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Neural Network Localization With TOA Measurements Based on Error Learning and Matching

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ABSTRACT Due to the widespread application of location information, the neural network localization method with the advantage of high localization accuracy has received significant interests in recent years. In this paper, we present two new neural network localization methods with time-of-arrival (TOA) measurements. In order to deal with three types of error about TOA measurements such as measurement error, non-line of sight (NLOS) error, and synchronization error, the proposed methods contain an offline training stage and an online localization stage. In the offline stage, the artificial neural network (ANN) or radial basis function (RBF) neural network is utilized to train the range measurements with the output of range errors rather than the position of the mobile terminal (MT). Moreover, due to the unknown signal propagation condition whether it is the line of sight or NLOS propagation, the k-mean clustering algorithm is used to classifying the range errors into different clusters. In the online stage, the range errors are predicted and updated, and then, the linear least square algorithm with the adjusted range measurements is applied for the position estimate of MT. Comparing with the ANN or RBF neural network localization methods, the simulation results show that the proposed methods can effectively reduce the localization error, especially when the training sample is not adequate. In addition, they are insensitive to measurement error, synchronization error, and the distribution of NLOS error. Finally, the memory requirement and computational complexity about different algorithms are analyzed and compared.

INDEX TERMS Artificial neural network (ANN), localization, linear least square (LLS), non-line of sight (NLOS), radial basis function (RBF), time of arrival (TOA).

I. INTRODUCTION

Location information is an integral and crucial component of ubiquitous computing applications. Accurate indoor and outdoor localization about Mobile Terminal (MT) is an important technology for commercial, public safety, and military application. In outdoor environments, the satellite-based localization technology, such as the Global Positioning System (GPS) is an effective and accurate localization technique. However, the absence of direct line of sight (LOS) propagation with satellite will lead to severe deterioration of the localization performance [1]. There are some important supplements to the satellite-based technique, such as Wireless Sensor Network (WSN), Wireless Cellular Network (WCN) and Wireless Local Area Network (WLAN) [2], [3] techniques are used to localize the MT, especially in indoor environments and some outdoor environments where the satellite signals are heavily attenuated or blocked. These supplemental techniques have common principle to localize the MT. By measuring some signal parameters between MT and Fixed

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Terminals (FTs), such as Received Signal Strength (RSS), Angle of Arrival (AOA), Time of Arrival (TOA), or Time Difference of Arrival (TDOA) [4]–[7], the nonlinear relationship between these parameters and the position of MT together with the position of FTs is formulated. Then some algorithms are developed to estimate the position of MT through utilizing this nonlinear relationship. However, many difficulties intrinsic to the wireless environment make accurate localization challenging. These challenges include signal fading, multipath conditions and non-line of sight (NLOS) propagation [8].

Recently, neural network localization methods have received significant attentions due to the advantages of anti-noise, fast operation speed, and high precision. The neural network localization techniques discussed in open literature can be categorized into two groups' namely RSS-based and TOA-based localization. The RSS-based localization which is a low-cost localization technique without any additional hardware has been investigated intensively. Instead of the appropriate propagation-loss model about RSS measurement, the work in [9] builds a flexible mapping between RSS and position of the sensor nodes, and proposes the neural network and grid sensor training phase for accurate localization of sensors. The recorded RSS values through experiment are used to train a feed-forward type of neural network in [10], it is shown that the neural network-based localization method is better than the well-known weighted k-nearest neighbor (KNN) method in term of cumulative distribution function. Three types of dynamic neural network (DNN) which can reduce the impact of non-stationarity of RSS on localization performance are used to localize the wireless device in [11]. By using Gaussian filter to process RSS value and fuzzy clustering to determine the center of radial basis function (RBF), two RBF neural network localization methods are proposed in [12]. One is to learn the mapping relationship between RSS and position of MT, the other is to add the difference of RSS into the input layer of previous RBF neural network. Combining with Jensen-Shannon divergence as a measure of similarity, a probabilistic neural network (PNN) localization method is proposed in [13]. By transforming the problem of localization into classification problem, the work in [14] proposes a multi-layer neural network (MLNN) method for RSS-based indoor localization. A denoising autoencoder based on the deep learning model is introduced in [15] to reduce the effect of noise, and then a KNN method is applied for location estimate with a weighted average of those related reference locations. However, the main problem in RSS-based localization is the severe fluctuation of RSS even for a static position and the localization accuracy is greatly affected by the change of environment.

Comparing with RSS-based localization, TOA-based localization has higher localization accuracy and is more robust to the change of environment. However, it requires precise time synchronization between MT and FTs, and the localization accuracy degrades greatly when the NLOS propagation is present. In [16], it indicates that neural networks are a viable option for solving TOA-based localization problems, and three different families of neural networks: Multi-layer Perception (MLP), RBF, and Recurrent Neural Networks (RNN) are compared in terms of localization accuracy, computational and memory resources. The work in [17] proposes an artificial synaptic network for localization, comparing with MLP and RBF, it has the lowest localization error and highest efficiency in term of memory cost. In order to deal with the miscellaneous noise sources and harsh factory conditions, an artificial neural network (ANN) approach is developed in [18]. Lagrange programming neural network or its improved forms based on the TOA measurements are proposed in [19]–[21] to locate a mobile source, it is shown that the localization accuracy of this method approaches to the Cramer-Rao lower bound. By using AOA derived from phase differences in the signal received at the multiple antenna array, a structured deep neural network [22] is proposed to infer the position of MT. However, all the simulation or experiment results of the above works are based on perfect assumption that only LOS propagation is present. In fact, signal NLOS propagation always happens in indoor or outdoor environments where signal is blocked by walls, buildings or other obstacles. By utilizing the statistics of radio propagation channel metrics, a neural network architecture is introduced to identify and mitigate the NLOS conditions in indoor environments [23]. A machine learning approach [24] is proposed to mitigate the range error based on the features extracted directly from received waveform. By utilizing particle filtering to reduce the TOA range error, a fingerprinting localization algorithm is proposed in [25]. The channel parameters extracted from the down link signals in the long term evolution (LTE) system are selected as the feature or fingerprint [26], a feedforward neural network whose input is feature or fingerprint vector and output is the known position of user equipment (UE) is trained and used to estimate the unknown positions. An indoor fingerprint localization system with channel state information is proposed in [27], a deep learning is utilized to train all the weights of neural network in the offline stage, while a probabilistic method based on the RBF function is presented to obtain the estimated location in the online stage. Two forms of neural network localization methods combining with hybrid lines of position algorithm are proposed in [28] to determine the position of MT without priori information about NLOS error. Based on the NLOS channel classification and ranging error regression model, a convolutional neural network (CNN) localization method is proposed in [29]. To sum up, the above research works mitigate the effect of NLOS error from two aspects. One is to use the existing NLOS mitigation algorithm combining with different types of neural network, the other is to extract more features from propagation signal combining with fingerprint or neural network method.

