Indoor localization Via Neural Networks and Wi-Fi Signal

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Abstract:

Receiver localization indoors is the key element of Location Based Services (LBS) creation for wireless applications nowadays. Estimating the exact location is the key factor. Specific spatial estimation methods, such as Angle of Arrival, Time of Arrival have certain localization limitations. Indoor localization schemes based on received signal strength(RSS) may also be used to estimate receiver position. In this paper Neural Network based algorithms such as Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive with External Input form (NARX) have been used to estimate the receiver's location in KLEF Library Block, Vaddeswaram, India. From our results it is clear that NARX performs better than NAR. For NARX the effective location rate is about 0.35 and the standard positional error deviation is also small.

Key words: Indoor Localization, GPS, RSS, MLNN, NAR, NARX.

1.Introduction:

Location Based Services (LBS) are being revolutionized as part of the wireless communications systems current and future generations. Global Positioning Systems (GPS) act as the primary device for various wireless technologies. In indoor environment scenarios the GPS positional accuracy is limited[1,2]. So it is very much needed to provide cheap LBS services with alternative GPS options. For position estimate, the obtained signal strength (RSS), fingerprinting, time of arrival (TOA) and angle of arrival (AOA)[3-6] may be used. RSS measurements are the key elements of location estimation techniques and can be translated to distance and in effect to position without any wireless device hardware modification[7, 8]. Estimation techniques based on RSS position can be divided into either propagation based models or traditional finger printing methods. The positional accuracy of the propagation models depends on pathloss model selection and features of the radio channels. The methods of finger printing are very good for location. Online RSS Map and off line RSS Maps will be used for position identification in this process. Finger printing system is stated to provide better estimate of position compared to propagation based models. Finger printing methods however require a high degree of computational complexity. Investigation of Euclidean distance fingerprinting of the region stored in the database returns a sample signal power and offline RSS data[11]. A Cramer-Rao Lower Bound (CRLB) is established which consists of the signal power and frequency of the transmitter[12] to improve the localisation efficiency. The localisation problem is to boost the fluctuation of the transmitted signal strengths by using a novel approach, where the robust signal function is extracted using IEEE 802.11 MAC software[13]. The Neural network with one hidden layer has been implemented for position estimation in most cases[15], where input involves data handling methods and location accuracy has not been satisfactory. Therefore, two combined techniques can be applied to improve location performance; they are non-supervised clustering and majority voting committees of artificial neural network back-propagation[16]. Visual classification[18] and audio recognition[19] display the benefits of multi-layer neural network (MLNN). In this paper, the location technique based on RSS is implemented using MLNN which consists of transforming RSS signal, denouncing raw data, and locating unknown nodes[20]. To enhance MLNN's position accuracy a boosting approach is introduced. This method requires a database, i.e., offline map of the RSS and its positions. The database is used to train the MLNN to get all of the parameters of the network. The wireless channels are unstable, so high localization accuracy is very difficult, so a multi-layer neural network (MLNN)[21] is used without taking the pathloss model into consideration.

2. Methodology

Neural networks are essentially node sets. The general architecture of the Neural network is as shown at fig.1. The first layer is the input layer which trains the system for series of input samples. The second layer is the secret layer, where many machine learning algorithms are used to train the given input samples. The last layer is the output layer where we get feedback based on the sample that is being trained in the hidden layer in relation to the specified data. The calculated RSS samples will be given at the input layer so that the position can be predicted as output learned.

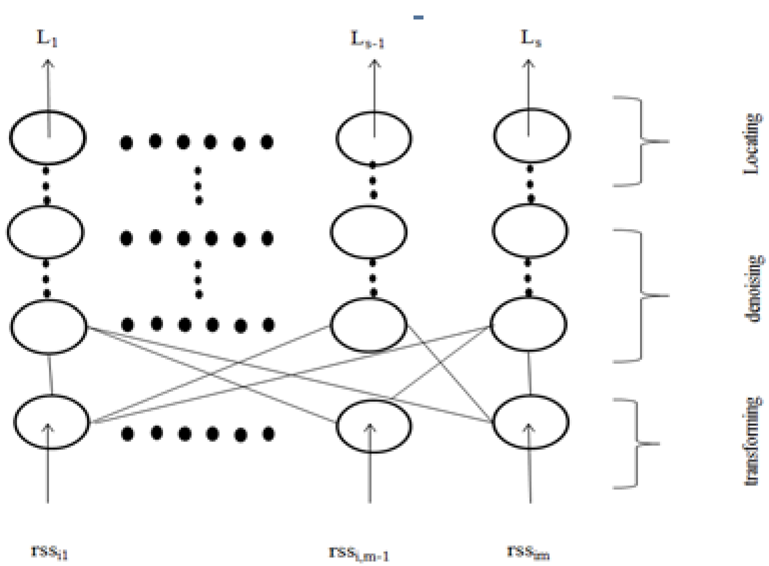

Fig .1. Layout of General Neural Network

A Multi-Layer Neural Network is used to improve the efficiency of output prediction so that noising effect can be reduced in the considered system.

