Time of Arrival (TOA) Based Radiolocation Architecture in CDMA Systems and Its Performance Analysis

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Abstract: A popular approach, called as Radiolocation, measures parameters of radio signals that travel between a Mobile Station (MS) and a set of fixed transceivers, which are subsequently used to derive the location estimation of MS. The purpose of this research was to investigate the performance of Time of Arrival (TOA) based Radiolocation approach for finding the location of MS in the CDMA cellular networks. Another aim was to find out suitable location estimation algorithm using measured parameters by Radiolocation approach. Finally, the accuracy of the Radiolocation was examined by comparing two different location estimation algorithms. Two different algorithms for position estimation methods, named as Neural Networks and Least Square algorithms, were used to determine the location of MS. The simulation results suggested that the Neural Network algorithm provides better accuracy in position estimation which were depicted by supportive simulation results in the article.

Key words: Time of arrival (TOA), radiolocation, neural networks, least square algorithms.

1. Introduction

Time of arrival (TOA), the strength of a signal and Angle of arrival (AOA) techniques are among those techniques that can be utilized to approximate and evaluate the position of Primary users. In case of multipath environments, AOA technique might be an abortive attempt since it is implemented using antenna arrays. For short ranges, measuring the signal strength technique can be employed in order to acquire indoor positioning approximation in addition to high accuracy. Measuring the signal strength methodology performs depending on the channel parameter, CRNs, but this method cannot be controlled by the parameter. TOA technique offers better performance for position estimation method because the accuracy of the TOA process significantly rely on the parameter that is controllable by the Trans-receiver. To obtain position estimation in WSNs, Time of arrival (TOA) positioning system is also executed. The two most notable problems of the TOA technique are the exact synchronization and None-line-of-sight (NLOS). However, the accurate synchronization mainly rely on the bandwidth [1].

In cellular network systems, nowadays, to localize a Mobile Station (MS) by three Base Stations (BS) two-stage closed-form estimator is employed. Range estimator derived by distance-dependent bias model then trilateration used to find an estimate of the MS position.

Mean square error (MSE) of the estimator is derived and numerically evaluated the Cramer–Rao lower bound (CRLB) as a benchmark [2]. The TOA-based factor graph (TFG) also provides rough estimation of position which helps to find out the spot [3]. Radio direction finding (RDF) techniques particularly Angle of Arrival (AoA) and radio localization technique named Time Difference of Arrival (TDoA) algorithms is used to estimate the position of objects in non-collaborative scenarios [4]. Advance TOA trilateration algorithms such as the line intersection algorithm also shows good performance for general cases. But the comparison approach of intersection distances in the specific case has better performance for estimating the MS location [5].

In this Paper, the Network based technique is applied to estimate TOA Radiolocation in IS-95 CDMA cellular networks. Here, the distances between Mobile Station (MS) and several Base Stations (BS)s ware measured according to the time of arrival of the CDMA Pilot signal arrived at the receivers of BSs'. In this system, the signal propagation delays were estimated by using PN code synchronization and correlation circuits in the receiver side at Base stations. Where, the receiver synchronized the locally generated PN sequences with the received PN sequences and estimated the delays in received signals. The estimated propagation delays were multiplied with the velocity of light to get the distances profiles between MS and BSs'. This distances profiles were used in Neural Networks (NN) or Nonlinear Least Square (NLS) location estimation methods in order to find the position of MS in Cartesian coordinate (X,Y) in a cell area.

One-hidden-layer Multi-layer Perceptron (MLP) Neural Network is considered with a training technique that uses Levenberg-Marquardt algorithm, which converged faster than the back-propagation algorithm with adaptive learning rates and momentum. The performances of Neural Networks is compared with Nonlinear Least Square location estimation methods. In this proposed system, Line of site (LOS) propagation of radio signal has only been considered for the calculation simplicity.

The rest of the paper is organized as follows: section 2 introduces about Least Square (LS) approach and Neural network approach to find out the error, section 3 discusses about the simulation model and parameters used in this experiment. Section 4 analysis about overall performance of this techniques and comparison between two techniques section 5 concludes the paper.

2. Techniques of Error Calculation

2.1. Least Squares (LS) Approach

In order to make the calculation simple, some measurements including large errors have been excluded, based on the assumption that a reliable NLOS detection methodology has been executed. Hence, every measurements has been used for locating the MS which in turn comes from LOS propagation.