In this paper, we investigate the TOA-based neural network localization method by relaxing the assumption of precise time synchronization between MT and FTs. When TOA range measurements are corrupted by measurement error, NLOS error and synchronization error, two new neural network localization methods are proposed. In offline stage, unlike the existing methods, we use the ANN or RBF neural network to build the nonlinear mapping relationship between the range measurements and range errors. Moreover, due to the unknown link condition between MT and FTs, the range errors can be further classified into different clusters whose number is related to the number of FTs. In online stage, for the range measurements, the corresponding range errors can be predicted by the ANN or RBF neural network, and updated by matching the training range error. Then linear least square (LLS) algorithm with the adjusted range measurements is applied for the position estimate of MT. Simulation results show that the proposed methods are better than ANN or RBF neural network and they are insensitive to measurement error, synchronization error and the distribution of NLOS error. The main contributions of this paper are as follow: 1) we break the viewpoint that RBF neural network localization method always has higher localization accuracy than ANN. It is concluded that the performance of RBF neural network degrades and fluctuates significantly when both the NLOS error with random assignment and synchronization error are present. 2) two new neural network localization methods based on the learning model of range errors are proposed. For different parameters, they are always better than ANN, especially when the training sample is not adequate. 3) the comparisons of different algorithms are simulated and analyzed in terms of localization accuracy, memory requirement and computational complexity.

The remainder of this paper is organized as follow. The related TOA localization methods about ANN and RBF neural network are presented in section II. The proposed localization methods are presented in section III. The performance comparison and results discussion are shown in section IV. Section V concludes the paper.

II. RELATED TOA LOCALIZATION METHODS WITH SUPERVISED LEARNING

A. TOA LOCALIZATION MODEL

In a wireless network, the FTs are assumed to synchronize with each other, while MT is not synchronized with those FTs. FT is usually a base station in WCN, an anchor node in WSN, or an access point in WLAN. Thus, the TOA measurements are significantly affected by NLOS propagation error and time synchronization error. Denote the position of FTs by $(\mathrm{x_i}, \mathrm{y_i})$, $\mathrm{i} = 1, \cdots, \mathrm{M}$, and the position of MT by (x, y). The range measurements of TOA can be modeled as:

$$\begin{aligned} r_i &= c \times t_i = d_i + \varepsilon + e_i + n_i, \quad i = 1, 2, \cdots, M \\ \varepsilon &= c \times \Delta t, \quad d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \end{aligned} \tag{1}$$

where c is the speed of light, t_i is the measured TOA between MT and i-th FT, Δt is time synchronization error between MT and FTs, M is the number of FTs, e_i and n_i are the non-line of sight (NLOS) error and range measurement noise, respectively. Generally, $n_i \sim \mathrm{N}(0, \sigma^2)$ is a white Gaussian random variable with the same variance σ^2. However, the NLOS error is caused by the signal's reflection and diffraction whose propagation path is longer than LOS path, and it depends on the wireless propagation environment and the specific technology under consideration (e.g., WCN, WSN, WLAN, etc.). Thus, the NLOS error is modeled as positive random variable with different probability density distribution, such as exponential distribution $e_i \sim \mathrm{E}(\gamma)$ [30], [31], uniform distribution $e_i \sim \mathrm{U}(0, B)$ [32]–[34], and Gaussian distribution $e_i \sim N(\mu, \sigma^2_{nlos})$ [35], [36]. If a signal between MT and FT experiences LOS propagation, then $e_i = 0$.

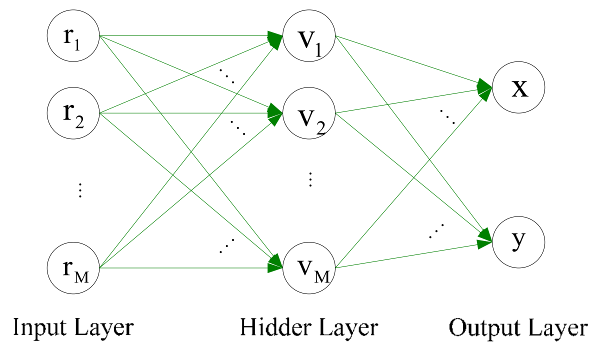

FIGURE 1. The architecture of ANN to localize the MT in two-dimensional.

B. ANN LOCALIZATION

The ANN localization method shown in Fig.1 is proposed in [16] and [18]. It has three layers consisted of input layer, hidden layer and output layer. The hidden layer receives the range measurements from input layer and builds the nonlinear mapping relationship between range measurements and position of MT. The output layer receives and transforms the process information to response the corresponding location information. The number of neurons in hidden layer is the same as the input layer, and output layer only has two neurons in two-dimensional space. The activation function is set as sigmoid function in the hidden layer, while it is set as linear transfer function in output layer. Neurons in hidden layer compute their activations using following formulas

$$\mathrm{v_j(n)} = \varphi\Big(\sum_{\mathrm{i=1}}^{\mathrm{M}} \mathrm{w_{ji}(n) \cdot r_i(n) + b_j(n)}\Big), \quad \mathrm{j} = 1, \cdots, \mathrm{M}, \quad \mathrm{n} = 1, \cdots, \mathrm{N} \tag{2}$$

where $\mathrm{w_{ji}(n)}$ is the connection link weights between input layer and hidden layer, $\mathrm{b_j}$ (n) signifies the bias terms on neuron j in hidden layer, $\mathrm{r_i}$ (n) is the range measurement between MT and the i-th FT, N is the number of training samples, $\varphi(\cdot)$ is the sigmoid activation function. Neurons in output layer compute their activations with following formulas

$$\begin{aligned} \mathrm{x(n)} &= \sum_{\mathrm{j=1}}^{\mathrm{M}} \beta_{\mathrm{j1}}(\mathrm{n}) \cdot \mathrm{v_j}(n) + b'_1(n) \\ \mathrm{y(n)} &= \sum_{\mathrm{j=1}}^{\mathrm{M}} \beta_{\mathrm{j2}}(\mathrm{n}) \cdot \mathrm{v_j(n)} + \mathrm{b'_2(n)} \end{aligned} \tag{3}$$