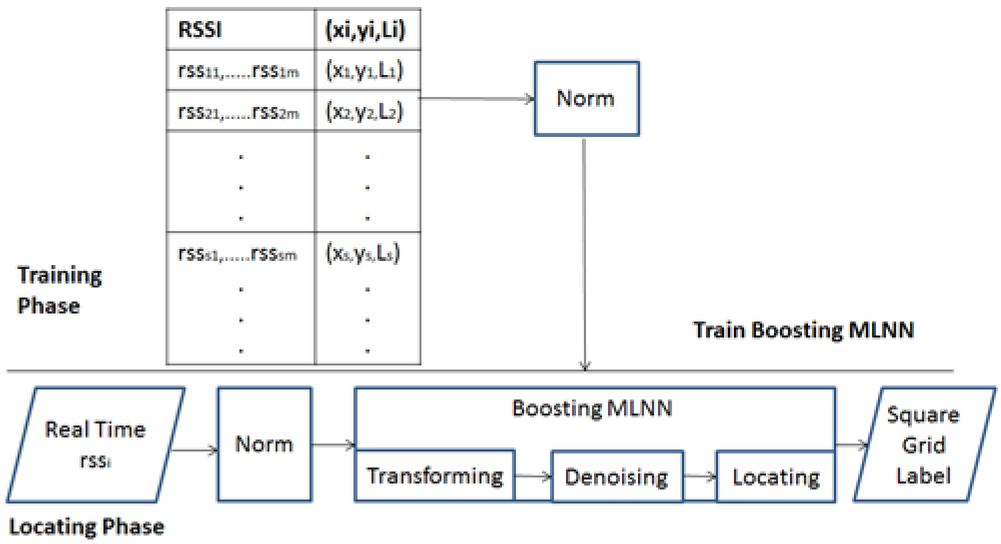

Fig.2.Architecture of MLNN

Fig.2. Shows MLNN architecture for indoor localization based on RSS where MLNN is a technique that is used as a feed-forward structure of artificial neural network. These neural networks will have more than a hidden layer between their inputs and outputs. In MLNN it consists of phase of training and phase of venue. Whereas the input RSS values with the correct position samples are normalized in the training phase. The real-time RSS values are standardized in locating process and given to boosting MLNN consisting of three stages such as transforming, denouncing, and locating. Two types of MLNN algorithms have been studied in this paper to predict position such as Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive with External Input (NARX) form.

A. Non-linear Autoregressive (NAR):

Nonlinear Autoregressive is a model of the time series in which exogenous inputs are not present. The actual time series value depends on the past time series values. As we know the output is estimated by the device in autoregressive method based on the previous inputs. In NAR it only takes the appropriate outputs as the inputs from the generated database. NARX solutions are however more detailed than this approach. Therefore, the present approach can be implemented if past y (t) values are not available at deployment time.

The y(t) sequence may be expressed as

$$y(t) = f\left\{y(t-1), y(t-2), \ldots . y(t-d)\right\} \ldots (1)$$

B. Non-linear Autoregressive with External Input type (NARX):

Nonlinear Autoregressive model is used to predict future processes based on the previous outputs and the inputs given. The output does not alter proportionately with the input in a nonlinear system whereas the autoregressive model is the representation of some random functions occurring in a sequence. In this paper, we gave positions to the input sequence, and the neural networks predict the output position based on their previous experience and the inputs given. If d and x(t) are given where, d is past values of y(t) and x(t) is another sequence, it predicts series y(t). The y(t) series can be expressed as follows

$$y(t) = f\left\{x(t-1), x(t-2)....x(t-d) : y(t-1)\, y(t-2)...y(t-d)\ \right\}....(2)$$

A effective localization rate (SLR) and standard error deviation is calculated for both methods The SLR is given by

$$SLR = \frac{N_S}{N_{all}} \text{ --- (3)}$$

Where Ns is number of successful location and N_{all} is the total number of samples

3. Experimental Setup:

For experiment and validation purpose a data base of RSS samples need to be created for that a closed room (ECE-301) , AITS,Rajampet, India is considered.