The actual position of MS has been assumed to be $\mathbf{u} = [\mathbf{x_s}, \mathbf{y_s}]^T$ and the coordinates of the i^{th} BS be $[\mathbf{x_i}, \mathbf{y_i}]^T$, i=1,2,...,M, where M is the total number of receiving LOS BSs. The distance between the i^{th} BS and MS is assumed as [6]:

$$d_i=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}\ ,\ i=1,2,\ldots.M \tag{1}$$

The one-way propagation time (excluding error in measurement) taken by the signal to travel from the MS to the ith BS is given by $t_i = d_i/c$ $(i= 1,2,\ldots,M)$. Where c= 3×10^8 ms^{-1} is the speed of light. The measurement of the range based on t_i in the presence of disturbance, denoted by r_i, is modeled as [6], $r_i = d_i + n_i$.

$$r_i=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}\ +n_i\ ,\ i=1,2,\ldots.M \tag{2}$$

Here, n_i represents the error in measurement in r_i at the ith BS. To make the calculation simple, it has been assumed that each measurement error n_i is a zero-mean white process with variance $\boldsymbol{\sigma_i^2}$. When errors in the measurement are not taken into consideration, equation (2) changes to:

$$r_i=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}\ , i=1,2,....M \quad (3)$$

Squaring both sides of equation (3) yields:

$$r_i^2=(x_s^2+y_s^2)-2x_sx_i-2y_sy_i+(x_i^2+y_i^2)$$

$$x_sx_i+y_sy_i-0.5R_s^2=\frac{1}{2}(x_i^2+y_i^2-r_i^2),\ i=1,2,M \quad (4)$$

From equations (3) and (4), $R_s^2=\sqrt{x^2+y^2}$ where R_s is the range variable.

If the equation is expressed in matrix form, it yields:

$$A=\theta b \quad (5)$$

where:

$$A=\begin{bmatrix} x_1 & y_1 & -.5 \\ \vdots & \vdots & \vdots \\ x_M & y_M & -.5 \end{bmatrix},\ \theta=\begin{bmatrix} x_s \\ y_s \\ R_s^2 \end{bmatrix},\ b=\frac{1}{2}\begin{bmatrix} x_1^2+y_1^2-r_1^2 \\ \vdots \\ x_i^2+y_1^2-r_i^2 \end{bmatrix}$$

If measurement errors are considered, then θ can be calculated with unconstrained LS [6]:

$$\hat{\Theta}=\arg\min\,(A\Theta-b)^T(A\Theta-b)$$

$$=(A^TA)^{-1}A^Tb \quad (6)$$

For, Weighted Least Squares (LS) with Constraint, a weighting matrix W can be added to (6) and restricted to satisfy the basic relationship:

$$R_s^2=x_s^2+y_s^2 \quad (7)$$

This creates a constrained optimization problem as follows [6]:

$$\hat{\Theta}=\arg\min\,(A\Theta-b)^T W(A\Theta-b) \quad (8)$$

Subject to,

$$q^T\Theta+\Theta^T P\Theta=0 \quad (9)$$

$$P=\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix},\quad q=\begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}$$

The above mentioned equation (9) is a matrix representation of (7).

2.2. Neural Networks (NN) Approach

For positioning the location and lessening the error in distance, neural network model proves to be an efficacious option. This network system can function without the information of the distance of the access points and without detail information of their location. This is very user-friendly method because the user can use this without requesting the information. Estimating the non-linear functions can be done in an effective method by the neural networks that has been proven and suggested by several authors [7], [8].

In order to establish the structure of the neural networks, several different types of networks are available. Feed-forward backdrop, cascade-forward backdrop, generalized regression, hopefield etc are some of the examples of neural networks that are available [9]. At the training mode, the neural network has access to the training set of data that is accessible to it. The neural network has the job of recognizing the particular composition of data that is available to it. The overall performance of the neural network is affected by the training function of the network itself. Various types of neutral network are available in order to train a feed-forward backdrop neutral network. This includes Levenberg-Marquardt algorithm, conjugate gradient algorithms, and Quasi-Newton algorithms. Factors that distinguish the types of neutral network logarithms are speed, memory space consumed, and performance. Among these networks, Levenberg-Marquardt has been proven to provide one of the fastest algorithms in addition of keeping up the overall performance at the required level [9].

A function approximation problem must be taken into consideration while implementing the neutral network algorithms. These problems consist of a non-linear mapping of signal strength at the input that are received at several different Access Points. The mapping is performed onto an output with double variable and characterizing the position co-ordinates of the travelling object. A learning strategy must be acquired to specialize the specifications of the parameters of the network model (known as the “weight” of the model). This strategy initiates from a certain pack of set examples to build the structure of the model which in turn shall be generalized in a suitable manner. The pack must contain new data, which shall be confronted by the strategy, not with data existing in the training set.