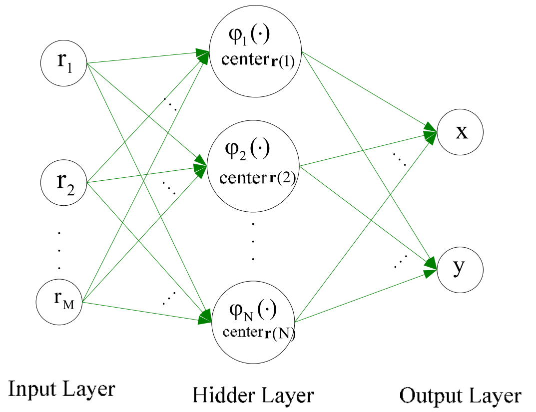

FIGURE 2. The architecture of RBF to localize the MT in two-dimensional.

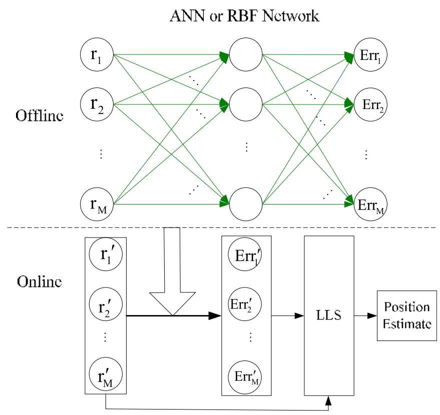

FIGURE 3. Method I: ANN or RBF + LLS.

where $\beta_{j1}(n)$ and $\beta_{j2}(n)$ are the connection link weights between hidden layer and output layer, $b'_1(n)$ and $b'_2(n)$ signify the bias terms in output layer.

In the training stage, the weights and biases are initialized from a uniform distribution. Each neuron in output layer compares its computed value with its target value to determine the corresponding error and then propagates this error back to the neurons in the previous layers to update the weights and biases between neurons. Some existing algorithms, such as back-propagation algorithm [18] and Levenburg-Marquardt algorithm [28] can be used to update the weights and biases.

C. RBF NEURAL NETWORK LOCALIZATION

The RBF neural network localization method shown in Fig.2 is proposed in [12] and [16]. It also has three layers. Input layer and output layer are the same as ANN. Unlike ANN, the links between input layer and hidden layer are direct connections with no weights and biases. The number of neurons in hidden layer is the same as the size of the training sample. Each neuron is mathematically described by a RBF. The output of RBF neural network can be expressed as the following formulas

$$\begin{aligned} x(n) &= \sum_{i=1}^{N} \beta_{i1}\varphi_i(\mathbf{r}-\mathbf{r}(n)) \\ y(n) &= \sum_{i=1}^{N} \beta_{i2}\varphi_i(\mathbf{r}-\mathbf{r}(n)) \end{aligned} \tag{4}$$

where β_{i1} and β_{i2} are the connection link weights between hidden layer and output layer, $\mathbf{r}(n) = [r_1(n), r_2(n), \cdots r_M(n)]^T$ is the n-th input sample point, $\varphi_i(\cdot)$ is a Gaussian RBF, which is defined by

$$\varphi_i(\mathbf{r}-\mathbf{r}(n)) = \exp(-\frac{1}{2\sigma_i^2}\|\mathbf{r}-\mathbf{r}(n)\|^2), \quad i = 1, 2, \cdots N$$

where σ_i is a measure of the width of the i-th Gaussian function with center $\mathbf{r}(n)$. Let $\mathbf{d}(n) = [x(n),y(n)]^T$ and $\boldsymbol{\beta}(n) = [\beta_{n1}, \beta_{n2}]^T$, the equation (4) can be transformed into vector form

$$\boldsymbol{\varphi}_{N\times N}\boldsymbol{\beta}_{N\times 2} = \mathbf{d}_{N\times 2} \tag{5}$$

where $\boldsymbol{\beta} = [\boldsymbol{\beta}(1), \beta(2), \cdots, \boldsymbol{\beta}(N)]^T$, $\mathbf{d} = [\mathbf{d}(1), \mathbf{d}(2), \cdots, \mathbf{d}(N)]^T$,

$$\boldsymbol{\varphi} = \{\varphi_{ij}\}_{i,j=1}^{N}, \quad \varphi_{ij} = \exp(-\frac{1}{2\sigma_j^2}\|\mathbf{r}(i)-\mathbf{r}(j)\|^2)$$

If the inverse matrix of $\boldsymbol{\varphi}$ exists, we can solve (5) for the weight vector $\boldsymbol{\beta}$, obtaining

$$\boldsymbol{\beta} = \boldsymbol{\varphi}^{-1}\mathbf{d} \tag{6}$$

III. IMPROVED ANN AND RBF NEURAL NETWORK LOCALIZATION METHODS

In section II, we briefly introduce the principle of ANN and RBF neural network localization methods. Their main ideas directly build the nonlinear mapping relationship between the corresponding range measurements and position of MT. However, from the range measurement model in (1), we know that the extra error of each range measurement which is the sum of NLOS error, synchronization error and measurement error may deviate the nonlinear mapping relationship between range measurements and position of MT, and greatly degrade the localization accuracy. In addition, the information about the position of FTs is not used in ANN or RBF neural network localization method. The following sections will explain the proposed localization methods in detail.

