Probabilistic Neural Network For RSS-Based Collaborative Localization

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***Abstract*—One critical challenge for accurate localization with Received Signal Strength Indicator (RSSI) is the anisotropic environment, which causes the RSS-Distance Relationship (RDR) to vary spatially. To alleviate localization error caused by RDR anisotropy, most of existing works adopt multiple RDR algorithms. However, we have found that the arbitrary RDR selection in these algorithms can lead to large localization error. Moreover, localization accuracy can be further enhanced by utilizing information provided by more Access Points (APs). To address these problems, we propose a Probabilistic Neural Network based localization algorithm in this paper. The algorithm features two steps: Global Optimization and Regional Compensation, during which all APs exchange information about the Blind Node (BN) to locate it collaboratively. Simulation result shows that the proposed algorithm can achieve a localization accuracy 35% higher than that of multiple RDR algorithms.**

I. Introduction

Localization for Wireless Sensor Network (WSN) has become a research hot topic recently. The locations of nodes are important reference for data processing and Location Based Service (LBS). Existing localization schemes can be summarized into two categories: range-free and range-based, with the latter achieving higher accuracy. In the range-based schemes, various ranging methods have been proposed, among which the Received Signal Strength Indicator (RSSI) has been proven to be the best choice, for its virtue of low power consumption and low implementation cost.

Most RSSI-based localization systems estimate distances between Blind Node (BN) and Access Points (APs) according to an RSS-Distance Relationship (RDR). After the distances have been measured, the location of BN can be calculated with triangulation procedures [1] or probabilistic procedures (e.g. Multi-Dimensional Scaling, Maximum Likehood Estimator [2]). Hence, if a high localization accuracy is required, the RDR should be precisely captured. However, the difficulty of capturing RDR lies in the fact that instead of being identical in every direction, it varies all over the deployment area. Such anisotropy of RDR is caused by the *anisotropic environment* [3,4], where RDR is affected by multi-path effect and Non-Line-Of-Sight propagation.

To approximate RDR in an anisotropic environment, the optimal approach is to pre-establish a *fingerprint database* [5], which is comprised of signal strength/signal noise ratio data manually collected or theoretically calculated at possible BN locations during an off-line phase. While in the on-line phase, locating the BN becomes a multi-dimensional matching problem: the RSS measurements are matched with the registered entries in the fingerprint database with matching algorithms (e.g. Nearest Neighbor in Signal Space [6]). The higher fingerprint dimension is adopted, the more accurate localization results can be obtained. However, this fingerprint-based approach requires huge human labor in establishing and maintaining the fingerprints. To reduce human involvement, lots of existing works [7-9] aim to develop algorithms that could perform unsupervised on-line RDR calibration. In many algorithms, the basis for such on-line calibration is the cross AP RSS measurements, which can be utilized to estimate distance between APs. Since the location of APs is usually known a priori, the accuracy of estimated cross AP distance can be evaluated as a metric of the preciseness of RDR. Many existing algorithms focus on deriving a single RDR that can minimize the overall localization error of all APs, assuming the RDR generated in this manner will also be able to minimize the localization error of BNs.

Unfortunately, such assumption is invalid when it comes to anisotropic environments, where a single RDR will not be precise enough to give accurate distance estimation over the whole deployment area. To address this problem, a heuristic manner named *Proximity in Signal Space* (PSS) is proposed in [10], where multiple RDRs are established and exploited. In PSS, RDRs are established between each AP and all its adjacent APs. Each RDR is so generated that it minimizes the error in estimation of distance between its associated APs. When estimating the distance between BN and a certain AP, only the RDR associated with the AP nearest to BN in signal space will be chosen to perform distance estimation. Although PSS and other similar multiple-RDR algorithms improve localization accuracy to some extent, they discard valuable information obtained from other APs near the BN, by choosing only one RDR for distance estimation. Moreover, in some cases this arbitrarily chosen RDR can be an inappropriate one, leading to large localization error.

