A WLAN Fingerprinting Based Indoor Localization Technique via Artificial Neural Network

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Summary
WiFi infrastructure provides a great opportunity for indoor localization due to its low cost. Two-dimensional (2D) WLAN based indoor fingerprinting approach has been widely adopted. In 2D positioning scenario, latitude & longitude coordinates of the user are used. But in the real indoor position, condition the position height of mobile device of a user is also an important factor to consider for getting better accuracy in indoor, environment, thus motivates the study into three-dimensional (3D) indoor fingerprinting. To verify mobile height dependency of RSS signal strength on anchor points, a Chi-Square statistical analysis is carried out. RSS based localization is sensitive to various indoor fading effects, which are the main cause of the localization error. A spatial filtering approach is implemented to minimize the fading effects. This paper presents an Indoor positioning system based on 2D and 3D on WiFi Received Signal Strength (RSS) using Artificial Neural Networks (ANN) approach. The obtained results show that using ANN with the proposed method of collecting test data, maximum accuracy of using test data achieved an average distance error of 1.2244m and 1.9065 in 2D & 3D implementation. Future work consists of optimizing the ANN by using genetic algorithms and testing the algorithm over a larger area to test the robustness of the algorithm.

Key words:
Artificial Neural Network; 2D & 3D, distance error; fingerprinting; indoor localization; WLAN.

1. Introduction

Due to development in the wireless technology, location tracking whether it's indoor or outdoor has received ample attention from researchers from last many years. The most popular technology for outdoor satellite based navigation is global positioning system (GPS) [1]. GPS technology is applied into various location-based services, such as navigation, tourism, vehicle and military applications etc. However, GPS does not perform well in urban canyons, close to walls, buildings, trees, indoors, and in underground environments as the signal from the GPS satellites is too weak to come across most buildings thus making GPS ineffective for indoor localization [2].

In recent years, wireless communication techniques have been widely used in developing the indoor positioning system. These techniques include the wireless local area network (WLAN), Radio frequency identification (RFID), Bluetooth, wireless sensor network (WSN) and so on. With the expansion of free WLAN services and popularity of smartphones, location-based services have drawn benefits in many applications. WLAN coverage can be found in common places such as homes, shopping mall, offices, or campuses. In addition, WLAN networks and devices have recently become cheaper; hence there is no need to employ any additional hardware and infrastructure for the purpose of indoor tracking. Hence, WLANs that are also cheap and easy to deploy, become an attractive solution Thus, it is feasible to utilize the existing WLAN infrastructure for the purpose of indoor location tracking [3].

To determine the location of a Mobile Unit in an indoor environment, three basic methods are commonly used such as Angle of Arrival (AoA), Time of Arrival (ToA)/Time Difference of Arrival (TDoA) and Received Signal Strength (RSS). The most common approach to positioning in WLAN networks relies solely on the use of the pattern matching algorithm using RSSI. AoA and ToA techniques depends on timing measurements and require additional hardware [4]. Furthermore, pattern matching algorithms can be classified as deterministic and probabilistic. The deterministic algorithms are based on non-linear methods, e.g., artificial neural networks and genetic algorithms, whereas the probabilistic algorithms are based on statistical theories. Most indoor localization approaches adopted fingerprint matching as the basic scheme of location determination [5].

In two dimensional positioning only latitude & longitude coordinates of the user are used, but in the actual indoor position situation the position height of a mobile device by user from ground level is also an important factor to consider for getting better accuracy in an indoor environment [6]. For this, we implement chi-square statistical test to verify our height consideration. Chi-square test is for independence, which is used to determine,

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whether there is a significant association between the two variables in chi-square analysis. We implement the test between anchor points used as one variable with respect to three different heights (60cm, 90cm, and 125cm) from the ground level as another variable.

In indoor environments, the RSSI-based localization method is affected by fading effects and noise while transmitting the actual data. Due to this, the signal amplitude is not always smooth. The use of filtering the data is to get the clear signal which can indicate the presence of the human body, causing interference in wireless signal while standing or walking in the indoor environment. To overcome with fading effect and get the clear signal, we are using spatial filtering approach in our work on RSS data before the data can use for localization.