A. IDEAS OF OUR PROPOSED METHODS

The ideas of our proposed localization methods are shown in Fig.3 and Fig.4, respectively. Different to the traditional ANN or RBF neural network localization method, the proposed methods indirectly obtain the position estimate of MT. In offline stage, we first construct the nonlinear mapping between range measurements and range errors by ANN or RBF neural network. In online stage, when the range measurements with unknown position are obtained from different FTs, we can use the trained ANN or RBF

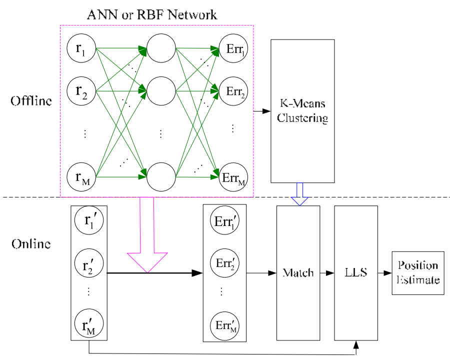

FIGURE 4. Method II: ANN or RBF + Match + LLS.

neural network to get the range error of each FT. If we subtract range errors from the range measurements, the adjusted range measurements are got. Then the position estimate of MT can be obtained with the adjusted range measurements by the LLS algorithm. That's the scheme of our proposed method I shown in Fig.3. Moreover, for each link between MT and FTs, it may experience LOS or NLOS signal propagation, which leads to different range error. Therefore, the training range errors in offline stage can be further classified. In online stage, this classification may be helpful to revise the predicted range error. That's the scheme of our proposed method II shown in Fig.4.

B. LLS ALGORITHM

Comparing with nonlinear least square algorithm, LLS algorithm is an efficient localization algorithm with low computational complexity [37]. If the adjusted range measurements $\hat{r}_i$ are obtained, we can set nonlinear range equations as follow

$$\hat{r}_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}, \quad i = 1, 2, \cdots, M \tag{7}$$

In order to obtain linear equations, we can cancel out the nonlinear terms in (7) by fixing one equation and subtracting it from the rest equations. A simple way to select this equation is to choose the smallest one among the adjusted range measurements. The index of the equation is given by [5], [37]

$$j = \arg\min_{i} \left\{\hat{r}_i\right\}, \quad i = 1, 2, \cdots, M \tag{8}$$

By doing some mathematical manipulation, the nonlinear range measurements in (7) can be transformed into linear equations

$$AX = P \tag{9}$$

where $X = [x, y]^T$

$$A = \begin{bmatrix} x_1 - x_j & y_1 - y_j \\ x_2 - x_j & y_2 - y_j \\ \vdots & \vdots \\ x_M - x_j & y_M - y_j \end{bmatrix}_{(M-1)\times 2},$$

$$P = \frac{1}{2}\begin{bmatrix} \hat{r}_k^2 - \hat{r}_1^2 - x_j^2 - y_j^2 + x_1^2 + y_1^2 \\ \hat{r}_k^2 - \hat{r}_2^2 - x_j^2 - y_j^2 + x_2^2 + y_2^2 \\ \vdots \\ \hat{r}_k^2 - \hat{r}_M^2 - x_j^2 - y_j^2 + x_M^2 + y_M^2 \end{bmatrix}_{(M-1)\times 1}$$

The least square solution for (9) can be written as

$$X = (A^T A)^{-1} A^T P \tag{10}$$

C. K-MEANS CLUSTERING AND MATCHING

Because K-mean clustering algorithm is simple to implement and effective in performance, it is used to classify the training range errors. In offline stage, given a set sample of range errors $\{Err(1), Err(2), \cdots, Err(N)\}$, where each sample is a M-dimensional vector, K-means clustering algorithm aims to partition the N samples into sets $\mathbf{S} = \{S_1, S_2, \cdots, S_K\}$. For each range measurement, its range error has two conditions LOS or NLOS. So the number of cluster is equal to $K = 2^M$. Given an initial set of K means $\mu_1^{(1)}, \mu_2^{(1)}, \cdots, \mu_K^{(1)}$, where each mean is a M-dimensional vector whose element is zero or the mean of NLOS error. The K-means clustering algorithm proceeds in two steps:

(1) Assignment step

Assign each sample $Err(p), p = 1, \ldots, N$ to the cluster $S_i, 1 \leq i \leq K$ whose mean has the smallest squared Euclidean distance, this is intuitively the nearest mean. It can mathematically be expressed as

$$S_i^{(t)} = \{Err(p) : \left\|Err(p) - \mu_i^{(t)}\right\|^2 \leq \left\|Err(p) - \mu_j^{(t)}\right\|^2 \forall j, \; 1 \leq j \leq K\}, \quad i = 1, \cdots, K$$

where t is the number of iteration and $t = 1$ is the initialization.

(2) Update step

When all the samples are assigned, the new means can be calculated to be the centroids of the samples in the new cluster

$$\mu_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{Err(j)\in S_i^{(t)}} Err(j)$$

The algorithm goes back and forth between these two steps and it has converged when no further change is happened in the cluster assignments. In the end, this algorithm outputs the set of K means $\mu_1, \mu_2, \cdots, \mu_K$.

In online stage, by using the ANN or RBF neural network, the range errors $Err' = [Err'_1, Err'_2, \cdots, Err'_M]^T$ can be predicted with the input of range measurements. We compare it with the output of K means μ_i and update the range errors as following

$$j = \arg\min_{1\leq i\leq K}\{\left\|Err' - \mu_i\right\|\}$$
$$Err' = \frac{1}{2}(Err' + \mu_j) \tag{11}$$

The position estimate of MT is obtained by LLS algorithm shown in section III.B with the updated range errors and corresponding adjusted range measurements.

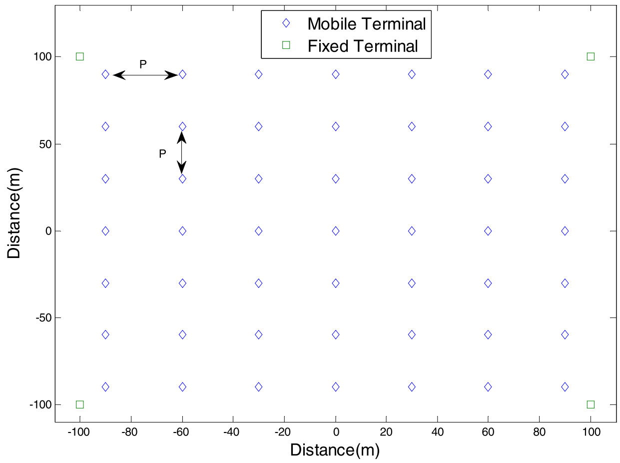

FIGURE 5. Layout of Simulation Setup.