To address the problems mentioned above, we propose a Probabilistic Neural Network (PNN) based collaborative localization scheme in this paper. The introduction of PNN allows our algorithm to fully utilize the information provided by all APs, and remove the risk of choosing inappropriate RDR. In

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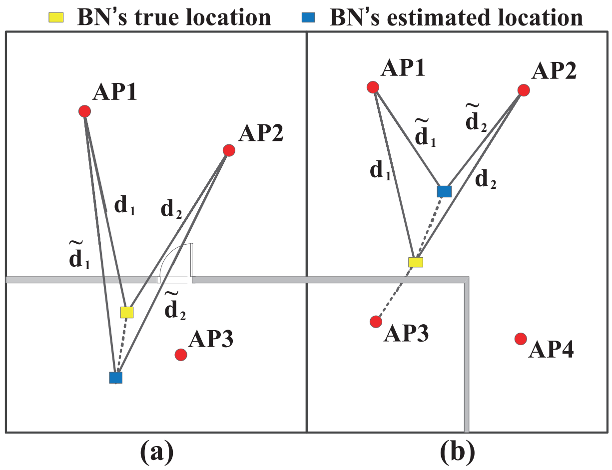

Fig.1 Typical Anisotropic Environment.

order to guarantee system real-time capability, the computational complexity of our neural network is reduced through adopting Exact Training Method [11]. In the simulation, our algorithm shows an enhanced capability to precisely capture the RDR and achieve improved localization performance.

The rest of this paper is organized as follows: Section II analyzes the special problem introduced by anisotropic environments. In section III we illustrate our algorithm in detail. Simulation results and associated analysis are presented in section IV. Section V concludes this paper.

II. Anisotropic Environment

In this section, we analyze the problems localization systems can encounter in an anisotropic environment. As discussed in the last section, most systems depend on RDR for distance estimation. The most widely adopted RDR is as follows [5]

$$P_d[dBm] = P_{d_0} - 10\alpha log(\frac{d}{d_0}) + X_\sigma, \tag{1}$$

where P_{d_0} is the transmission power at distance d_0, α is the propagation attenuation factor, and X_σ stands for a Gaussian noise with standard deviation σ, which is usually assumed removable with proper filtering techniques. We can see that Eq.(1) describes a non-linear function $P = f(d)$ with only one variable d. However, in anisotropic environments, the real-world RDR should be $P = f(x, y, n)$, where (x, y) is the coordinate of BN, and n is the number of the AP the RDR is associated with.

Fig.1 shows two typical anisotropic environments with ordinary obstacles. In the environment shown in Fig.1(a), one BN is being located by three APs. The deployment area is divided into two parts by a wall, with the BN and AP3 on the bottom side, AP1 and AP2 on the top side. Let $\mathbf{R}= (\mathrm{rss}_1, \mathrm{rss}_2, \mathrm{rss}_3)$ denote signal strength of BN measured by the three APs. If we use Eq.(1) to estimate the distance between BN and the APs, i.e. $\tilde{\mathbf{D}}= (\tilde{\mathrm{d}}_1, \tilde{\mathrm{d}}_2, \tilde{\mathrm{d}}_3)$, the deviation in distance estimation denoted as $\Delta\mathbf{D}= (\mathrm{d}_1, \mathrm{d}_2, \mathrm{d}_3) - (\tilde{\mathrm{d}}_1, \tilde{\mathrm{d}}_2, \tilde{\mathrm{d}}_3)$ will be large, especially for $\Delta\mathbf{D}_1$ and $\Delta\mathbf{D}_2$. This is because the attenuation caused by wall is not considered in Eq.(1), which causes $\tilde{d}_1$ and $\tilde{d}_2$ to be much larger than their actual values.

Such deviation can be reduced by including the influence of obstacles into RDR, when the obstacles' distribution is known beforehand. However, detailed map of surroundings is not available in most WSN application scenarios. Hence the best approach to alleviate obstacles' influence is to utilize cross AP RSS measurements. Let RSS_{ij} denote the measured RSS between APi and APj, then for a scenario with N APs, we can obtain the cross AP RSS matrix $\mathbf{RSS}= [\mathrm{RSS_{ij}}]$ $i, j \in [1, N]$. The ith column of the cross AP RSS matrix stands for the received signal strength of the ith AP at all APs (The diagonal elements of the matrix, i.e. self RSS, are set to be zero). Meanwhile, because the coordinates of APs are known a priori, we can calculate the theoretical cross AP RSS matrix $\widetilde{\mathbf{RSS}}= [\widetilde{\mathrm{RSS_{ij}}}]$ $i, j \in [1, N]$. If $\widetilde{\mathbf{RSS}}$ deviate largely from $\mathbf{RSS}$ in all columns, then it's likely that the deviation is caused by inaccurate parameters in RDRs. However, if large deviation appear only in several columns, it's more likely that the source of deviation is the anisotropic environment.

