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Differential radio map-based robust indoor localization

Jie Wang^{1*}, Qinghua Gao¹, Hongyu Wang¹, Hongyang Chen² and Minglu Jin¹

Abstract

While wireless local area network-based indoor localization is attractive, the problems concerning how to capture the signal-propagating character in the complex dynamic environment and how to accommodate the receiver gain difference of different mobile devices are challenging. In this article, we solve these problems by modeling them as common mode noise and develop a localization algorithm based on a novel differential radio map approach. We propose a differential operation to improve the performance of the radio map module, where the location is estimated according to the difference of received signal strength (RSS) instead of RSS itself. The particle filter algorithm is adopted to realize the target localization and tracking task. Furthermore, to calculate the particle weight at arbitrary locations, we propose a local linearization technique to realize continuous interpolation of the radio map. The indoor experiment results demonstrate the effectiveness and robustness of our approach.

Keywords: Indoor localization, differential radio map, RSS, particle filter

Introduction

Ubiquitous computing and communication have become popular with the development of wireless communication technology over the last decade. The need for location information to capture contexts and configure them into the computing and communication processes, coupled with the unavailability of global positioning system (GPS) in indoor environment, has triggered increased research interest in indoor localization. Recently, numerous localization systems have been developed based on the received signal strength (RSS) of the wireless local area networks (WLANs). The advantage of these systems is that the cost of deploying a specialized infrastructure is avoided. However, building an indoor localization system based on WLAN is a challenging problem due to the complex indoor signal propagation character and different hardware solutions of different mobile devices.

Radio map-based approach is the most widely adopted method to realize indoor localization [1-11]. The essential idea is to construct the radio map by dividing the whole deployment area into cells and then collecting the

RSS measurements from various access points (APs) at each cell, and thus a mobile device can be localized by matching the observed RSS vector with the radio map. In the indoor environment, the RF signal propagation is unpredictable and affected by several factors, such as the presence and movement of human beings, relocation of furniture, multi-path fading, humidity and temperature variations, and closing or opening doors. In such a dynamic environment, the radio map obtained in one time period may not be applicable to other time periods. To solve this problem, Chen et al. [9] built multiple radio maps under various environmental conditions and used sensors to identify the current environment so as to select the most approximate map. Yin et al. [10] offset the variational environmental factors by adding some reference points as sniffers to capture the dynamic characters of the environment and rebuilt the radio map with regression method. Although these methods partially overcome the negative effect of dynamic environment, the need for specific infrastructures, such as the environmental sensors and sniffers, makes these methods impractical. More recently, Fang and Lin [11] adopted a temporal sequence of RSS samples as the character vector of the radio map so as to overcome the multipath problem. While this approach demonstrates the effectiveness for the multipath effect, it is of little

* Correspondence: wangjie@dlut.edu.cn

¹Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, No.2 Linggong Road, Ganjingzi District, Dalian, Liaoning Province 116024, People's Republic of China

Full list of author information is available at the end of the article

use for other problems. The question of how to adapt to the dynamic complex environment without any additional infrastructure is a promising and challenging problem. Because with the changing of environment, it is most likely that the RSS measurements in one location from different APs are prone to shift in the same direction, we can model the dynamic of the indoor environment as the common mode noise. Inspired by the fact that differential signals are widely used in the circuit design to restrain the common mode noise, we adopt the difference of RSS from different APs as the characteristic signal of the radio map. Suppose the RSS measurement vector from three APs are (RSS_1, RSS_2, RSS_3) . Instead of treating it as the fingerprint to realize localization, we adopt the differential vectors $(RSS_1 - RSS_2, RSS_1 - RSS_3, RSS_2 - RSS_3)$ as fingerprint. Compared with the traditional RSS vector, the differential vector can be effectively adapted to the dynamic indoor environment. Furthermore, it can accommodate the receiver gain difference of different mobile devices. We are aware that the receiver gains of even the same type of devices are different, let alone different types of devices. If the device used in the localization phase is different from that used in the radio map building phase, then the estimation error will be increased dramatically. Because the difference of receiver gain offsets the RSS measurements in the same direction, we can also model it as common mode noise.

In this article, we propose a novel robust indoor localization algorithm under the framework of Bayesian filter. The particle filter (PF) [12,13] is adopted to achieve the localization and tracking task, which makes full use of the history observation to improve the estimation accuracy. The differential radio map is used for building the observation likelihood for the PF algorithm so as to solve the dynamic environment and different receiver gain problem. For the sake of predicting signal strength measurements at arbitrary locations so as to calculate particle weight and improve localization accuracy, we also adopt a local linearization technique to realize continuous interpolation of the radio map.

This article is organized as follows. Section II provides a brief overview of the indoor localization problem. In Section III, the definition of the differential radio map is given, and the localization architecture is described from the view of system. The detailed implementation of our differential radio map-based PF algorithm is presented in Section IV. Section V validates our algorithm by evaluations. Finally, the conclusion is drawn in Section VI.

Related works

Indoor localization with WLAN has been an active research area in the last decade. Honkavirta et al. [14] presented a survey of location fingerprinting methods,

and Seco et al. [15] reviewed the indoor localization algorithms from the aspect of mathematic. In this section, we give a brief overview of some key research findings in this area. Considering the needs of building the radio map, we divide the methods into map-based and non-map based algorithms.