IV. RESULTS AND DISCUSSION

A. PERFORMANCE COMPARISON

In order to train the ANN or RBF neural network, a wireless network containing 4 FTs and some grid MTs is arranged in a square area of 200m × 200m shown in Fig.5. The FTs are located at the edges of the squared area, while MTs are located inside the squared area with grid arrangement.

The range measurement model shown in section II.A is used to train the network and predict the range errors. Due to the unknown signal propagation environment about each link between MT and FTs, the NLOS error is randomly assigned to the range measurement model. The input layer contains the range measurement column vectors for every grid MT. Each range vector is composed of range measurement values obtained from all the FTs. The output layer contains the known position of the MTs or the range errors between MTs and FTs. The range errors can be computed by subtracting true distances from range measurements. Two important parameters denoted as T and P significantly affect the performance of the training ANN and RBF neural network, where T is the number of range measurement about each MT and P is the adjacent distance between MTs shown in Fig.5. We set $\sigma_{\text{los}} = 2m$, $e_i \sim$ U(0, 20) and $\varepsilon = 0$ in (1), table.1 shows the different types of location error with different combinations about T and P. For RBF neural network, the direct mapping relationship between range measurements and position of MT is not a feasible localization scheme when the NLOS error with random assignment is present. Formulation of RBF neural network shown in section II.C is based on interpolation theory. Unfortunately, the use of interpolation based on noise data could lead to misleading results [38]. Due to the range measurement noise and NLOS error as well as the unknown propagation condition, the range measurements fluctuate heavily for different position of MT. Therefore, incorrect position estimate is happened by utilizing RBF neural network. The ideas applied to RBF neural network can remarkably improve the localization accuracy, and the proposed method II has higher localization accuracy than the proposed method I. However, they easily fluctuate with the change of parameters and don't show regular change. For ANN, ANN localization method can adapt to the random NLOS error and achieve comparatively high localization accuracy, especially when the training sample is adequate enough. Unlike the case of RBF neural network, the training of ANN is achieved by the back-propagation algorithm rather than interpolation. As a general rule, every training sample presented to the back-propagation algorithm should be chosen on the basis that its information content is the largest possible for the task [38]. Due to the radically different range measurements from different position of MT, the back-propagation algorithm can search more of the weight and bias space. Therefore, ANN-based localization is suited for our localization model. However, as the value of P increases, the localization error of ANN increases. It means that the performance of ANN localization method degrades when the training sample is reduced. In addition, as the value of T increases, the training sample also increases, but it has little improvement in terms of average location error. When the training sample is not adequate, the proposed method II has the highest localization accuracy, followed by the proposed method I and then ANN. As the training sample increases, these three methods perform nearly the similar localization performance. Comparing RBF neural network with ANN, most of the time, we see that ANN-based localization methods have higher localization accuracy than RBF-based ones when the NLOS error with random assignment is existed.

TABLE 1. The Location Error with different parameter for different algorithms.

T	P	Location Error (m)	RBF	RBF+ LLS	RBF+ Match+ LLS	ANN	ANN+ LLS	ANN+ Match+ LLS
5	10m	Min	5.67	0.78	0.33	0.23	0.28	0.22
		Max	195.1	31.73	27.16	22.79	20.25	20.69
		Ave	91.77	12.90	8.49	6.90	6.64	6.73
5	30m	Min	3.10	0.50	0.37	0.31	0.11	0.09
		Max	241.8	28.42	22.38	23.18	18.01	17.36
		Ave	124.7	14.11	9.20	7.25	6.77	6.62
5	50m	Min	3.36	0.26	0.22	0.07	0.19	0.33
		Max	191.2	23.25	21.28	31.21	37.95	25.0
		Ave	92.56	9.19	7.37	9.70	8.41	7.00
10	10m	Min	3.10	0.58	0.24	0.12	0.18	0.34
		Max	228.9	24.30	20.90	17.78	16.82	17.10
		Ave	116.9	9.07	7.64	6.62	6.49	6.53
10	30m	Min	0.89	0.36	0.07	0.10	0.10	0.04
		Max	186.0	27.22	23.32	19.86	18.74	17.97
		Ave	91.60	9.14	7.53	7.02	6.48	6.46
10	50m	Min	2.24	0.76	0.04	0.10	0.04	0.04
		Max	220.7	29.63	25.23	36.71	24.43	20.50
		Ave	103.7	12.23	8.53	10.92	7.68	6.99

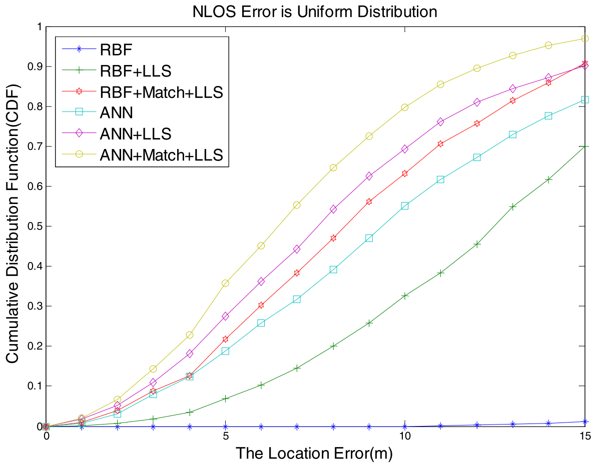

FIGURE 6. The CDF of location error when NLOS error is uniform distribution $e_i \sim U(0, 20)$.

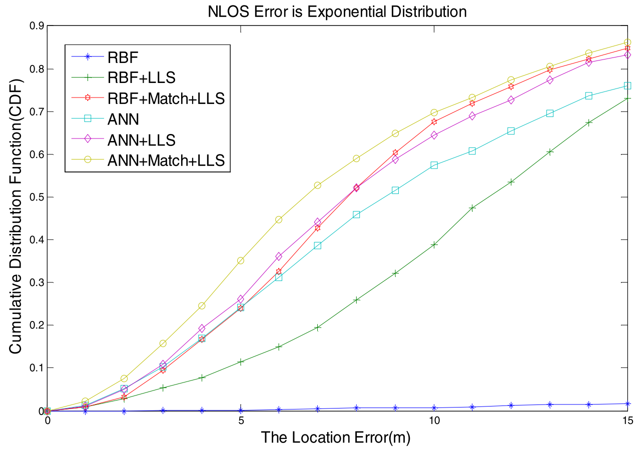

FIGURE 7. The CDF of location error when NLOS error is exponential distribution $e_i \sim E(10)$.