After the source of deviation is identified, calibration can be performed accordingly. To calibrate the deviation caused by anisotropic environment, multiple RDR solutions like PSS can be adopted as discussed in the last section. However, the RDR selection step in PSS will lead to inevitable loss of valuable network information, and in some cases choosing an RDR arbitrarily may cause large deviation. Let us consider the scenario shown in Fig.1(b), where the BN is being located by four APs. Let RDR_{ij} denote the RDR associated with APi and APj. When estimating d_1 and d_2, the PSS will refer to RDR_{13} and RDR_{23}, because the BN is closest to AP3 in signal space. However, as the propagation path between AP$1, 2$ and AP3 is blocked by wall, RDR_{13} and RDR_{23} will have large attenuation factor in Eq.(1). Although RDR_{13} and RDR_{23} can minimize localization error of AP3, they unfortunately cause $\tilde{d}_1$ and $\tilde{d}_2$ to be much smaller than their actual value. The chosen RDR is also likely to be unprecise when APs are all far from the BN. Moreover, when there are several APs near the BN, PSS cannot fully exploit the information provided by these APs. In situation shown in Fig.1(b), the information provided by AP4 is lost, because its associated RDRs aren't considered.

To address the problems mentioned above, we present a Probabilistic Neural Network based localization scheme in this paper. The proposed scheme presents several desirable features. First, the algorithm is calibration-free, which means no human involvement is needed. Second, the calibration is performed collaboratively with information of all APs near the BN considered, thus removing the deviation caused by loss of information and arbitrarily chosen RDR.

III. Probabilistic Neural Network based Localization

In this section, we present Probabilistic Neural Network based localization approach that can alleviate the influence of anisotropic environment. The structure of proposed neural network is illustrated in Fig.2. In our client-based scheme, the localization process include two phases. The first phase starts with the blind node broadcasting a beacon signal, then the APs receive and measure the strength of the beacon signal. In the second phase, those APs that have received the beacon signal perform cross AP RSS measurements. All the measured RSS data will be sent to a localization server to be further processed. If a centralized localization server is not available, sink nodes can function as servers instead, because the algorithm's computational cost is actually low.

Given a localization system that includes N Access Points (AP), we denote the RSS vector of the BN with

$$\mathbf{rss} = (\mathrm{rss_1}, \mathrm{rss_2}, ..., \mathrm{rss_N}),$$

where rss_i stands for the signal strength of beacon signal received by the ith AP. The received signal strength is measured by dBm. Similarly we define the RSS vector for the ith AP as follows

$$\mathbf{RSS_i} = (\mathrm{RSS_{i1}}, \mathrm{RSS_{i2}}, ..., \mathrm{RSS_{iN}}).$$

All RSS vectors of AP will form the $N \times N$ cross AP RSS matrix $\mathbf{RSS} = [\mathbf{RSS_i}]\ i \in [1, N]$.

Our proposed algorithm locates the BN at the localization server with two steps, the Global Optimization and the Regional Compensation. The two steps are presented in the following subsections.

A. Global Optimization

During this step, the task is to derive a single global optimal RDR in least mean square sense.

As the locations of APs are known in advance, we can derive the cross distance matrix of all APs

$$\mathbf{D} = [\mathrm{d_{ij}}],$$

where $d_{ij}\ i, j \in [1, N]$ denotes the distance between the ith and jth AP.

First,we define *linearizing function* $L(d_{ij}) = log(d_{ij})$ and gain

$$RSS[dBm] = P_0 - 10\alpha L(\frac{d}{d_0}). \tag{2}$$

Thus a linear *RSS-L(d)* relationship is established, with which we can easily calculate α and P_0 in a *Least Mean Square Error* sense by the following equation,

$$A^T A \begin{bmatrix} P_0 \\ \alpha \end{bmatrix} = A^T v. \tag{3}$$

$$A = \begin{bmatrix} 1 & -10L(\frac{d_{12}}{d_0}) \\ 1 & -10L(\frac{d_{13}}{d_0}) \\ \vdots & \vdots \\ 1 & -10L(\frac{d_{N-1,N}}{d_0}) \end{bmatrix} v = \begin{bmatrix} RSS_{12} \\ RSS_{13} \\ \vdots \\ RSS_{N,N-1} \end{bmatrix}$$

However, such a LMSE RDR cannot eliminate the deviations introduced by anisotropic environment. To achieve better accuracy, regional compensation should be performed.

