from the targets. If the input pattern belongs to the specific class, connection weight will equal to 1, otherwise, it will equal to 0. A decision output will be finally generated according to the competitive rule (winner takes all) [24].
The RBF network has not the feature of iteration to create weights for matching the inputs and target outputs. It is, for this ANN network, a key feature that make it so fast to train [25]. When the network is in the training stage, it sets the connection weights between the input and the hidden layer equal to the already specified samples. The distance from the input vector to the training patterns is computed by the hidden layer through the test stage, and a vector of inputs which are close to the training pattern is generated [26].

The summation layer a vector of elements each of which describes the likelihood of “input vector to each class”. The values of the summation vector will be monitored and any summation node in the network that has the maximum value will be a competitive winner. A class winner is determined in the decision layer by represented the winner as ‘1’. All other classes are represented as ‘0’s. So, in this case, a winner is always exist [27].

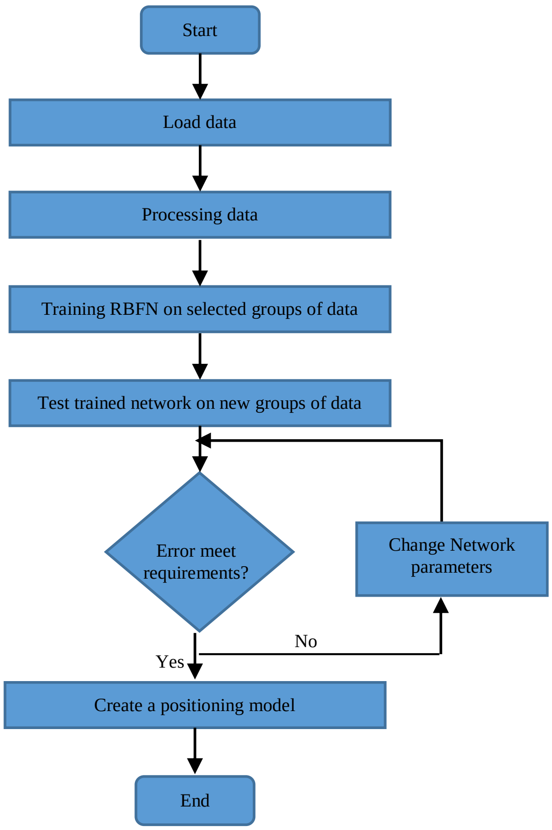

Fig. 6 . Flow chart for RBFNN

5. SYSTEM IMPLEMENTATION

5.1 System model

The project was achieved at Mosul Technical College, department of Computer Engineering Technology on the second floor of the building. The walls are built of concrete and ceilings are secondary ceilings. It is 80 square meters of area. The floor plan map and the location of APs are shown in Fig. 7. Three TP-LINK-WR841HP APs were used, one of them is installed in line of sight and other two are non-line of sight and 56 reference points were chosen. The distance between each two reference points is 1.16 meters. The received signal strength readings are collected in four directions (North, East, West, and South) for each reference point.

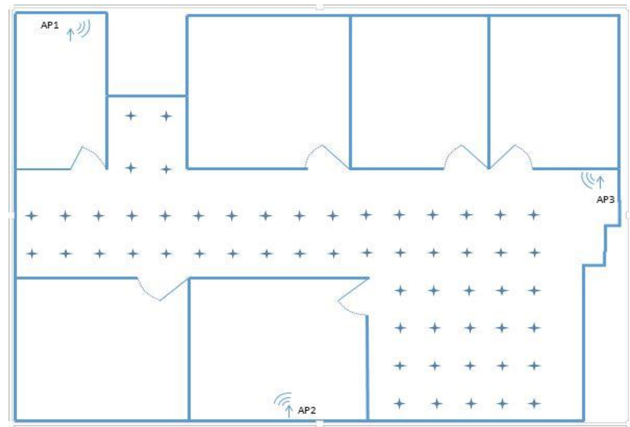

Fig. 7. Distributing reference points and APs in the bed test area

5.2 Proposed system

As mentioned in section 2, the values of the RSS are collected in the offline phase of location fingerprinting. There are many factors affecting the signal including reflection, multi-path, interference with induction signals, variation of wireless network cards, and other unpredictable factors influence spread of WLAN signal in an indoor environment. NetSurveyor application has been used to read the RSS values of all three APs and to save these readings for each reference point in Microsoft Excel file format and so a database has been created. Then, the offline phase of this network was implemented in Matlab. Fig. 8 shows screenshot of NetSurveyor.