In Fig. 1 the “standard” Multi-Layer Perception (MLP) architecture [10] has been considered. The weights are connected with the nearby layers and the sum squared differences energy functions are defined as:

$$\mathrm{E(w)}=\frac{1}{2}\sum_{p=1}^{p} E_p=\frac{1}{2}\sum_{p=1}^{p}(\, t_p - o_p(w))^2 \tag{10}$$

where t_p is the target and $\boldsymbol{o_p}$ is the current output value for pattern p, as a function of the network weights w.

In this research paper, the neutral network has been assumed to consist of three layers namely as input layer, the hidden layer and the output layer. The coefficients, mostly known as the “weights”, are the prime constituents of the neural structure which are connected with the neurons- the constituents of the hidden layer. These neurons are also called as processing elements (PE) since they are responsible for processing the information inside the hidden layer. The PE consists of weighted inputs, transfer function and one input. The balance between the inputs is maintained by the PE [11].

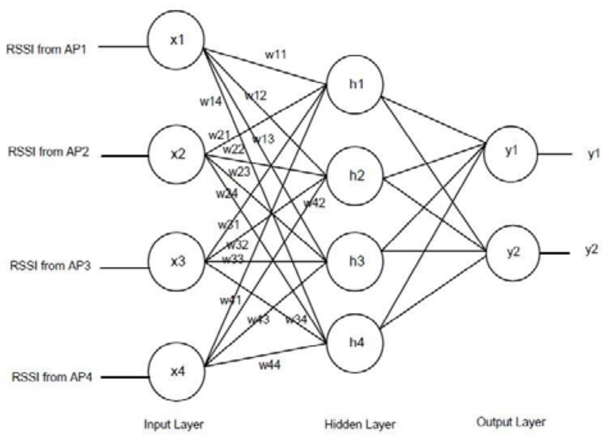

Fig. 1. 4-4-2 neural network.

In Fig. 1 above a neuron structure is shown. The inputs are marked by x^1, x^2, x^3, x^4 and each of the inputs are weighted by corresponding weights w_{11}, w_{12}……………w_{44} of the weight W

$$W = \begin{bmatrix} w_{11} & w_{21} & w_{31} & w_{41} \\ w_{12} & w_{22} & w_{32} & w_{42} \\ w_{13} & w_{23} & w_{33} & w_{43} \\ w_{14} & w_{24} & w_{34} & w_{44} \end{bmatrix}$$

In the above matrix shown, the column components represents the destination neuron connected with the corresponding weights, and the row of the matrix corresponds to the source of the input to which the weight is connected. Therefore, the element w_{32} in the matrix represents that the neuron from the second source is connected to the weight from the third source. Hence the matrix representation for the hidden layer shall be as shown below:

$$\begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{21} & w_{31} & w_{41} \\ w_{12} & w_{22} & w_{32} & w_{42} \\ w_{13} & w_{23} & w_{33} & w_{43} \\ w_{14} & w_{24} & w_{34} & w_{44} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

The neuron output can be written as: $Y=f(WX+b)$

The neuron output equation represents that the incoming inputs are multiplied with the corresponding weights and then the product is combined and then propagated through a transfer function (f). This mechanism provides the output for a particular neuron. The weighted addition of the neuron's inputs make the activation function and the tan-sigmoidal function makes up the transfer function for the hidden layer of the neural network (eq 11). To form the net output the neuron bias b has been added to the weighted inputs. The network has adjustable scalar parameters that w and b. In order to acquire the required output, the parameters w and b are adjusted based on the transfer function [12].

2.3. Architecture of the Multi-layer Perception (MLP)

A particular feature of this architecture includes the motion of the signals through the distinct layers from input to the output but in a sequential manner. First of all, the weighted vectors and the vector of the output given at the previous stage are multiplied to give a scalar product by each unit of the neuron of each layer. The input at the next layer is produced by applying a transfer function to the result obtained at the previous layer. The tan-sigmoidal function defines the transfer function for the hidden layer which is shown below:

$$\textbf{tan sig (x)}=\frac{1-e^{-2x}}{1+e^{-2x}} \tag{11}$$

The identity has been defined for the output layer so that no boundary condition could be provided for the output signal. In order for the approximation of a continuous function to a predefined precision, a network with more than two hidden layers shall be affluent, while assuming that the hidden layers are enough in numbers [13]. Based on this assumption, this research paper considered two hidden layers MLP and to implement the Levenberg-Marquardt a training technique is used. By virtue of adjustable learning speed and drive, this technique merges at a greater rate than the back propagation algorithm. The Levenberg-Marquardt technique for updating parameters is given by:

$$\Delta W=(J^TJ+\mu I)^{-1}J^Te \tag{12}$$

Here e denotes error vector, μ is a scalar parameter, w represents a networks weight matrix and J is the Jacobian matrix of the partial derivatives of the error components with respect to the weights.