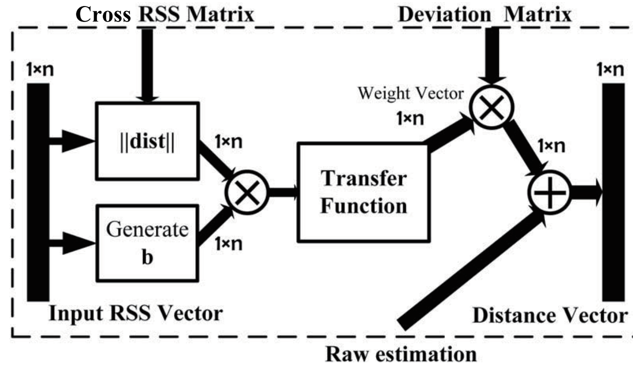

Fig.2 Adopted Probabilistic Neural Network.

B. Regional Compensation

We introduce the Regional Compensation to calibrate the raw distance estimation given by the global RDR. Our calibration is based on the rationale that nodes close to each other geographically will be affected by the environment in a similar manner. Since the locations of APs are known a priori, we will be able to model the deviation pattern near APs and counteract these deviations when the BN to be located is near the APs.

To complete the calibration, we first need to model the deviations near the APs. With the calculated global RDR and cross AP RSS matrix we can obtain the estimated cross AP distance matrix $\tilde{\mathbf{D}}$. Then the we calculate the *deviation matrix* $\Delta\mathbf{D}$ as follows

$$\Delta\mathbf{D} = \mathbf{D} - \tilde{\mathbf{D}}, \tag{4}$$

where the ith column contains the distance estimation error of the ith AP. When BN is near one or several AP(s), it is reasonable to infer that the raw distance estimation of BN will have same deviations. However, how to counteract such deviations properly is still a key problem, inappropriate strategies may lead to reverse effect as discussed in Section II. To address this problem, we present a calibration strategy based on Probabilistic Neural Network.

Probabilistic Neural Network (PNN) is a type of Radial Basis Function Neural Network (RBFNN) based on Bayes strategy for pattern recognition. In this paper, we adopt PNN to generate a *Weight Vector*, the elements of which reflect the effect of the associated AP's deviation upon the distance estimation of BN. Compared with multi RDR approaches, our proposed strategy is more appropriate because it considers the deviation of all the APs that are close to BN. And when BN is far from all APs, our strategy can suppress the calibration by assigning low weight to all APs instead of mistakenly calibrating the BN's estimation. Furthermore, among all neural networks for pattern recognition we choose PNN to perform on-line adaptive calibration, because of its low-complexity and instantaneous training method, which is called the Exact Training Method (ETM) [12]. The ETM adopts training samples as center vectors of the hidden layer directly, thus achieving instantaneous learning of new samples. However, when the number of training samples increases, the computational cost also increases, which leads to loss in real-time performance of the system. Such a problem does not exist in our system, because it discards prior samples when new cross AP RSS measurement is taken.

In our application scenario, the training sample for the PNN is the RSS vectors of the APs, extracted from the cross AP RSS matrix $\mathbf{RSS}$. After training the PNN with ETM, the RSS vector of BN $\mathbf{rss}$ can be inputted. PNN will calculate the Euclidean distance between APs and the BN in signal space and store the results in a $1 \times N$ vector $\mathbf{dist_i}$.

$$\mathbf{dist_i} = \|\mathbf{rss} - \mathbf{RSS_i}\|. \tag{5}$$

Subsequently, the signal distance vector will be multiplied with a bias vector $\mathbf{b}$ to gain the dot product M_i, which will be a metric for the geographic distance between BN and the ith AP. The elements in bias vector is generated according to the following rule,

$$b^j = \begin{cases} 0.3 & \mathbf{RSS_{ij}} \geq -60\text{dBm} \\ 1.5 & \mathbf{RSS_{ij}} < -60\text{dBm} \end{cases}. \tag{6}$$