In the recent years, many research works have been done in two-dimensional WLAN based indoor fingerprinting approach [7]. Due to the powerful learning and adaptive capabilities, Artificial Neural Networks with gradient descent with momentum (ANN-GDM) technique has been employed in our research work. Artificial Neural Networks (ANNs) were used to model the nonlinear mapping between the RSS signals and the position coordinate of Mobile Unit. Through a training process, the well-trained neural model then can be used to estimate the object's location based on the RSS measurements. Beside this, selection of using an ANN approach is because of its robustness against noise and interference which are one of the major factors affecting the accuracy of the Indoor Position system [8].

The study is organized in four parts, the first part of the study discusses the height analysis on chi square & fingerprinting matching approach in two and three dimensions, the second part discusses ANN, third part discuss real experimental setup, the fourth part comprises of the results and discussion and last part discuss conclusion and future work.

2. Related Work

The WLAN fingerprinting localization system has gained major attention, because of relatively simple and cheap compared to other methods such as angle-of-arrival (AOA), time-of-arrival (TOA), and time difference of arrival (TDOA) systems, that systems require also attaching additional sensor device to each beacon node.

Several efforts have been mde to develop Location determination system based on RSS like Bayesian classification and filtering, K-Nearest Neighbors, GPS like triangulation, Kalman Filtering, neural networks, and support vector machine (SVM) [9] have been employed for solving this problem.

RADAR [10] the first system developed by the Microsoft Research Group, which combines the empirical fingerprinting method (K-Nearest Neighbor)and the theoretical propagation model to locate and track a mobile user. RADAR experiments both KNN and weighted KNN (WKNN) schemes to estimate the location of a mobile user. Horus system is another star of indoor positioning systems. It uses the probabilistic method and several modules to increase the location accuracy and reduce the computational requirements of the location determination algorithm [11].

In 3D fingerprinting positioning approach, Thomas M et al. [12] proposed work on 3D Indoor Positioning with pedestrian activity classification (PAC) assist Pedestrian Dead Reckoning algorithm by using activity recognition based on Bayes Filtering.

Gansemer et al. [13] proposed a method that extends isolines algorithm in multistory buildings, used in 2D WLAN indoor positioning to 3D space. In this work, discrete vertical position can be estimated using WLAN localization algorithms.

T. Kim et al. [14] proposed a used of floor information in the service set identifier (SSID) of AP which contains the location information to allow users to detect their locations by scanning the WLAN signals.

Jiujun Cheng et al. [15] proposed hybrid approach that uses k-medoids algorithm to partition the set of fingerprints into several subsets, which trains a multi-category support vector machine (SVM) on each subset data. The authors conclude that this hybrid approach can be used to solve 3D WLAN indoor positioning.

The above algorithms and new research provide a number of solutions in indoor positioning determination using Euclidean distance and Bayes rule in two dimension implementation. Previous 2D fingerprinting indoor localization based research work in collecting experimental data in offline (training data) and online (testing data), they didn't consider the height of the mobile device especially in online (testing) data collection. In our work, when collection training data and test data, we specify the vertical height on which the both the data were collected. Vertical height plays an important role in getting better accuracy. The Comparison has been shown in Table 1 which summarizes the results of previous researches.

Table 1: Comparison of indoor positioning algorithm in 2D implementation

Position Algorithm	Implementation Approach	Number of Training Points	Number of Testing Points	Average Distance Error Achieved	Height specification for collecting training & testing Points.
Papapostolou, A et al. [16]	Probabilistic	166	60	2.54	No considered
L. Jiang [17]	Deterministic & Probabilistic	60	100	1.70	No considered
Huang, Hao [18]	Deterministic	20	12	1.4	No considered
H. Mehmood et al. [19]	Deterministic	40	10	1.38	No considered