3. Simulation Models and Analysis

3.1. Reverse Link System Model

For estimating and executing the method of approximating the TOA of the received signal at BSs, the reverse link of the IS-95 CDMA system is the only considerable factor. The components used must match up to the IS-95 CDMA cellular standard [14]. The configurations of the base station utilized for this research simulation is based on a hexagonal cellular layout as shown in the Fig. 2 below:

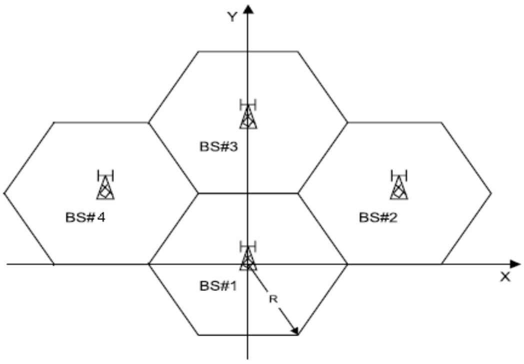

Fig. 2. Four base station configuration.

In this simulation, a typical macro-cellular environment with 3 km radius is used. The two stations, namely Base Stations (BS) and Mobile Station (MS) are regarded as coplanar. It is assumed that the base station, controlling the network, is at the shortest possible distance from the mobile station. The MS is designed as the CDMA transmitter. The MS is considered to be using a half-wave dipole antenna with unity gain. A center frequency of 900 MHz and a bandwidth of 1.2288 MHz are assigned for the Reverse link channel.

The CDMA receiver is the model used for the BS receiver and considered to be utilizing an omni-directional isotropic antenna having unity gain. The base stations are also presumed to be perfectly synchronized using a common reference. Consequently, relative clock drift and bias is assumed to be zero. This is a realistic assumption as the CDMA cellular systems use the GPS signals for synchronization. The users' PIN code is also assumed to be perfectly synchronized along with the assumption that it has a perfect phase tracking.

3.2. Spreading Codes

In IS-95 CDMA cellular standard, the long PN spreading sequence is used which introduces a processing gain of N = 4 chips/symbol after the 1/3 rate convolutional encoder. Then, the 64-ary orthogonal modulator is subjected to a processing gain of N = 32. As a result, total processing gain of N = 128 has been introduced. Therefore, in all the simulations a processing gain of N = 128 is considered. However, a *Maximum-Length Sequences* or *m-sequences* PN spreading code has been used. In IS-95 systems, a zero is inserted in each sequence after the contiguous succession of fourteen zeros to generate the pilot PN sequence of length 2^{15} chips. The detail of *Maximum-Length Sequences* or *m-sequences* PN spreading code has already been discussed.

3.3. Channel Modelling

Zero-mean additive white Gaussian noise are summed up with the signal at the user end so that the simulation to observe the effect of thermal and background noise at the receiver end can be analyzed. The process mentioned in [14] has been utilized in order to supplement noise according to the required level of E_b/N_0. A precise details of this is analyzed below.

Usually in case of digital communication, the SNR is denoted as E_b/N_0, where the numerator E_b represents the transmitted energy per bit and N_0 is a function of the noise power spectral density. Hence, the energy per bit in terms of the transmitted signal power is given as:

$$E_b = P_s T_{bit} \tag{13}$$

where T_{bit} denotes the bit interval and P_s is the signal power at the receiver input. Because of the coding gain, N, provided by the Pseudo-Noise (PN) spreading sequence and the sampling of the signal by N_s, the energy is spread over many more symbols . The noise power, assuming a AWGN channel with two-sided power spectral density of $N_0/2$, is given by

$$\sigma^2{}_n = \frac{N_0}{2} \tag{14}$$

Based on these assumptions, the variance of each noise sample obtained is, [10]

$$\sigma^2{}_n = \frac{A^2 N N_s}{2E_b / N_0} \tag{15}$$

Here, A denotes the amplitude of the user's signal. In this simulation, unity signal power has been used which results in A = 1. Therefore, the noise power for a given E_b/N_0 is,

$$\sigma^2{}_n = \frac{N N_s}{2E_b / N_0} \tag{16}$$

Hence, zero-mean Gaussian noise samples with variance given by equation (35) are added to the signals of all the users.