The hardware specifications of devices used are as follows
Transmitter: HP Router (J9846A)
Model: IEEE 802.11n/ac @2.4 GHz
Transmitting Power 20dB
Data Rate –MCS23-450Mbps
As a receiver Dell Wireless 1705 802.11b /g/n/ac(2.4 GHz) was used.

During the measurement cycle the entire hall is divided into equal square grids as shown in fig.3, and accordingly, 6, 9 access points have been mounted. Initially a route is generated with portable receiver by collecting the RSS values at specific locations. Later the RSS samples were provided to predict the path as input for the various NN methods. We now have the device trained using 10 hidden layers and 2 delays. As the number of hidden layers increases, the accuracy of performance predictions increases. The program can be retrained so as to reduce possible false predictions. This experiment has started by putting the Wi-Fi Routers once at 6 access points and at 9 access points at a different time. This experiment is carried out in a 8mx9.42 m dimensional room consisting of 10 blocks and 0.8x0.8 m per block. Firstly, as shown in Fig 3, we considered 6 access points. The experiment was later performed using 9 access points as shown in Fig 3.

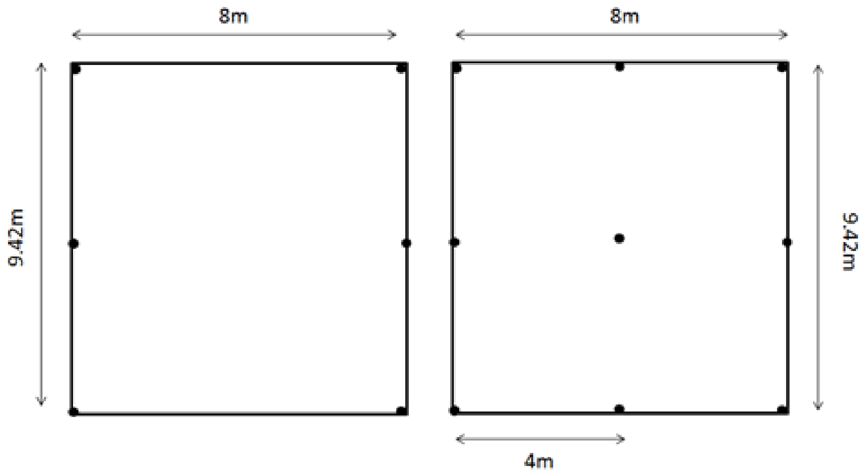

Fig.3 .Lay out for access Points

4.Results and Discussion:

We performed this experiment with 6 access points and 9 access points in consideration. By using neural networks, RSS values are obtained using two different methods such as Nonlinear Autoregressive with external input type and Nonlinear Autoregressive sort. The actual path is plotted against the obtained path for 6 access points using NARX and NAR as shown in figure. 4. Similarly the diagram is plotted in fig.5 for 9 access points. In both cases it is clear that the actual path is similar to the path expected. Fig.6.describes the mistake with the realestiamed co-ordinates when calculating coordiantes.