3. Mobile Height Dependency on Indoor Positioning Estimation

An extensive research work has been done in two-dimensional (2D) WLAN based indoor fingerprinting approach. In 2D positioning, only latitude & longitude coordinates of the user are used for positioning estimation. They do not consider the mobile height from the ground level for positioning estimation. But in the actual indoor position situation, the position height of mobile device from the ground level of the user is also an important factor to consider for getting better accuracy in an indoor environments. In our research work, we studied and analyzed the dependency of mobile height on indoor positioning. For this, we implemented the Chi-Square [20] statistical test to determine whether there is a significant association between the height and RSS signal intensity at anchor points in an indoor environment. For chi-square test implementation, we collected RSS values from one access point at each anchor point using three different heights (60cm, 90 cm and 125 cm). A Total of 28 anchor points were used for chi-square test analysis. The measurements of the signal intensity in the 84 different points are shown in Figure 1. TheChi-square test is a statistical test for independence that is used to determine whether there is a significant association between two variables. It is also called a "goodness of fit" statistic [21], because it measures how well the observed distribution of data fits with the distribution that is expected if the variables are independent. In order to determine the association between height from the ground level and signal strength at anchor point using one access point to collect the RSS signal, the null and alternative hypothesis are designed as

H0: There is no association between Height and Anchor point strength.

Ha: There is association between Height and Anchor point strength.

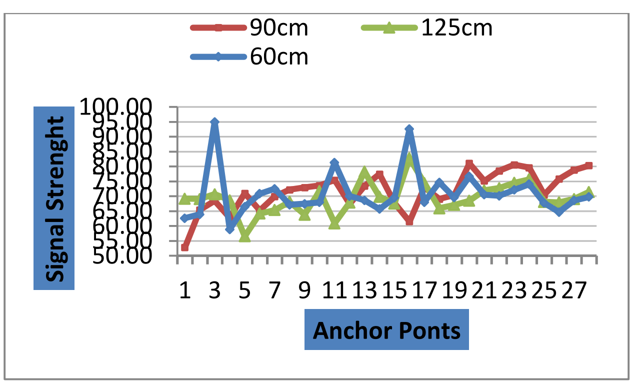

Fig. 1 RSS signal analysis with three different heights

In our case we use three height levels, which are 60cm, 90cm, and 125cm from 28 levels of anchor points. The null hypothesis states that the change in the height does not affect the reading of the signal and consequently does not alter the determination of the position, whereas the alternative hypothesis states that the change in height affects the reading of the signal and consequently the calculation of the position. The degrees of freedom for the three levels (r) of Height and 28 levels (c) of Anchor points are 54 (= (c-1)*(r-1)). The expected frequencies using the observed frequencies are calculated in Eq. 1:

$$E_{r,c} = (S_r * S_c)/GS \tag{1}$$

Where Sr and Sc are the corresponding sums of row and column respectively, and GS represents the grand sum of the observed frequencies. The χ^2 test statistic is calculated as in Eq. 2.

$$\chi^2 = \sum \left[\frac{(O_{r,c}-E_{r,c})^2}{E_{r,c}}\right] \tag{2}$$

The calculated value for $\chi^2 = 28.33$ is greater than the tabulated value $\chi^2 = 28$ [22] at 99% level of significance therefore we accept the alternative hypothesis and conclude that there is association between Heights and Anchor points. This result strengthens our belief that changes in height affect the reading of the signal and consequently the calculation of the position.

4. Fingerprinting Matching Approach in Two & Three Dimensional

Most indoor localization approaches adopted fingerprint matching as the basic scheme of location determination. Location fingerprinting, which utilizes radio signals, is a technique that identifies the location of a user by characterizing the radio signal environment of the user. Fingerprinting method consists of two phases. Phase 1 is the so-called calibration phase, offline phase, or training phase in which received signal features from all Access Points (APs) at selected locations in a building are recorded during the offline calibration phase in a database called radio map.

Phase 2 is the localization phase or online phase, in which the location of an object is then, determined by matching online measurement with the closed location against the database. This method does not require specialized hardware in either the mobile device or the receiving end nor is no time synchronization necessary between the stations. The major drawback of the fingerprinting approach is the laborious and time-consuming calibration process [23].