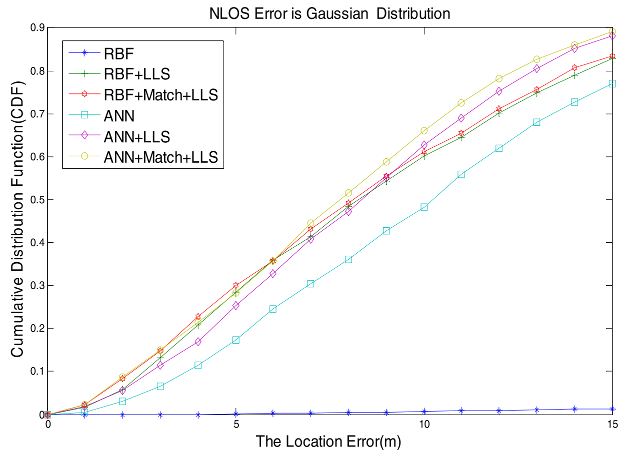

FIGURE 8. The CDF of location error when NLOS error is Gaussian distribution$e_i \sim N(10, 100)$.

We first compare the performance of the different neural network localization methods. From Fig.6 to Fig.8, they show the cumulative distribution function (CDF) of different methods' location error with three different NLOS error distribution. The results are obtained by setting $P = 50$, $T = 5, \sigma_{\rm los} = 2$, and $\varepsilon = 0$. For different NLOS error distribution, the CDF curves show that the location errors of our proposed methods are smaller than ANN and RBF neural network methods, and the proposed method II is better than the proposed method I. In our simulation, the mean of the NLOS error with different distribution is the same. The variance of the NLOS error with exponential distribution is the same as Gaussian distribution, while the variance of uniform distribution is the smallest. Therefore, from Fig.6 to Fig.8, we know that the location error with exponential or Gaussian distribution is higher than uniform distribution. Taking the ANN + Match + LLS algorithm as an example, the 80% location error is less than 10m when the NLOS error is uniform distribution, while the 70% location error is less than 10m when NLOS error is exponential or Gaussian distribution. Location-based service (LBS) is usually achieved through cellular network or assisted global navigation satellite systems (A-GNSS) due to widespread use of cellphone. At present, the 67% location error is less than 50m for cellular network, while it is less than 10m for A-GNSS [39]. Therefore, our proposed neural network localization method is suited for the application of LBS due to the high localization accuracy.

We then examine the effect of different parameters, i.e. the standard deviation of range measurement σ, the NLOS error e, and the synchronization error ε, on the accuracy of different localization methods. Due to the large location error about the RBF neural network localization method, it is not used as a comparison. Average location errors (ALEs) is chosen as the performance criteria, which is defined as

$$ALEs = \frac{1}{1000}\sum_{i=1}^{1000}\sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2} \tag{12}$$

where the position of MT (x_i, y_i) is randomly generated inside the square area shown in Fig.5, $(\hat{x}_i, \hat{y}_i)$ is the estimated position of MT.

The simulation parameters are set as $P = 30$, $T = 5$, $\sigma = 2$ and $\varepsilon = 0$, respectively. Fig.9-Fig.11 depict the effect of σ on the localization accuracy with different NLOS error distribution. It is easy to see that, most of time, ALEs of ANN-based methods increase as σ gets larger, while ALEs of RBF-based methods fluctuate greatly. Besides, the ALEs of the proposed methods are smaller than ANN, and the proposed method II is better than the proposed method I. Fig.12-Fig.14 show the effect of NLOS error on the localization accuracy with different NLOS error distribution. As the mean of NLOS error increases, ALEs get higher. But the ALEs do not increase linearly as the mean of NLOS error. For ANN + Match + LLS algorithm, when the mean of NLOS error increases 10m, ALE only increases about 7-8m. This demonstrates that the proposed methods can remarkably reduce the effect of NLOS error. As expected, the proposed methods have better performance, and the proposed method II

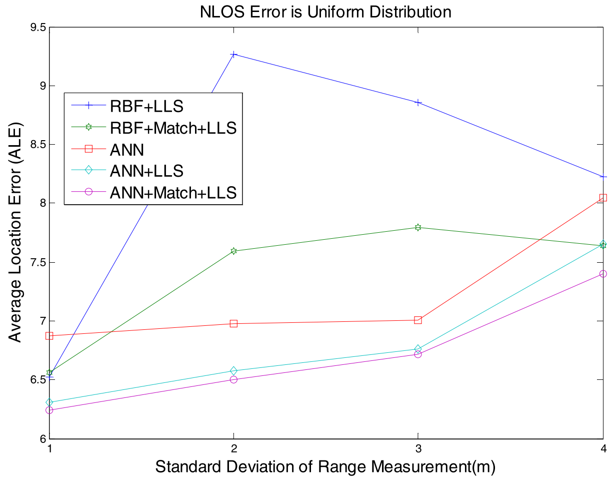

FIGURE 9. The ALE VS standard deviation of range measurement with uniform distribution $e_i \sim U(0, 20)$.

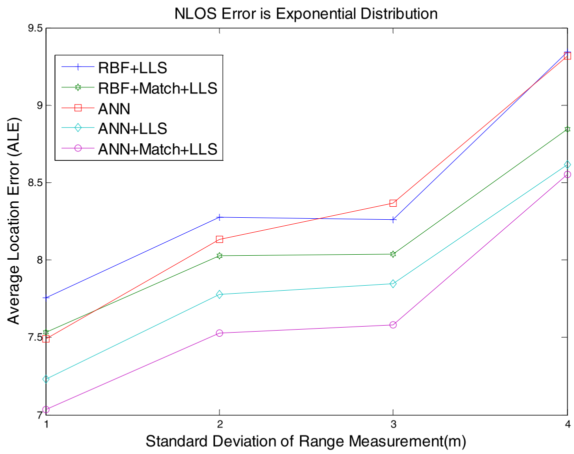

FIGURE 10. The ALE VS standard deviation of range measurement with exponential distribution $e_i \sim E(10)$.