Such dot product will be calculated respectively for each AP, forming a $1 \times N$ vector $\mathbf{M}$, which will be sent to the Radial Basis Function to calculate the Weight Vector $\mathbf{w}$

$$w_i = e^{\frac{(M_i-\mu)^2}{2\sigma^2}}, \tag{7}$$

where $\mu = 0$, and σ is set to fit the specific scenarios. The elements in the weight vector $w_i \in [0, 1]$ indicate the graphic closeness of BN to the associated AP. If w_i is close to 1, then APi is near BN, which means the raw distance estimation of BN is affected more by the deviation modeled at APi. Hence, we calibrate the raw estimation $\tilde{\mathbf{d}}$ obtained with $\mathbf{rss}$ and the global RDR by the following equation

$$\mathbf{d} = \tilde{\mathbf{d}} + \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{w_i} \mathbf{\Delta D_i}. \tag{8}$$

To elaborate our algorithm more clearly, we present the following pseudo codes.

Algorithm 1 Global Optimization.

- Calculate the cross AP distance matrix $\mathbf{D}$ with locations of APs (known a priori).
- Measure the RSS vector of BN: $\mathbf{rss}$.
- Measure mutual AP RSS and obtain the cross AP RSS matrix: $\mathbf{RSS}$.

for $i = 1$ to N **do**
  for $j = i + 1$ to N **do**
    - Generate the $i + j$th row of A: $[1, log(\frac{d_{ij}}{d_0})]$.
    - Generate the $i + j$th element of v: RSS_{ij}.
  end for
end for

- Calculate α and P_0 according to Eq.(3).

Algorithm 2 Regional Compensation.

- Calculate the estimated cross AP distance matrix $\tilde{\mathbf{D}}$ with $\mathbf{RSS}$ and the global RDR gained in global optimization.
- Generate the deviation matrix $\mathbf{\Delta D}$ with Eq.(4).

for $i = 1$ to N **do**
  - Calculate the signal distance vector $\mathbf{dist_i}$ with Eq.(5).
  - Generate the bias vector $\mathbf{b}$ for $\mathbf{RSS_i}$ with Eq.(6).
  - Obtain w_i according to Eq.(7).
  - Calculate M_i by $M_i = \mathbf{b} \bullet \mathbf{dist_i}$.

end for

- Calculate the estimated distance vector $\tilde{\mathbf{d}}$ according to RDR and $\mathbf{rss}$.
- Calibrate $\tilde{\mathbf{d}}$ with Eq.(8).

IV. Simulation Results

We construct a virtual 30×40m anisotropic environment for simulation. The anisotropy is introduced by the obstacles (walls) in the area. In the simulation, we assume that $P_0 = -45dBm$, $\alpha = 2.6$ and the zero-mean Gaussian noise X_σ in Eq.(1) has a standard deviation of $3dBm$. If the propagation path is block by a wall, a path loss factor $L = N(7, 1)$ will be added. As in most WSN application scenarios, nodes are scattered randomly in the deployment area. Among all these 110 nodes, ten are assumed to be equipped with GPS modules, which will serve as the APs in this network.

When locating a BN, we firstly estimate the distance between the BN and all APs. The estimation process is carried out by our proposed algorithm and a typical multiple RDR algorithm (PSS) respectively. In our algorithm, the σ in Eq.(7) is set to be 8 and the α derived by the global optimization is 3.2. While measuring one RSS value, ten single measurements are filtered with a median filter to gain the final RSS. After the distances are obtained according to specific algorithms, we calculate the location of the BN through triangulation approach with the measured RSS at four APs that are closest to the BN.

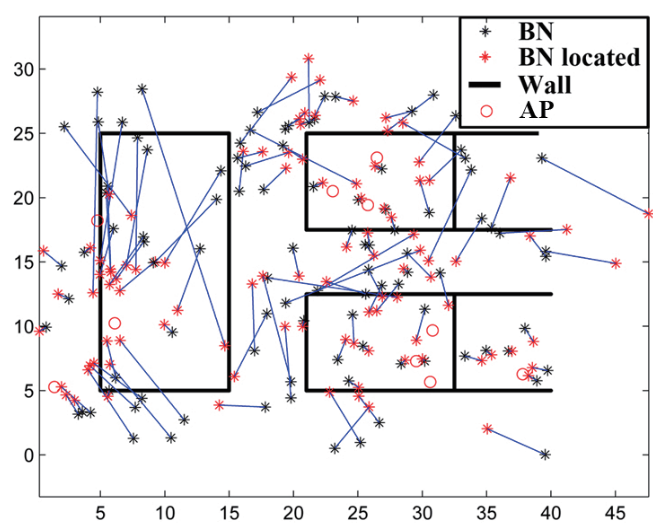

Fig.3 Localization result of PSS.