Beside this, the main challenge to the techniques based on location fingerprinting is sensitivity to various indoor fading effects which are the main cause of the localization error. The fading effects can be divided into the slow fading's and the fast fading's. Slow fading's are effects caused by the environment, such as the radio block or shadow fading. Fast fading is a temporary or random effect, such as the interference, random noise, and the multipath effects. They work together making the RSSI value hard to predict the distance, thus introducing a large localization error [6]. To overcome with fading effect, we are using spatial filtering approach in our work.

In this work, we implement the 2D & 3D based WLAN indoor fingerprinting approach. In the 2D & 3D fingerprinting implementation, we collect a set of RSS fingerprints from four access points (AP's) and stored in a database as a function of the user's location information (latitude, longitude and height covering the entire zone of interest. During the second phase, which is online phase, a RSS fingerprint is measured by a receiver and applied on pattern-matching algorithm which is implemented in ANN model as shown in "Figure" 2.

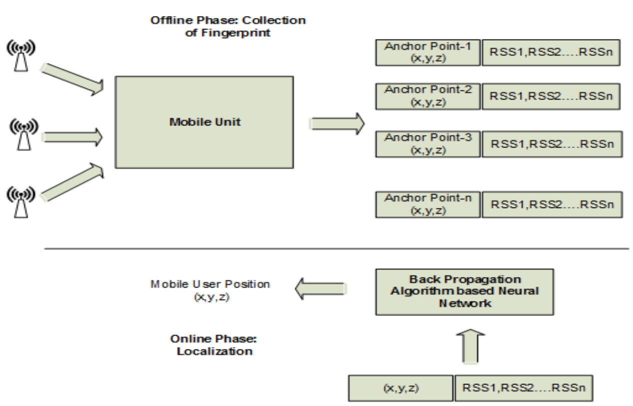

Fig. 2

5. Artificial Neural Network

Artificial Neural Networks (ANN) Neural network methods assume that the RSS cannot be analyzed mathematically because they are too complex. ANN use non-linear discriminant functions for classification. Due to the powerful learning and adaptive capabilities, ANN technique has been employed into the positioning applications especially in fingerprinting technique. A widely used ANN structure among modelers is the feed-forward back propagation neural network. It is also considered one of the simplest and most general methods used for supervised training. Back propagation works by approximating the non-linear relationship between the input and the output by adjusting the weight values internally [24].

5.1 Implementation of Back propagation Neural Network

We implement the position algorithm based on back-propagation in following steps:

i) Feed-forward computation
ii) Back propagation to the output layer & weight adjustment
iii) Back propagation to the hidden layer & weight adjustment
iv) Global Position Error Calculation

A. Feed-Forward Computation

Training pattern is fed to the input layers the weighted sum of the input to the jth node in the hidden layer is given by Eq.3

$$net(y) = \sum_{i=1}^{n} w_{ij} x_j \qquad (3)$$

After the training step of neural networks, appropriate weights are obtained. A multi-layer Perceptron network with two hidden layer is used for ANN-based positioning system. The input vector of signal strengths is multiplied by the trained input weight matrix, and then added with input layer bias as shown in Eq. 4

$$net(y) = \sum_{i=1}^{n} w_{ij} x_j + b \qquad (4)$$

The result is transmitted to the activation function (sigmoid) of the hidden layer neuron as in Eq. 5

$$net(y) = sigmod(\sum_{i=1}^{n} w_{ij} x_j + b) \qquad (5)$$

B. Back Propagation To The Output Layer & Weight Adjustment

The output of this transfer function is multiplied by the trained hidden layer weight matrix, and then added to the hidden layer bias. The output of the system is the estimated location as shown in Eq. 6

$$\delta_k = (t_k - O_k) O_k (1 - O_k) \qquad (6)$$

Where t_k = Actual activation value of the output node, k,
O_k = Expected target output for node k

$O_k(1-O_k)$ = Derivative of the Sigmoid function.