In CDMA, there is a significant difference in channel and signal bandwidth; the channel bandwidth is generally smaller than the signal bandwidth. As a result, inter symbol interference (ISI) is introduced in the time domain by the production of frequency selective fading. Thus, the signal received at the output shall be comprised of several copies of the real signal which has attenuation in power and delay introduced in the time. Each component of the signal is itself composed of many specular components which add together with different phases. In the absence of a powerful LOS carrier, it can be shown that the envelope of this fading for any component follows a Rayleigh distribution [15]. Additionally, there is an inverse relation between the signal variation rate (known as the coherence time of the channel) and the Doppler spread of the channel [10]. Generation of fading envelopes for the multipath components is taken from the method stated in [16]. This method exploits Gan's model for the Doppler power spectrum [17]. According to Gans model, for an omni-directional antenna with a gain of 1.5, the Doppler spectrum of the received signal can be expressed as [10]:

$$S_{Ez}(f) = 1.5/\pi f_m \sqrt{1 - \left(\frac{f - f_s}{f_m}\right)} \tag{17}$$

where f_c is the center frequency and f_m is the maximum Doppler spread. The maximum Doppler spread can be found by:

$$f_m = \frac{v}{\lambda^2} \tag{18}$$

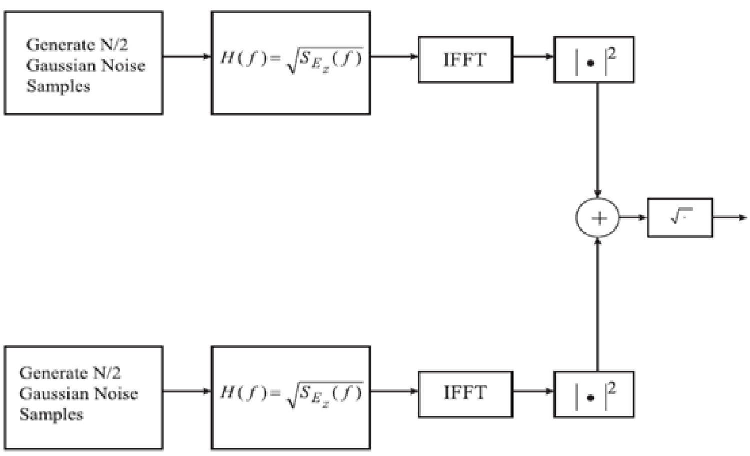

Fig. 3. Rayleigh fading simulator [4].

where, $\boldsymbol{v}$ is the velocity of the MS and λ is the wavelength of the center frequency $\boldsymbol{f_c}$. Using the model in (17) for the Doppler spectrum, a Rayleigh fading envelope can be simulated by first generating independent complex Gaussian noise samples and filtering them using a Doppler shaped filter defined by $\boldsymbol{H(f)} = \sqrt{\boldsymbol{S_{Ez}(f)}}$ as shown in Fig. 3. The filter outputs are then inverse Fourier transformed. After taking the absolute value, each stream is squared and summed to provide the Rayleigh fading envelope. This envelope is then applied to the simulated signal. This method is done for all the components of the signals from all the users [10].

3.4. System Description and Location Estimation Method

In DS-CDMA system, the signal propagation delay is estimated by using PN code synchronization and tracking circuits in the receiver side. Here, the receiver synchronizes the locally generated PN sequence with the received PN sequence and estimates the delay in received signal. The estimated propagation delay is multiplied with the velocity of light to get the distances between MS and BSs'. These distance profiles are used to estimate the location of MS in 2 dimensional Cartesian coordinates. In the simulations, mainly two methods have been utilized to estimate the location of MS. These are:Multi Layer Perceptron (MLP) Neural Networks approach and Least Square approach.

In the Neural Networks approach it is required to form a database of actual location coordinates with respect to distance profiles for each position of MS for training the Neural Networks. Location fingerprinting technology is the appropriate way to build this database. The following Fig. 4 shows the fingerprinting technique to find location of MS in a testbed.