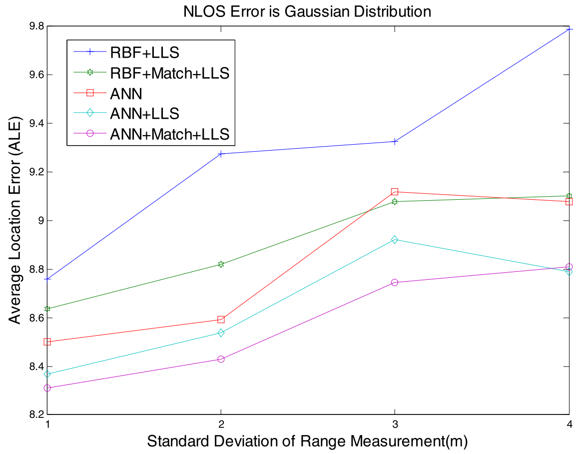

FIGURE 11. The ALE VS standard deviation of range measurement with Gaussian distribution $e_i \sim N(10, 100)$.

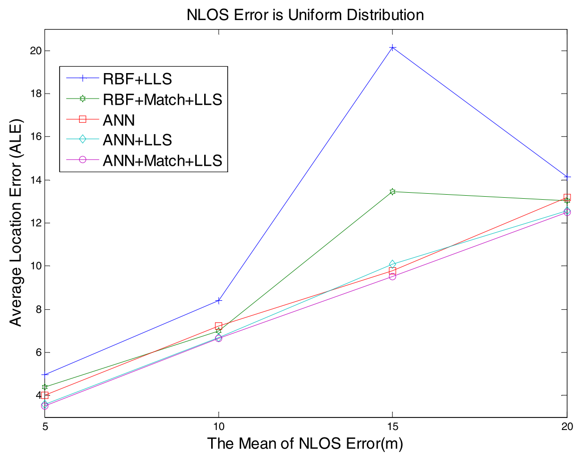

FIGURE 12. The ALE VS the mean of NLOS error with uniform distribution.

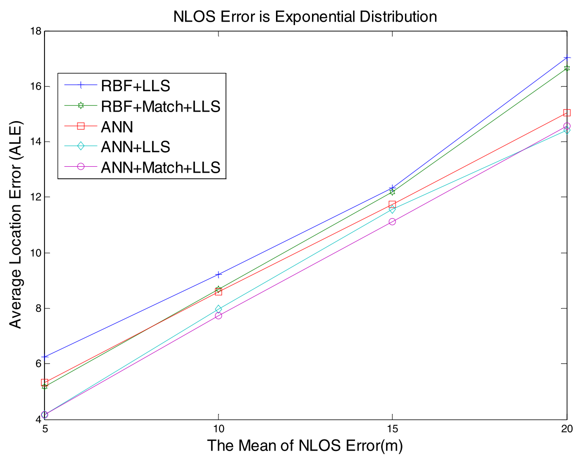

FIGURE 13. The ALE VS the mean of NLOS error with exponential distribution.

is superior to the proposed method I. Fig.15-Fig.17 show the effect of synchronization error on the localization accuracy with different NLOS error distribution. It is shown that the ALEs of RBF-based localization methods fluctuate greatly as the increase of ε, but ALEs of ANN-based localization methods almost have no change. Therefore, the synchronization error has little effect on ANN-based localization methods. The same conclusion can be also obtained that the proposed method II has the highest localization accuracy, followed by the proposed method I and then ANN.

B. ALGORITHM COMPARISON

The memory requirement in offline stage and computational complexity in online stage are chosen as the criteria of algorithm comparison. In the following expressions for algorithm comparison, M is the number of neurons in input layer, N is the number of training samples, and K is the number of clusters. In offline stage, some trained parameters are used to predict the output. So these parameters need to be saved.

The memory requirement of ANN or RBF neural network as compared to the proposed methods is described in table.2. Clearly ANN has the least memory requirement, and the large number of neurons in hidden layer results in the increased

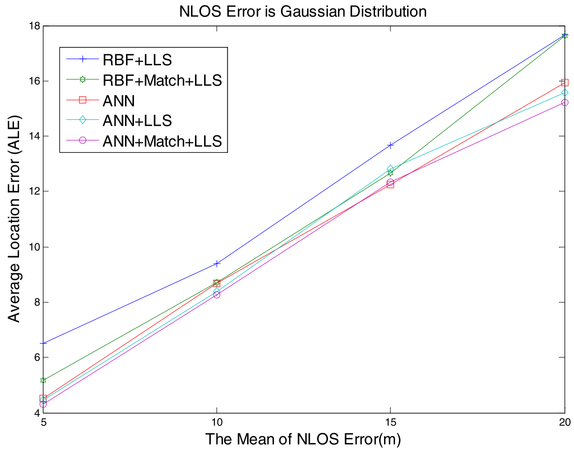

FIGURE 14. The ALE VS the mean of NLOS error with Gaussian distribution.

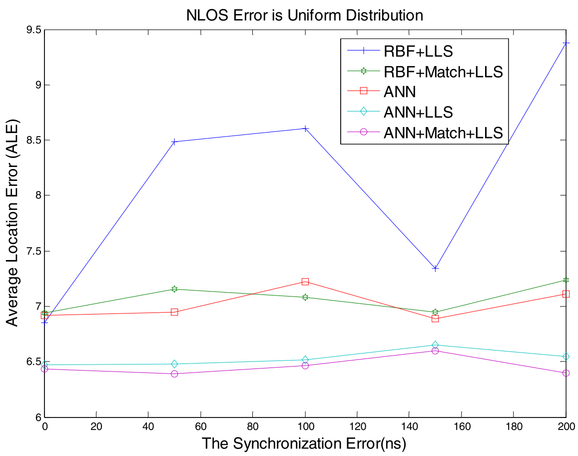

FIGURE 15. The ALE VS the synchronization error with uniform distribution $e_i \sim U(0, 20)$.