The weight adjustment wj,k, between the output node k, and the node, j is shown in Eq. 7:

$$\Delta w_{j,k}^{n} = I_r \delta_k x_k + \Delta w_{j,k}^{(n-1)} \mu \qquad (7)$$

Where $I_r = Learning\ rate$

μ = *Momentum*

C. Back Propagation To The Hidden Layer & Weight Adjustment

The error signal for hidden nodes and adjust the weight, wi,j, between the input node, i, and the node, j are calculated as in Eq. 8

$$w_{ji} = w_{ij} + I_r \delta_j x_j + \Delta w_{ji}^{(n-1)} \mu \quad (8)$$

D. Global Position Error Calculation

Target data require normalization before feed to ANN. X and Y coordinates are in meters with a range from -25 to 25 m, while the Z coordinate is in centimeters, ranging from 0 to 150 cm. The X, Y & Z ranges above refers to the extension of the space where the measurements were taken. Beside this, the X, Y and Z must be normalizing between 0 to 1, according to this linear transformation.

$$\vec{X_j}\ norm = \frac{\vec{X}}{25} * (0.4) + (0.5) \quad (9)$$

As $-25 < x_j < 25 \rightarrow 0.1 < x_{j,norm} < 0.9$

$$\vec{Y}\ norm = \frac{\vec{Y}}{25} * (0.4) + (0.5) \quad (10)$$

$$\vec{Z}\ norm = \frac{\vec{Z}}{150} \quad (11)$$

As the Input is the RSS signal from the four access points. The target training (testing) data is defined as in Eq. (12)

Target: $\vec{t_j} = \{X_j, Y_j, Z_j\}$ (12)

Output is shown in Eq. (13)

$$O_j = \{ X_{j\,out}, y_{j\,out}, z_{j\,out} \} \quad (13)$$

By inverting the formulas we get total positioning error as shown in Eq. (14)

Error = {25/0.4 $(X_{Jout} - X_{j\,target}) \frac{25}{0.4} \left(Y_{Jout} - Y_{j\,target} \right)$ (14)

$$Mean\ Error_{Position} < \| \overrightarrow{error_{position\,j}} \| > \quad (15)$$

Where mean extends over all training data and $< \| \overrightarrow{error_{position\,j}} \| >$ is the vector normalized.

The training process of a neural network must be adequate so that problems like over-fitting should not arise. Over-fitting occurs when too much training is applied to the ANN. On the other hand, a poor training makes the ANN not to learn adequately. The important factor to achieving better results from ANN model is tuning its parameters. However, there is no definite and explicit method to select optimal parameters for the ANN. Trial and error method is commonly used to choose appropriate ANN parameters [25]. Many parameters are involved in tuning the ANN, including the number of hidden layers, the number of neurons in each hidden layer, initial weights to start the training, the transfer function, learning rate and the momentum rate. The parameters of the back-propagation method, which give the least error, are given in Table 2.

Table 2: ANN Designed Parameters

Parameters	**Value**	**Remarks**
Number of inputs	4	3 – WiFi, 3 -WSN
Number of hidden layers	2	Log-Sigmoid activation function
Number of outputs	2	Linear activation function
Number of neurons in each hidden layers	20	For Layer 1 For Layer 2
Learning rate (LR)	0.1	Three learning rate is used for each layer
Momentum rate (mr)	0.8	Three momentum rate is used for each layer
Target error (goal)	0.001 m	