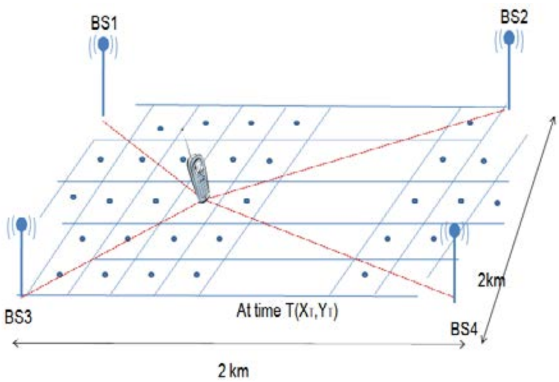

Fig. 4. Location fingerprinting technique for finding MS position in a test bed.

3.5. Building Database Using Location Fingerprinting

To build a fingerprinting database: (1) Reference Points (RPs) must first be carefully selected. (2) The combination of the distances measured by 4 BSs when the MS is at a certain RP forms the Fingerprint of that location. (3) Per location, a number of Fingerprints is stored in a database, needed by the next phase.

3.6. Training Phase of Neural Networks

The unknown MS broadcasts a signal at regular intervals and the four BSs estimate the Time of Arrival (ToA) upon reception of a signal. Then, the distances between MS and BSs are measured. (2)Afterwards, the best matches between the values in the distance sample and the values stored in the database are searched for. (3)The resulting matches, which could either be the value of the closest match or an average of a few best matches, determine the final position of the MS. The following Fig. 5 and Fig. 6 illustrate the signal propagation delay estimation in CDMA systems and how MS's location is estimated in Neural Networks approach.

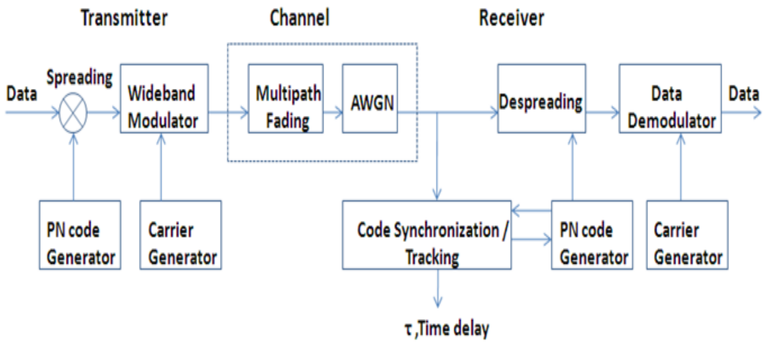

Fig. 5. Diagram for signal propagation delay estimation in CDMA systems.

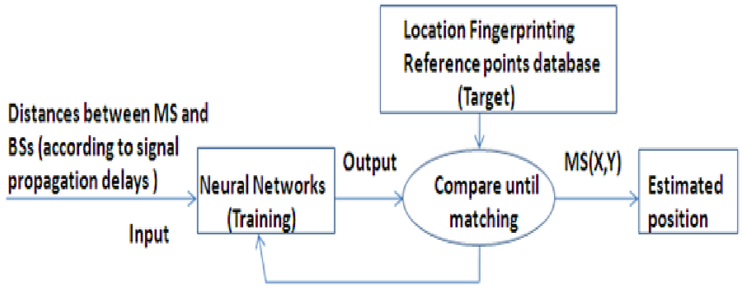

Fig. 6. Diagram for Neural Networks approach for MS location estimation.

3.7. Parameters Considered in the Simulation

In CDMA systems for signal's TOA estimation:

1. As per IS-95 standards, a chip rate of 1.2288MHz was selected. Hence, *Rc* = 1.2288 Mcps.
2. As per IS-95 standards, gain of the CDMA system is 128. Hence, *G*=128
3. As per IS-95 standards, PN code length = 32767
4. As per IS-95 standards, Modulation: QPSK
5. Channel: Frequency selective Rayleigh fading channel
6. CDMA receiver noise: Additive White Gaussian with various signal-to-noise ratios.
7. Nominal power of MS, *Pk* = 1
8. Speed of radio signal, C = 3×10^8 m/Sec

Parameters for Neural Networks in location estimations are:

1. Test bed area: 2 km. x 2 km.
2. Actual distance for traveling 1 location coordinates: 50 m.
3. Minimum no. of base station (BS) considered : 4
4. Neural Networks Standard: Multi-Layer Perceptron, MLP
5. No. of layers in Neural Networks: 3
6. No. of neurons in input layer: 4 (for, 4 BSs)
7. No. of neurons in hidden layer: 4
8. No. of neurons in output layer: 2

4. Results and Model Performances

In this simulation, Results are collected by varying different parameters of the system. Then analyze the data to find out the performance of the system in different conditions.