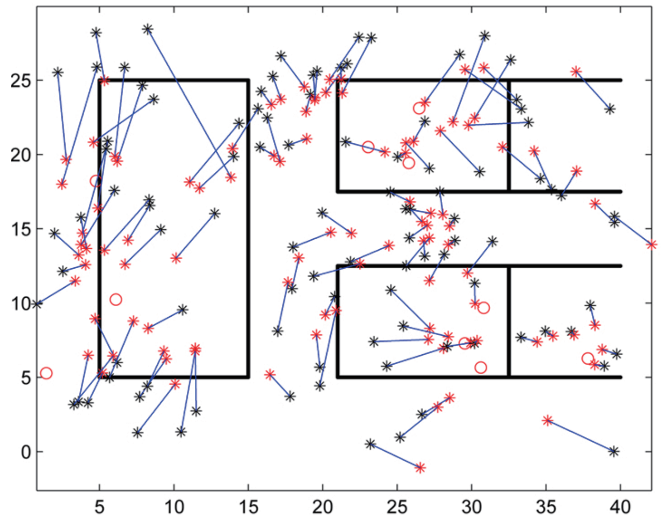

Fig.4 Localization result of PNN.

The localization results of PSS and our proposed algorithm are shown in Fig.(3) and Fig.(4), respectively. It can be seen that the deviations from the true locations are significantly alleviated with our algorithm. This is because when BN is close to several APs, our algorithm can include all these APs into the calibration procedure and achieve more effective calibration. Meanwhile, when BN is far from all APs, the distance vector of BN is estimated mainly according to the global optimal RDR instead of RDR only related to some specific APs. To illustrate the superiority of our algorithm, we present the Cumulative Distribution Functions (CDF) of the two algorithms' localization error in Fig.(5).

We can see that the localization error of our PNN algorithm is within about 4m when the confidence level is 80%. While for the PSS algorithm, the localization error is more than 6m under the same 80% confidence level. Our algorithm is 35.4% more accurate than the multiple RDR methods. Moreover, the maximal error of our PNN algorithm is less than 14m, and that of the PSS algorithm is more than 20m. Therefore, the performance of our proposed PNN algorithm is clearly superior than the traditional PSS algorithm.

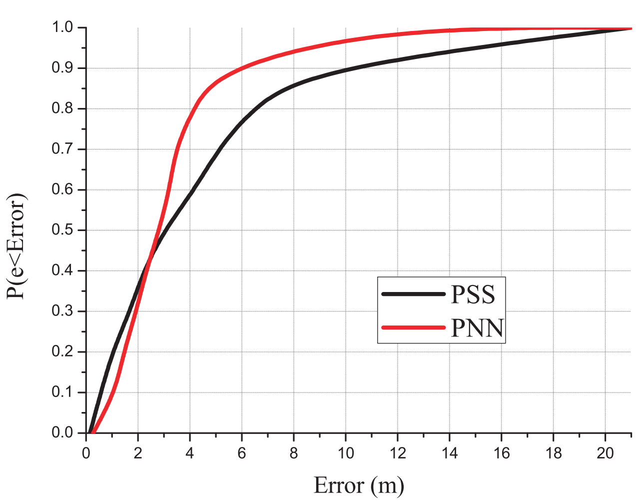

Fig.5 Cumulative Distribution Function of localization error.

V. Conclusion

In this paper we analyzed the problems the RSSI-based localization system encounters in anisotropic environments. Defects in current solutions, i.e. the multiple RDR algorithms were proposed and analyzed. To address these problems, we presented a Probabilistic Neural Network based localization algorithm. The proposed algorithm can achieve an enhanced accuracy by calibrating deviations collaboratively with multiple APs and suppressing inappropriate calibrations found in multiple RDR algorithms. Simulation results show that our proposed algorithm has a localization accuracy 35% higher than that of multiple RDR algorithms.

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