6. Experimental Setup

For indoor propagation analysis, initial data collection and analysis are important for location fingerprinting. This study examines the real measurement of the RSSI based on wireless card (IEEE 802.11b/g) and the access points (APs) accessible to the author. Experiment data set of RSS samples was collected at the basement of Faculty of Engineering and Built Environment, The National University of Malaysia (UKM), Malaysia. Experimental area is surrounded by various laboratories, long corridors, lecture halls, offices, meeting rooms. The layout of the experimental area is shown in figure 3. Existing WLAN communication infrastructure (Access Point) of the building is utilized. Positions of Access Points are not changed. The use of a real communication infrastructure enables the identification of practical limitations and difficulties and ensures a fair evaluation under realistic operating conditions. In the experimental work, four AP's were used for location estimation. The measurement set consisted of a laptop computer Lenovo G580 with a core i5 processor, an on-board Atheros AR9285 Wireless Adaptor is used for collection of RSS samples with Windows 7 operating system. Open Wi-Fi Scanner software "inSSIDer" by was used for collecting and analysis of RSSI values. Modification was made in the "inSSIDer" to show the times stamps, save the RSS data in text format with mac address along with signal strength values. The hardware apparatus used for data collection using adjustable (height) moving table is shown in "Figure 3". The measurement operation consisted of nearly uniformly distributed anchor points which is, 1 meter apart in X direction and each anchor apart 1.5 meters apart in Y direction. For RSS data collection from four access points, we marked total of 228 anchor points from which we collect data for 2D & 3D fingerprinting implementation. The study area is mapped with Cartesian coordinates system with starting coordinate as (0,0). Data were collected during a working day. More than 100 RSS samples (for about 2 min running INSSIDER software) were collected at each anchor point. Signal fluctuations were suppressed by computing average RSS from 50 samples.

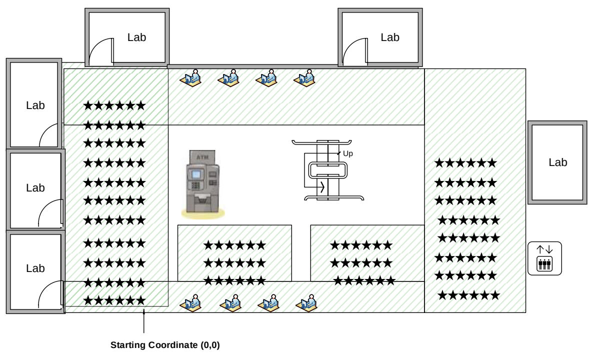

Fig. 4

6.1 2D Data Collection & Implementation

Two dimensional data collections were made and stored in a database with their respective (latitude & longitude) coordinates from total of 228 anchor points from four AP's. In the first scenario, and training data is collected and separate test data to testing purpose are collected. In the second scenario, from the pool of training data, and small test portion data is randomly selected (in percentage) and give it to ANN for training as shown in Table 3.

Table 3: Data selection for training

Total Numbers of Training Anchors Points	No of Training data points after applied Spatial Filter	Total Numbers of Testing randomly Anchors Points
228	180	18

6.2 Statistical Preprocessing of RSS Data

As mentioned earlier, WLAN based indoor fingerprinting techniques is sensitivity to environment changes such as object moving into the building (e.g., people, furniture), diffraction, and reflection, which result in changes in signal propagation and also main cause of the localization error. To over this problem the RSS data base must be statistically preprocessed before applying it in the location estimation phase. In this research work, we use spatial filtering concept to normalize the data which is as under.

1. Compute mean value of each anchor point value.
2. Compute standard deviation of each anchor point value.
3. Calculate for each anchor point, the average of signal of a 4-direction neighborhood anchor points.
4. Replace the previous average value with the calculated spatial average value.

6.3 3-D Data Collection & Implementation

Numerous research works have been done in two-dimensional WLAN based indoor fingerprinting approach during the recent years. In two dimensional positioning only latitude & longitude coordinates of the user are used, but in the actual indoor position situation the position height of mobile device of user is also an important factor to consider for getting better accuracy in indoor environment.
Three-dimensional data collection were collected from four AP's from total of 228 anchor point with their respective (latitude, longitude and height) coordinates and stored in a database. The important factor for consideration in 3D implementation is height of the mobile device from the ground floor. We took RSS data from three different heights (60cm, 90cm and 125cm) from ground level. For collecting different height RSS signals, we use adjustable moving table.
In this work, a two-layer feed-forward neural network with Back-propagation learning algorithm was used in online phase which is position module for indoor position estimation. Back-propagation is the most extensively used neural network training method. The back-propagation algorithm is an iterative gradient method based algorithm developed to introduce synaptic correction (or weight adjustments) by minimizing the sum of square errors (objective function). The four AP's normalized patterns are feed the input to the ANN together with location coordinates (x, y) and (x, y, z) in 2D & 3D fingerprinting pattern implementation respectively which is used as target values and feed as output of ANN as shown in "Figure 5". The proposed system was designed in Matlab.