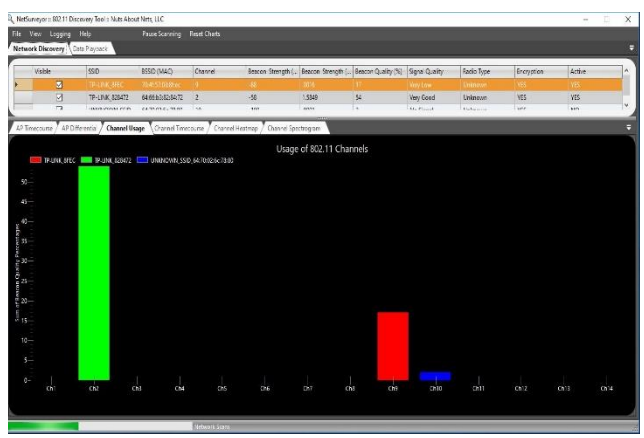

Fig. 8. NetSurveyor screenshot

The Radial Basis Function feed-forward artificial neural network used as a pattern matching algorithm in this positioning scheme has three inputs (measured RSS for three APs). Network also includes one hidden layer of radial-based neurons and one output layer of two neurons (corresponding to a user's place (x, y)). From the information of 54 measuring places, 70 percent patterns were used to train the network, 15 percent patterns were used for validation purposes, and the remaining 15 percent non-training patterns were applied to the network to test the positioning system designed. Iteratively, the RBF network is developed by adding one neuron at a time (newrb Matlab function). Fig. 9 illustrates the whole process of RSS technique.

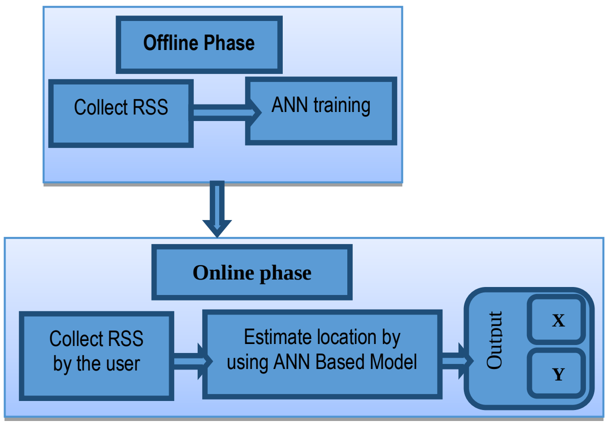

Fig. 9. Progress block diagram of the RSS technique

6. RESULTS

HP laptop was used to collect the RSS readings. The specifications of the laptop are shown in Table 2.

Table 2: Specifications of Laptop used in the project

Model	HP 15-ac135
Processor	Intel Core i3-5005U @2.0 GHz
RAM	4 GB
Graphics	AMD Radeon R5 M330
Operating System	64-bit Windows 10
Wi-Fi Adapter	802.11 bgn

6.1 RBF Based IPS

RBF applied to find the exact location of the mobile person inside the building that gave the results shown in Table 3.

Table 3: Results of RBF

Method	MSE in training	Time of running code	Best training performanc	Number of neuron	Number of epoch	MSE in Validation	MSE in test
RBF	0.00761775	69.63 sec	0.00761775	736	700	0.006856	0.013331

As shown in table 3, it is obvious that RBFNN can yield to MSE equal to 0.00761775 in 69.63 sec. The MSE for validation was 0.006856 and the MSE for the testing was 0.013331. After training the RBFNN the best value of MSE can be obtained when number of neuron in hidden layer are 736 neurons. Fig. 10 is a screenshot of the network after finished training that shows its structure which consists of input layer, with 3 neurons representing the 3 RSS values, one hidden layer with 736 neurons, and output layer representing the x,y coordinates which are represented by the 2 neurons. The number of neurons appears underneath each layer block.

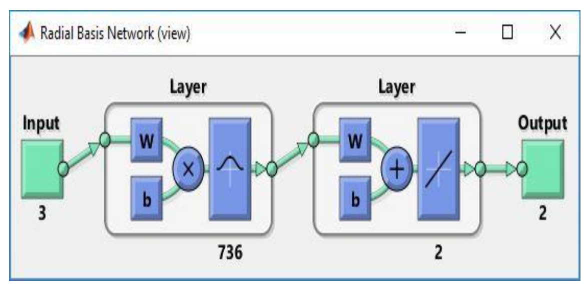

Fig. 10. Radial Basis Function Network

Mean Squared Error of training the ANN which is 10^1 at the beginning of training and decreases to 10^{-2} at epoch 500. The best training performance is 0.00761775 at epoch 500 where the network finished training as shown in Fig. 11.