1) Effect of varying the distance of MS on the accuracy of Radiolocation:

The following parameter was set to study the effect of varying the traveling distances of MS from a reference BS on the percentage error in radiolocation.

- No. of sample per chip = 8 & 16
- Number of BS's participating in radiolocation = 4.
- Radius of the cell = 2000 m.
- E_b/N_o = -12, -10, -5 & 0 dB

For every setting, Result obtained from an average of 100 random locations which were chosen within the central cell. Variation in the traveling distances of MS from a reference BS will have a considerable effect on the accuracy of location estimation.

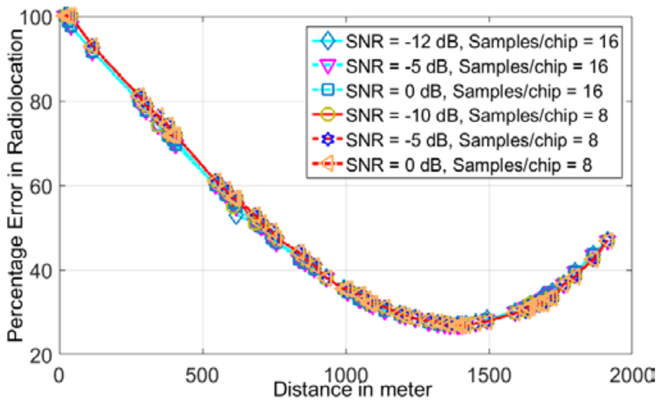

Fig. 7. Percentage error in Radiolocation with distance considering Rayleigh fading & AWGN.

From the Fig. 7, it can be concluded that for a given value of E_b/N_o, percentage error in Radiolocation decreases with the increase of traveling distances of MS from a reference BS up to 1400 meter. The percentage error is the lowest (i.e. about 26 percent) around the distance of 1400 meter. But percentage error has the increasing trend beyond 1400 meter of traveling distance with the same value of E_b/N_o. Varying the value of E_b/N_o has a very small change in percentage error in Radiolocation with varying distances of MS from a reference BS.

2) Effect of varying the value E_b/N_0 with AWGN on the accuracy of Radiolocation:

The accuracy of estimating the TOA depends on how closely the CDMA receiver could track the incoming signal by cross correlation with the locally generated PN code. So, the precision of the estimation is depended on the number samples per chip (i.e. sampling rate). To study the effect of variation of E_b/N_o with Additive White Gaussian Noise on the accuracy of estimation, we have performed experiments with sampling rate of 8 and 16.

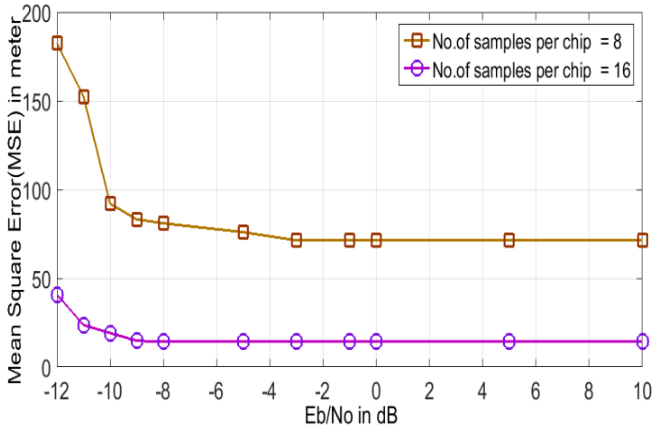

Fig. 8. Mean square error in Radiolocation with changing E_b/N_o considering AWG noise.

It can be concluded from the Fig. 8 that using the signal with sampling rate of 16 show the better accuracy in radiolocation than that of signal with sampling rate of 8. The minimum MSE in Radiolocation using signal with sampling rate of 16 is 14.2 meter. While, the minimum MSE for signal with sampling rate of 8 is 71.34 meter. So, Higher sampling rate is expected to reduce error.

3) Effect of varying the value E_b/N_0 with Rayleigh fading environment on the accuracy of Radiolocation:

To study the effect of variation of E_b/N_o with Rayleigh fading environment on the accuracy of estimation, experiments have been performed with sampling rate of 8 and 16.