7. Result and Discussion

To evaluate the performance of a position system, two prime parameters, namely: accuracy and precision are used. The error is obtained by calculating the error of a test data set, the test data contain a collection of fingerprints associated to a location; each test data fingerprint is processed by a positioning algorithm. The obtained estimated location is compared with the real location by calculating the Euclidean distance between the real and the estimated positions to obtain the deviation between the original and the estimated value. The average positioning error relies on the true and estimated location to calculate a value that correctly expresses the accuracy of the system. It is usually the error between the two positions expressed in meters or in centimeters. The second parameter is defined as the success probability of position calculation with respect to predefined accuracy. In order to evaluate our system with respect to both parameters, we will present the Cumulative Distribution Function (CDF) of the error, this error being the difference between the real and calculated coordinates of the locations.

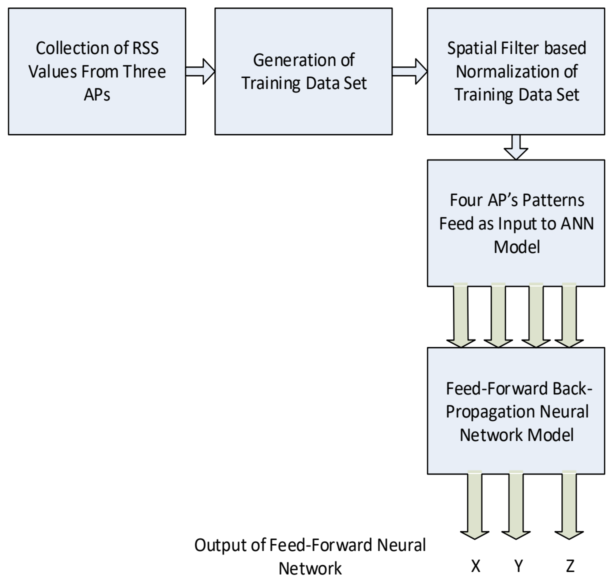

Fig. 5 Back-Propagation Neural Network

"Figure 6" shows the actual and estimated x-y coordinates of test data (18 anchor points) which are randomly collected from the whole experimental area. The total mean distance error achieved is 1.2244m. "Figure 7" show the test points of actual and estimated coordinates in 3D fingerprinting based Indoor localization. In 3D approach and total of 1.9065m mean distance error achieved. As described earlier the accuracy assessment for each training data was performed by computing the average distance error. The figure 8 shows the cumulative distribution function (CDF) of the distance error for optimally trained ANN model. The obtained results show that using ANN with the proposed method of collecting test data, maximum accuracy of using test data achieved an average distance error of 1.2244m and 1.9065 on 50 % in 2D & 3D implementation as shown in "Figure 8"