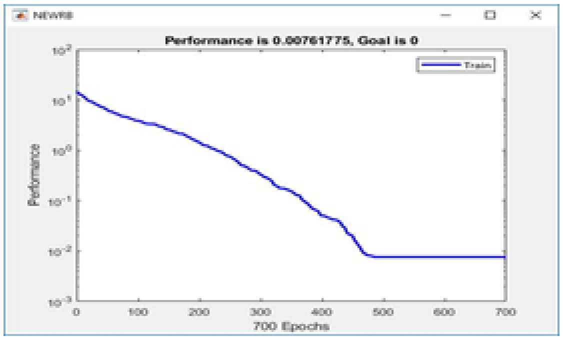

Fig. 11. Best training performance

To test the system implemented with RBFNN, an arbitrary point has been selected in the study area, recorded its coordinates, which was x=2.9, y=4.64, the measured RSS were: -58, -43, and -68 for the three access points respectively. Then using the MATLAB GUI previously designed and programmed, we got x=2.7417, y=4.2975. In Fig. 12, a solid black circle on x,y axes of the GUI indicates the real location and a red circle indicates the estimated location. So the error percentage for x is 5.45% and for y is 7.38%.

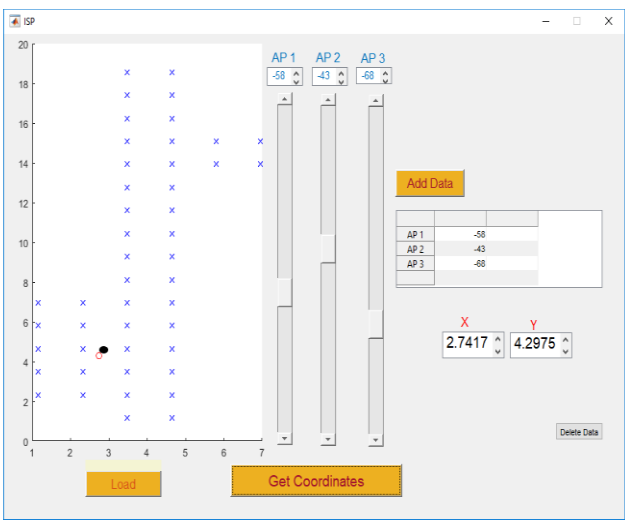

Fig. 12. Test 1 a not trained point using Matlab GUI

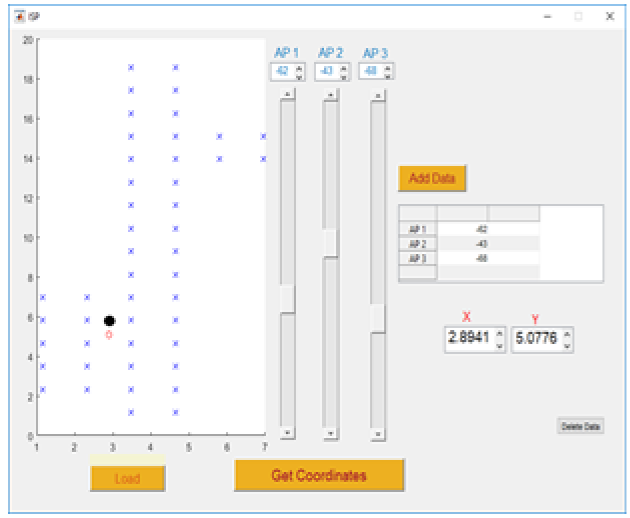

Fig. 13. Test 2 a not trained point using Matlab GUI

Another test has been applied to verify the result that we selected another arbitrary place which is also not reference point, i.e. not trained point, as shown in Fig. 13. The measured RSS were -62, -43, and -68. x=2.8941 and y=5.0776 for the estimated location, represented by the red circle. The black solid circle representing the real location, its coordinates is x=2.9 and y=5.8. So the error percentage for x is 0.203% and for y is 12.4%.
Experimental results indicate that the proposed method provides higher performance compared to other approaches and consumes very less time to for the network to be trained.

6. CONCLUSION

This project explores the possibilities of positioning and identification inside buildings. It is well known that Wi-Fi technology is used frequently in this field despite the problems and defects, but recent researches were interested with this technology because there is no need for additional investment in infrastructure. This technology is inexpensive, easily applied and fastly deployed. Why Wi-Fi is hardly predictable? It is because of the impact of bodies, multiple paths, obstacles and interference. However, the implemented system uses three access points to identify fingerprint of location reference points. In this work RBFNN can yield to MSE in training phase equals to 0.0198 in 69.63 sec and 0.013331 in testing phase. From the experimental results the RBFNN method provides fast training and more accurate location estimates in data test. Moreover, the underlying RBF architecture is scalable and can be easily applied to different WLAN setups, in which variable number of APs, reference points or fingerprints may be available. In addition, the accuracy of an indoor positioning system depends on some factors that must be taken into account when designing a location-aware 802.11 network, the number of Access Points, location of APs, Amount of samples data, and quality of samples data.

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