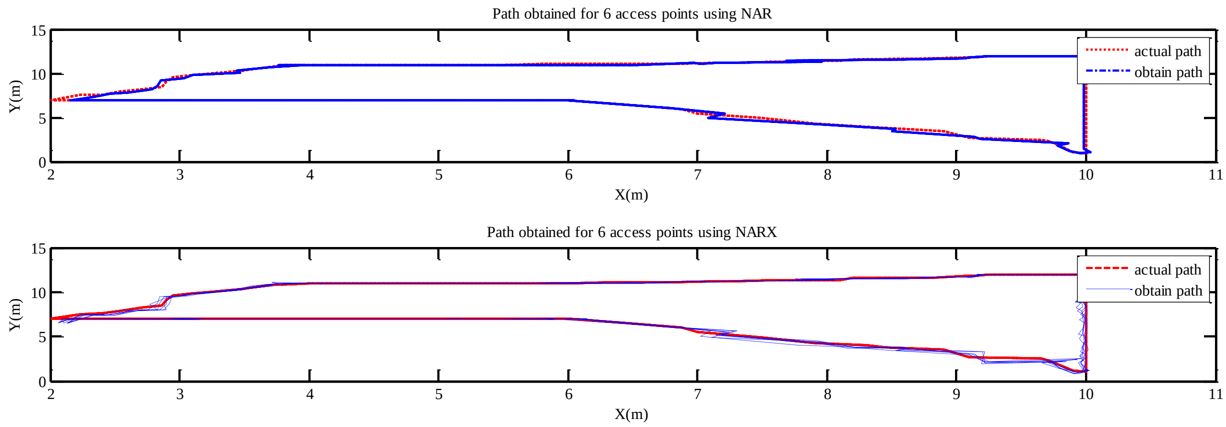

Fig.4. Path obtained for 6 access points using NAR,NARX

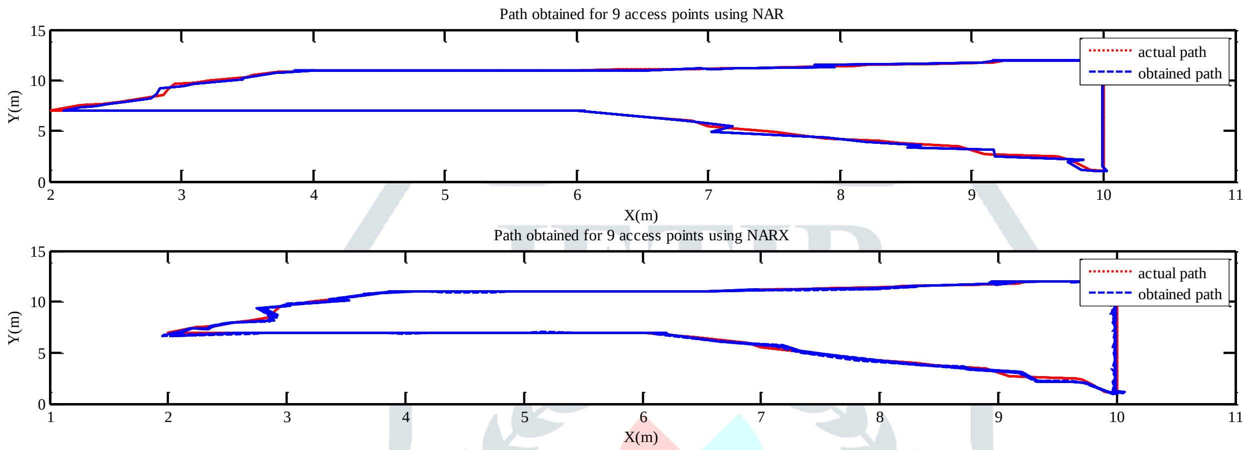

Fig.5. Path obtained for 9 access points using NAR, NARX

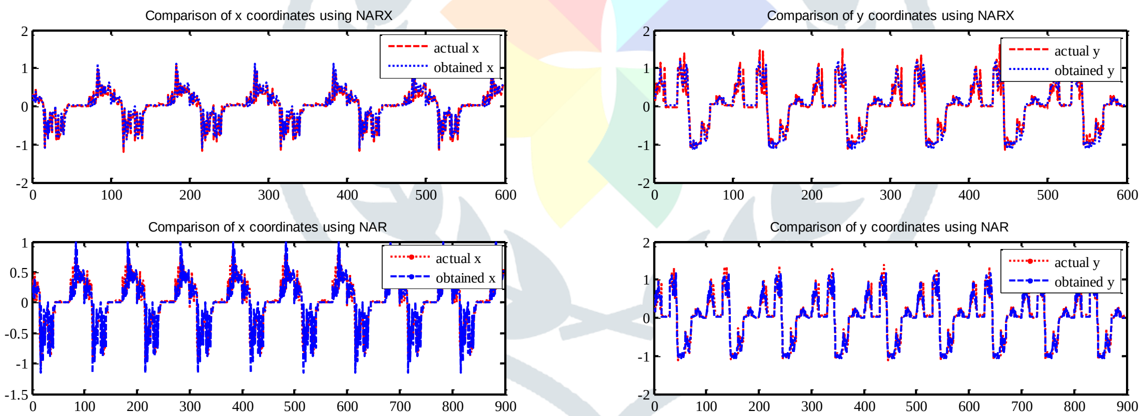

Fig.6.Comparison of error coordinates using NARX, NAR

In this article, for both approaches, SLR is determined as regards 6, 9 access points. NAR system SLR is 0.33 for 6 access points and 9 access points. On the other hand SLR for NARX is 0.35 and 0.38 respectively for 6 access points and 9 access points. The parameter measured in this paper is the standard deviation of the collected error co-ordinatesbetween expected and actual direction.