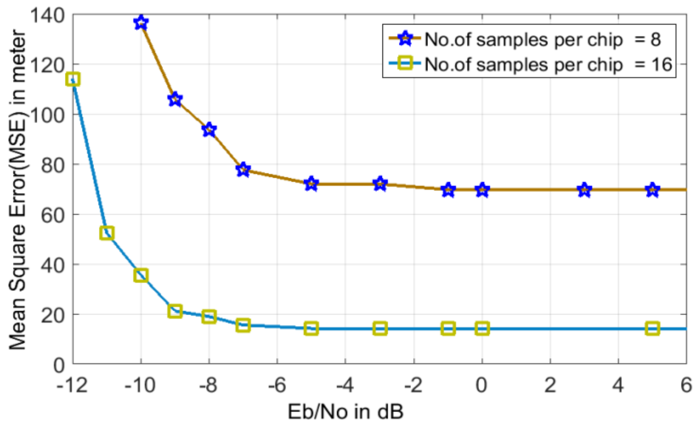

Fig. 9. MSE in Radiolocation with changing E_b/N_o considering Rayleigh fading channel.

It can be concluded from Fig. 9 that using the signal with sampling rate of 16 shows the better accuracy in radiolocation than that of signal with sampling rate of 8. The minimum MSE in Radiolocation using signal with sampling rate of 16 is 14 meter. While, the minimum MSE for signal with sampling rate of 8 is 69.68 meter. So, higher sampling rate is expected to reduce error with Rayleigh fading too.

4) Comparing the accuracy in location estimation with neural networks and least square approach:

This experiment was conducted to compare the accuracy in location estimation with MLP Neural Networks and Least Square approach considering Rayleigh fading channel. To carry out the experiment, the following data have been set:

- No. of sample per chip = 8 & 16
- No. of BS's participating in radiolocation = 4.
- Radius of the cell = 2000 m.
- Neural Networks architecture = 4-4-2 (i.e. 4 neuron in hidden layer)

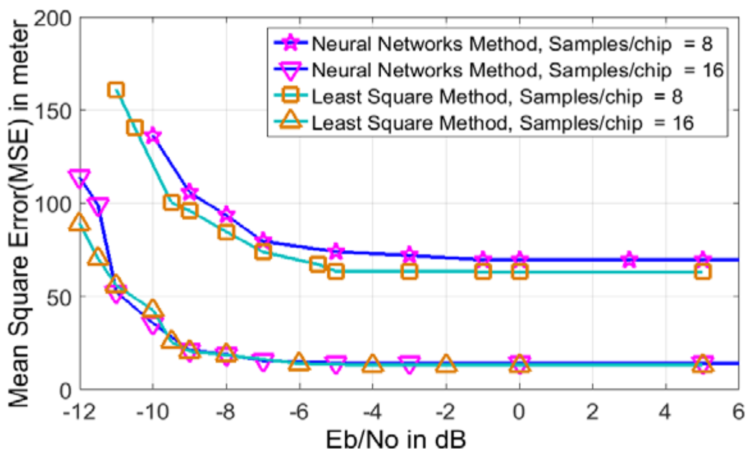

Fig. 10. Comparing accuracy in Radiolocation with neural networks and least square approach in Rayleigh fading channel.

It can be observed from the Fig. 10 that for Neural Networks approach, the minimum MSE in Radiolocation using signal with sampling rate of 16 is 14.203 meter and for sampling of 8 is 69.68 meter. While, For Least Square approach, the minimum MSE in Radiolocation using signal with sampling rate of 16 is 13.1058 meter and for sampling of 8 is 63.3314 meter. That means least square approach gives for accuracy in calculations.

5. Conclusion

In this paper, it has been observed that the variation in distances between MS and a reference BS has considerable effects on the accuracy of location estimation. For the both Networks and Nonlinear Least Square methods, the mean square error (MSE) in Radiolocation decreases with the increase of E_b/N_o up to certain limit. Then, MSE becomes steady state with the change of E_b/N_o. It is also found that both of methods have nearly similar performance in position estimation for certain sampling rate of CDMA Pilot sequences. Moreover, for comparatively lower sampling rate of Pilot signal the Nonlinear Least Square method shows lesser error in position estimation than that of Neural Networks. But neural network method using Extended Kalman filter may have the better accuracy in location estimation and that would be the future work. The higher the value to sampling rate of CDMA Pilot sequences is bounded by the hardware complexity of the tracking loop and time required for estimation.

It can be concluded that the location error can be reduced by increasing the number of BS's used in the Radiolocation process. Also, under perfect power control, cell sizes affect the accuracy of estimation. Finding suitable Radiolocation algorithm for reducing the effect of the multipath propagation below one chip duration of Pilot signal also would be the future work.

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