A NEW TDOA LOCALIZATION ALGORITHM BASED BP NEURAL NETWORK

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Abstract - In a localization system, time difference of arrival (TDOA) technique is widely used to estimate the location of a mobile station (MS). To improve the performance of MS location estimation, a novel algorithm based artificial neural network (NN) is proposed in non-line-of-sight (NLOS) environments. BP neural network is a classic artificial neural network and may be effectively used for mathematical modeling and prediction. The parameters, such as the weights and biases of the single neural network are obtained after the training. TDOA information data are given as input to the neural network models, and coordinates x and y of the nodes are taken as the outputs. The simulation results show that the proposed algorithm can obtain more precise location accuracy.

Index Terms - Localization, TDOA, BP neural network

I. INTRODUCTION

With the rapid development of sensor technology, the demand for positioning is becoming more and more popular. The source localization technique has become the research hotspot in recent years, which can be used in localization of sound, radio frequency and optical sensors[1].

There are 3 main approaches of position determination, including Angle of Arrival(AOA), Received Signal Strength(RSS) and Time Difference of Arrival (TDOA)[2-3]. However, AOA method by using directive antennas has an inaccuracy of some degrees about 5°, RSS method can be highly influenced by noise, obstacles, and the type of antenna used[3]. TDOA method uses the time difference of reception of signals received by the various sensors and the network reference sensor, and this method has a significant advantage in the ease of implementation, being widely used in practice. The non-line-of-sight (NLOS) problem is always the dominant factor that greatly affects the precision of MS location estimation[4].

To enable an improved accuracy of source localization, new methods based neural network were presented for the localization in arbitrary complex systems[4]. Back propagation neural network(BP) is one of the most widely used and most effective neural network models in the artificial neural networks, which has powerful processing ability of nonlinear decision. In this paper, TDOA information data are given as input to the BP neural network model, and coordinates x and y of the nodes are taken as the outputs.

The paper is organized as follows: Section 2 summarizes the related work about localization method using TDOA. Section 3 explains the BP Neural-network. Next, in Section 4, the TDOA location system based on BP neural network is described. In Section 5, the results are discussed and the performance are analyzed. Finally, in Section 6 the conclusions are presented.

II. LOCALIZATION USING TDOA

Assume that there is a master station (MS) in a sensor networks with unknown position coordinate (x,y). The distance from MS to the ith base station (BS) is:

$$R_i = \sqrt{(X_i - x)^2 + (Y_i - y)^2} i=1,2,\ldots,M \quad (1)$$

Where X_i and $Y_i$are the known coordinates of BS_i, M is the number of base stations.

The distance difference between this MS to BS_i and $BS_l$is:

$$\Delta R_{i,l} = R_i - R_l = \sqrt{(X_i - x)^2 + (Y_i - y)^2} - \sqrt{(X_l - x)^2 + (Y_l - y)^2} = ct_{il} \quad (2)$$

Where $R_l$is the distance between $BS_l$and this MS,t_{il} is the arrival time difference between MS to BS_i and BS_l, c is the propagation velocity.

III. BP NEURAL NETWORK

Back-propagation algorithm(BP) with a gradient descending strategy, has been formulated as the multilayered perceptions. In the learning process of BP network, the training pattern's input propagates forward from the output nodes to the inner nodes. BP network typically has a three-layer structure: input layer, hidden layer and output layer[9].

It is well known that a single hidden layer is sufficient to approximate a continuous function with arbitrary precision. To compute the net input to neuron, each input connected to the neuron is multiplied by its corresponding weight to form a weighted sum, which is added to the bias associated with neuron j. Given a unit j in a hidden or output layer, the net input net_j to neuron j is given by:

$$net_j = \sum_i w_{ij} f_i + \vartheta_j \quad (3)$$

Where w_{ij} denotes the weight for neuron ito neuron j, $f_i$is the output of neuron ifrom the previous layer, and ϑ_j the bias of neuronj. In this paper, the activation function of the hidden and output layers is treated as logistic transfer function.The initial weight matrix W

and bias vectors B of BP neural network, which is composed of w_{ij} and ϑ_j respectively, are randomly produce different trained neural networks.

IV. TDOA LOCALIZATION METHOD BASED BP NEURAL NETWORK

According to the viewpoint of geometric approach, distance measured from each BS can form a circle centered at the BS. Then the MS position is estimated by the intersection of circles form multiple TOA measurements. Each of the following three equations describes a circle for TOA.

$$\text{Circle 1: } (x - X_1)^2 + (y - Y_1)^2 = R_1^2 \quad (4)$$

$$\text{Circle 2: } (x - X_2)^2 + (y - Y_2)^2 = R_2^2 \quad (5)$$

...

$$\text{Circle M: } (x - X_M)^2 + (y - Y_M)^2 = R_M^2 \quad (6)$$

Where R_i is the distance between the ith BS and MS. Because NLOS error is always positive due to the excess path length[4], the TOA measurements always appear as a positive bias, greater than the true values. In our algorithm, $[X_{i1}, Y_{i1}, X_{i2}, Y_{i2}, X_{i3}, Y_{i3}, X_{i4}, Y_{i4}]$ are selected as the effective intersections to establish an input data set for training purposes. During training, neural network repeats and adjusts the weights of the connections in the network, and it is effective to reduce the input to minimize the difference between the actual MS location and the desired MS location. This paper presents two neural networks, which are used to predict MS coordinate of X and Y direction respectively. So, the input and output are represented as follows:

Input: $I_1 = [X_{i1} X_{i2}, X_{i3}, X_{i4}]$

Output: $O_{o1} = [x]$

Input: $I_2 = [Y_{i1}, Y_{i2}, Y_{i3}, Y_{i4}]$

Output: $O_{o2} = [y]$

The final prediction result O_o of neural network is $[O_{o1}, O_{o2}]$

V. SIMULATIONS AND ANALYSIS

To verify the effectiveness of the proposed approach, computer simulations are conducted for the comparisons with other methods. As it is shown in Fig.1, the coordinates of the BSs are respectively set to BS1:(0cm,0 cm), BS2:(0cm,60cm), BS3:(60cm,0cm), BS4:(60cm,60cm), the MS location is chosen randomly in accordance with a uniform distribution within the region formed by the BSs. Then 200 TDOA data from 4 BSs are obtained. In the experiments, the dataset is randomly split into two parts: Training Set and Testing Set, consisting of 80% and 20% of the samples respectively. Training set is used to train the individuals in the ensemble model, and ensemble's generalization ability is tested on the Testing Set. Regarding the NLOS effects in the simulations, the uniformly distributed noise model is applied in the simulation, in which the TOA measurement error is assumed to be uniformly distributed over (0, U), where U is the upper bound of the error. To start with the comparison of the localization methods, the results of the classical source localization method[5-8] are presented in Fig.2 and Fig.3, which show the experimental results obtained by sample points and signal to noise ratio (SNR) respectively. In order to show Fig.2(a) and Fig.3(a) in detail, Fig.2(b) and Fig.3(b) present the localization error with the unit of Decibel.

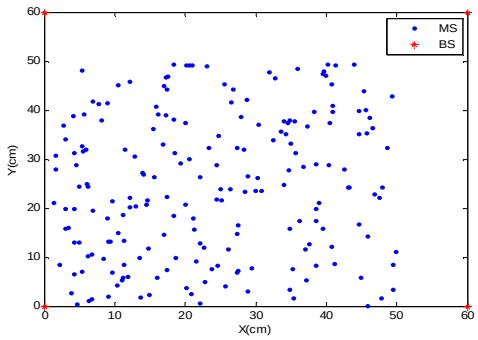
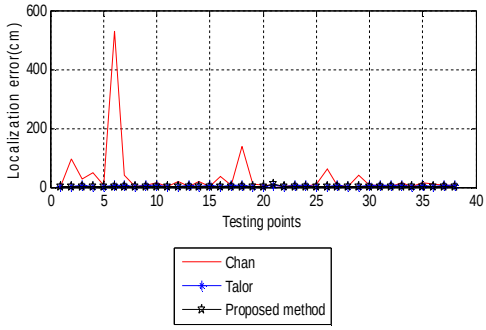
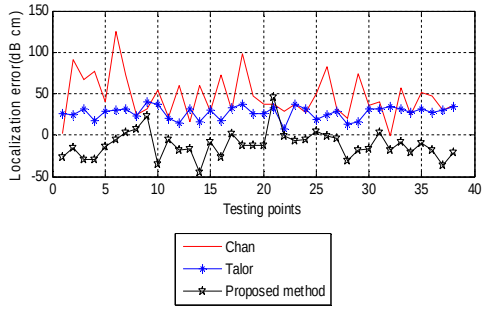


Fig. 1 Positions of the MSs and BSs



(a)

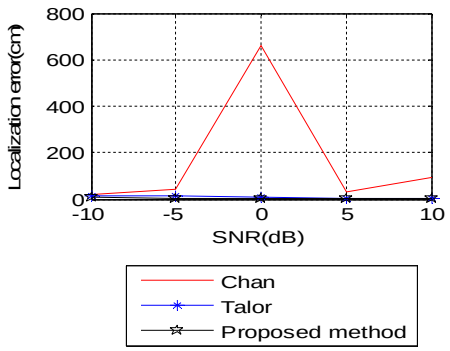


(b)

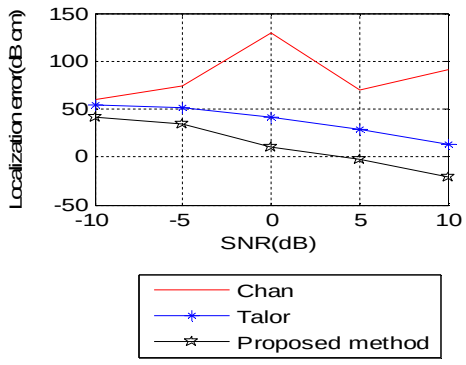
Fig.2 Performance of classical source localization methods

It can be observed that there is a systematically stronger deviation close to the sensor positions in the NLOS environment. This is because Taylor-iteration method and Chan's method respectively use the iterative and non-iterative solution to achieve optimum performance, which are greatly affected by the heavy noise due to NLOS fact. However, once one of the channels is in an NLOS condition where the propagation delay time is positively biased, they are severely lowered[4]. But it can be observed that the proposed algorithm can reduce the localization errors effectively, as the BP neural network has capability to recognize patterns and symbolic contexts from

examples without using explicit analytical functions to describe this context.



(a)



(b)

Fig.3 Performance of classical source localization methods

CONCLUSION

This paper presents a novel localization algorithm based on BP neural network model to estimate MS position in NLOS environments. The simulation results show that the proposed algorithm can obtain more precise location accuracy.

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