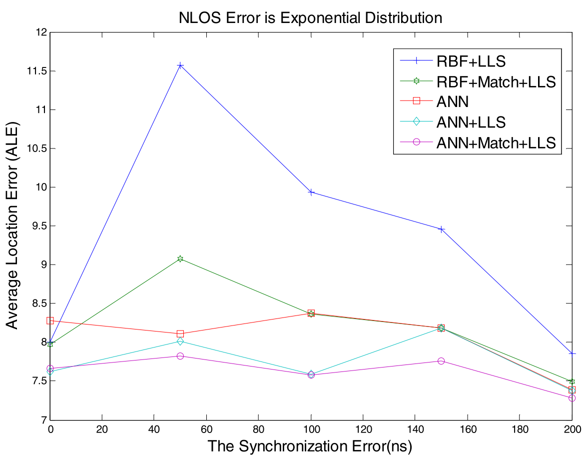

FIGURE 16. The ALE VS the synchronization error with exponential distribution $e_i \sim E(10)$.

memory requirement for the RBF neural network. It is easy to see that RBF neural network has more memory requirement than ANN. In addition, for ANN, the proposed method II has the highest memory requirement, followed by the proposed

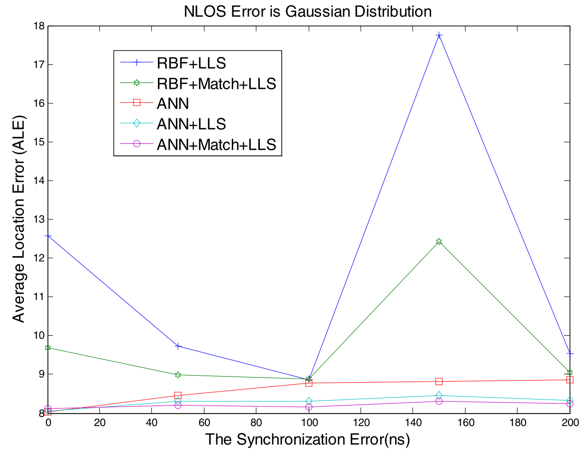

FIGURE 17. The ALE VS the synchronization error with Gaussian distribution $e_i \sim N(10, 100)$.

TABLE 2. Comparison of memory requirement among different localization methods.

Method	Memory Requirement
ANN	$M^2 + 3M + 2$
ANN+LLS	$2M^2 + 2M$
ANN+Match+LLS	$2M^2 + 2M + KM$
RBF	NM + 2N
RBF+LLS	2NM
RBF+ Match+LLS	2NM + KM

method I and then ANN. The same conclusion can be also obtained for RBF neural network.

In online stage, the computational complexities of different neural network localization methods are investigated. The number of multiplications and additions required in the computation of different localization methods are provided in table.3. In order to better understand these results, we take the proposed method II (ANN + Match + LLS) as an example to explain. To be specific, from input layer to output layer for ANN, the neurons in different layer are the same, the number of multiplications is the same as the number of additions whose value is $2M^2$. For each centroid of cluster, the matching procedure does M multiplications and M − 1 additions. It is assumed that the comparison operation in (11) is equivalent with addition operation. So the total number of multiplications is the same as the number of additions whose value is KM + M in matching and updating step. The final step is the LLS procedure. It first needs M additions to transform the range measurements into the adjusted measurements. Then constructing the matrix A and P in (9) needs 3M multiplications and 7M − 7 additions. In addition, the matrix operation in (10) needs 6M − 2 multiplications and 6M − 10 additions. It is shown in [40] that 6 multiplications and 4 additions are needed for performing the matrix inverse operation with the Gaussian elimination method. Thus, the LLS algorithm needs 9M + 4 multiplications and 14M − 13 additions

TABLE 3. Comparison of computational complexity among different localization methods.

Method	Number of Multiplications	Number of additions	Total	Complexity
ANN	M^2+2M	M^2+2M	$2M^2+4M$	$O(2M^2)$
ANN+LLS	$2M^2+9M+4$	$2M^2+14M-13$	$4M^2+23M-9$	$O(4M^2)$
ANN+Match+LLS	$2M^2+KM+10M+4$	$2M^2+KM+15M-13$	$4M^2+2KM+25M-9$	$O(4M^2+2KM)$
RBF	$NM+2N$	$2NM+N-2$	$3NM+3N-2$	$O(3NM)$
RBF+LLS	$2NM+9M+4$	$3NM-N+13M-13$	$5NM-N+22M-9$	$O(5NM)$
RBF+ Match+LLS	$2NM+KM+10M+4$	$3NM+KM-N+14M-13$	$5NM+2KM-N+24M-9$	$O(5NM+2KM)$

in total. From the above discussion, the total number of multiplications and additions for ANN + Match + LLS are shown in table.3. We can also easily get the results of other methods with the same analysis. From table.3, we see that the proposed method II has the highest computational complexity, followed by the proposed method I and then ANN or RBF neural network.

V. CONCLUSION

In this paper, unlike the traditional neural network localization methods, the NLOS error and synchronization error are introduced, and the mapping relationship between range measurements and range errors is formulated. Then LLS algorithm or together with clustering technique is applied to obtain the position estimate of MT. Thus, two new neural network localization methods based on the error learning and matching are proposed. Simulation results and algorithm comparison show that 1) Due to high memory requirement and computational complexity as well as bad location error, RBF-based localization method is not suited for the scenario when the NLOS error with random assignment and synchronization error are present. 2) The 70%-80% location error of our proposed method II is less than 10m. Comparing with ANN, the localization accuracy is improved more than 0.5 m. In addition, the proposed method II is better than the proposed method I, especially when the training sample is not adequate. But this improvement is slightly at the cost of high memory requirement and computational complexity. 3) The standard deviation of range measurement, synchronization error and different NLOS error distribution have little effect on the ANN-based localization method. But the RBF-based localization methods easily fluctuate by these parameters. 4) As the mean or variance of NLOS error increases, the performance of all the algorithms degrades. Although the simulation results can prove the effectiveness of our proposed localization methods, experiment results are more convinced. Due to the limitation of experimental condition, it is not possible at present. However, the advantages of our proposed methods make them very appealing to practical applications in different indoor and outdoor environments.

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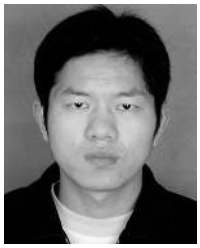

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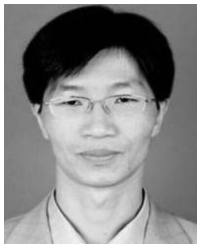

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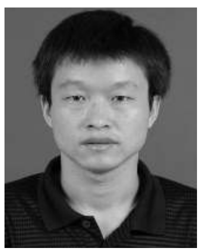

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