For 6 access NAR produces Standard deviation of location error is (0.381, 0.602) where as for NARX it is (0.382, 0.576).For 9 access points NAR having standard deviation of (0.704, 0.587) where as for NARX it is (0.393, 0.584).From the above discussions it is clear that the NARX is having better accuracy

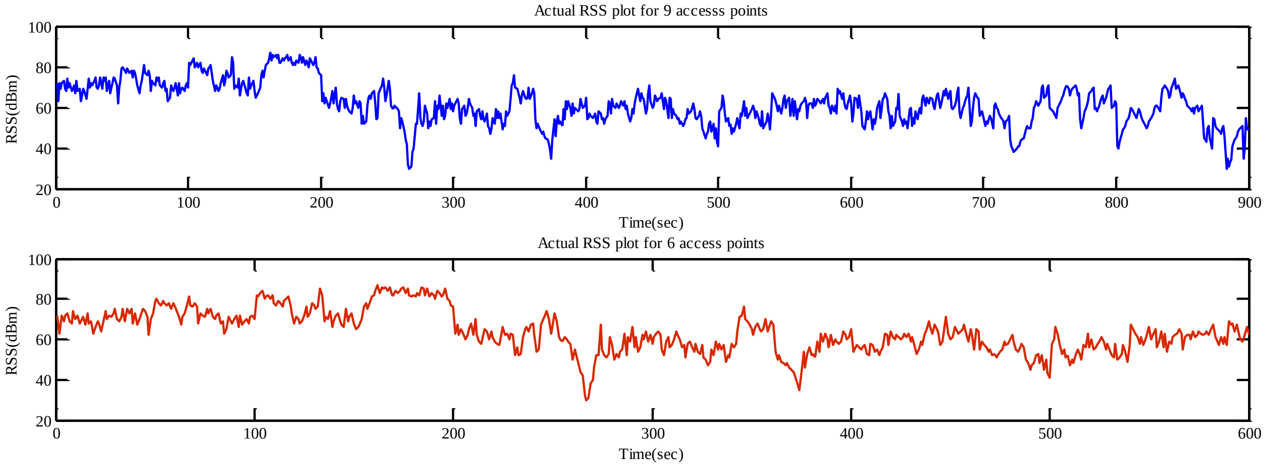

Fig.7.Actual RSS plots for 6 and 9 access points.

In this paper, we have used Acrylic software to predict RSS values at a location with respect to a particular access point where RSS values are being changed for every second while tracing the path, from this the sampling rate is estimated to be 1sec and sampling period is estimated to be 10 minutes for 6 access points and 15 minutes for 9 access points. In this we have taken 10 hidden layers based neural network. In case of 9 access points for training 70% (i.e. 631 samples), for validation 15%(i.e. 135 samples) and for testing 15%(i.e.135 samples), where in case of 6 access points for training 70% (i.e. 420 samples), for validation 15%(i.e. 90 samples) and for testing 15%(i.e. 90 samples) are considered by the neural network. From table.1 we can infer that, for 9 access points NARX method is more efficient and for 6 access points NAR method is efficient based on Mean square error (MSE) values. We can also note that the MSE value increases as the number of access points increases.

Method	Access points	Output Coordinate	Training% (samples)	Validation% (samples)	Testing% (samples)	MSE	Regression
NARX	9	X	70(631)	15(135)	15(135)	$2.834e^{-2}$	$9.9815e^{-1}$
NARX	9	Y	70(631)	15(135)	15(135)	$2.1549e^{-2}$	$9.9897e^{-1}$
NAR	9	X	70(631)	15(135)	15(135)	$2.93741e^{-2}$	$9.98068e^{-1}$
NAR	9	Y	70(631)	15(135)	15(135)	$2.89595e^{-2}$	$9.99670e^{-1}$
NARX	6	X	70(420)	15(90)	15(90)	$1.60515e^{-2}$	$9.98947e^{-1}$
NARX	6	Y	70(420)	15(90)	15(90)	$1.68819e^{-2}$	$9.99197e^{-1}$
NAR	6	X	70(420)	15(90)	15(90)	$1.46295e^{-2}$	$9.99038e^{-1}$
NAR	6	Y	70(420)	15(90)	15(90)	$1.48543e^{-2}$	$9.99291e^{-1}$

Table.1. Overview NAR and NARX performance with MSE

Conclusion:

In this paper a RSS based localization algorithm using MLNN is analysed with NAR and NARX methods. Two cases of 6 access points and 9 access points were considered to estimate the position of receiver in an indoor environment. From the results it was shown that the SLR and standard deviation of location error are of NARX are better accurate than that of NAR methods

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