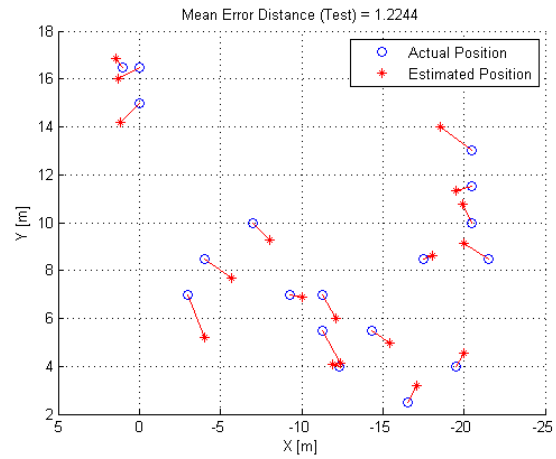

Fig. 6 Actual & Estimated position of mean testing data set in two-dimensional

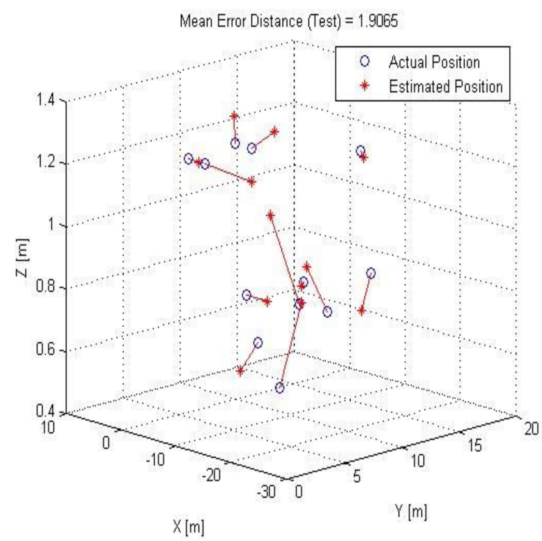

Fig. 7 Actual & Estimated position of mean testing data set in three-dimensional

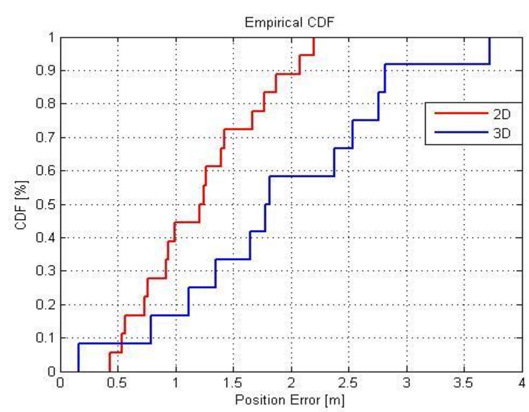

Fig.8 CDF Localization Error in 2D & 3D

8. Performance Comparison

In this section, we compare the accuracy and precision performances of our approach with the performance of well know indoor localization system “RADAR” and one other recent research work as shown in table 4. On average, our system achieves an error distance of 1.2244 meters in comparison to 2.2 & 2 meters in case of RADAR used and other most recent research work respectively.

Table 4: Comparison of indoor positioning system (Location Fingerprinting) in 2D & 3D.

Position Algorithm	Accuracy	Precision	Implementation	Scalability
RADAR [10]	2.2	1m within 33% 2m within 65%	Deterministic Model	2D
Improved KNN & Gaussian Process Regression[26]	2 m	1m within 25% 2m within 60%	Probabilistic Model	2D
Our Proposed Algorithm (2D)	1.2244	1m within 40% 2m within 90%	Deterministic Model	2D
Our Proposed Algorithm (3D)	1.9065	1m within 20% 2m within 60%	Deterministic Model	3D

9. Conclusion & Future Works

In this paper, 2D & 3D based indoor positioning system based on receiving signal strength in wireless networks with better accuracy was presented. For preprocess of RSS data, spatial filter concept was implemented to minimize the fading effect on the indoor environment. In two dimensional positioning only latitude & longitude coordinates of the user are used, but in the actual indoor position situation the position height of a mobile device of user is also an important factor. We use three different height’s (60cm, 90 cm and 125 cm for collecting RSS data in 3D fingerprinting approach. We did the height analysis by chi-square. The ANN model was tested with mean training data set in a heterogeneous environment.

The performance of the proposed system was analyzed in detail and comparison was made in term of accuracy and precision with proposed ANN based system compared with other well-known systems (Probabilistic & deterministic) which are used for indoor localization. Therefore, the indoor positioning system presented in this paper had the advantage of better accuracy, low cost and easy expansibility, and it could be used to locate people and assets in the fields of logistics, healthcare, and manufacturing. Future work consists of optimizing the ANN by using genetic algorithms for weight computation, research, extended on filter approach in 3D indoor fingerprinting implementation to achieve better accuracy. Beside this, proposed algorithm will be established over a larger area to test the robustness of the algorithm.

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