The principle of the radio map based method is to fingerprint each cell of the deployment area with a RSS measurement vector from various APs. A mobile device is then localized by matching the observed RSS against the radio map. To the best of our knowledge, radio map-based indoor localization was first introduced by Bahl and Padmanabhan [1]; they proposed the well-known RADAR system and realized the localization using the deterministic fingerprint. Since then some schemes have been proposed to reduce the manual calibration effort and make the radio map more robust so as to improve the localization accuracy. To reduce manual effort, Deasy and Scanlon [2] proposed a technique to estimate the radio map using a signal propagation model. They used an instrument to measure the signal propagation model parameters and built the simulated radio map automatically. Compared with the traditional measured radio map, although the building of the simulated radio map is time efficient, the localization accuracy degenerates significantly. Tsai et al. [3] also adopted the signal propagation model and the interpolation technique to build the map. Chai and Yang [4] proposed a scheme to reduce the sample location in the radio map building phase so as to reduce the manual effort and developed an interpolation technique to effectively patch a radio map. Philipp [5] introduced a collaborative way to build the radio map with the collaboration of users, each user could create and manage the map, and the whole map can be built gradually with the participation of more and more users. Recently, Chintalapudi et al. [6] also developed a collaborative localization system named EZ which did not require any knowledge about the RF environment. EZ adopted an improved genetic algorithm to solve the constraint equations defined by signal propagation models so as to calculate the parameters of the APs and training points. However, it requires the mobile device equipped with GPS, and it can work well only if there are enough APs to provide excellent coverage. In order to make the radio map more informative, Wu et al. [7] adopted the probability distribution function (PDF) as the fingerprint of the map. Youssef and Agrawala [8] also employed a stochastic description of the radio map. As has been discussed above, with the purpose of adapting the radio map to the dynamic environment, Chen et al. [9], Yin et al. [10], and Fang and Lin [11] have made some pioneering research contributions. As a continuation of these schemes, our proposed approach adopts the differential

radio map to make the algorithm more robust and a local linearization technique to realize continuous interpolation of the radio map.

Besides the above research studies, some schemes based on the deterministic and probabilistic framework have also been developed. Lim et al. [16] used the truncated singular value decomposition to calculate the signal-distance map (SDM) based on the online measurements between the APs. Although the dynamic SDM makes it possible to capture the challenging dynamic indoor environment, the requirements of the high AP density and the modification of commercial AP's software make the scheme impractical. Hossain et al. [17] proposed a robust localization algorithm that could make use of multiple wireless techniques. Schwaighofer et al. [18] first adopted the Gaussian process (GP) as a non-parametric tool to realize the approximation of the radio map of cellular network. Ferris et al. [19] introduced the GP into the WLAN-based indoor localization. Compared with other regression models, the GP takes into account the noise of the observation and provides the ability to approximate nonlinear signal propagation model. Madigan et al. [20] adopted a Bayesian hierarchical approach to realize indoor localization, which eliminated the need of knowing the locations of the training points. Huang et al. [21] proposed a similar Bayesian algorithm and introduced the stochastic properties of measurement errors and the reliability of the measurement data into the factor graph framework so as to improve the accuracy. Wymeersch et al. [22] also proposed a Bayesian localization algorithm and took the cooperation of the nodes into consideration to improve the accuracy. Feng et al. [23] employed the compressive sensing theory to analyze the localization problem. The localization problem is modeled as a sparse question and can be solved by the L1 minimization. While these methods cut down the measurement effort and partially adapt to the dynamic environment, they still require effort in terms of placing sniffers, modifying commercial AP's software, obtaining the knowledge of AP placement, and of complex computation.

Differential radio map and system architecture

In this section, we define the differential radio map and analyze its ability to restrain the dynamic environmental noise and receiver gain difference. The architecture of the proposed localization system is presented thereafter.

Differential radio map

The construction of the differential radio map is almost the same as that of the traditional radio map, except that a differential operation module is introduced. First, we divide the deployment area into equal square

training cells with their vertices set as the training points. Then, we perform off-line training to record RSS measurements transmitted by each AP and store these measurements into the radio map. The radio map has the following form:

$$\text{Map} = \{p_i, R_i | i = 1, \dots, M\}, R_i = \{R_{ij} | j \in N_i\}, \quad (1)$$

where M is the total number of training points, p_i and R_i indicate the location and fingerprint of the i th training point, respectively, N_i is the detected AP list at the i th training point, R_{ij} is a Gaussian PDF represented by $N(\mu_{ij}, \sigma_{ij}^2)$ with the mean μ_{ij} , and covariance σ_{ij}^2 , which is used to approximate the RSS measurements collected at the i th training point and transmitted by the j th AP.

Unlike the traditional radio map which adopts the fingerprint R_i directly for localization, we adopt the differential fingerprint \bar{R}_i which takes the R_i as input, and it is calculated as follows:

$$\bar{R}_i = \{R_{ij} - R_{im} | j \in N_i, j \neq m\}, R_{im} = \max\{R_{ij} | j \in N_i\}, \quad (2)$$

where R_{im} is the strongest RSS measured at the i th training point (the measurement with lower ID is adopted when equal RSSs are measured), and $R_{ij} - R_{im}$ is represented by $N(\mu_{ij} - \mu_{im}, \sigma_{ij}^2 + \sigma_{im}^2)$.

In theory, the propagation of radio signal is regulated by a certain principle. The shadowing model is widely adopted to approximate the signal propagation character in the indoor circumstance. With this model, R_{ij} is defined by

$$R_{ij} = G + P_j - L_j - 10\beta \log_{10} d_{ij} + v, \quad (3)$$

where G is the receiver gain, P_j is the transmitting power (dBm) of the j th AP, L_j is the signal attenuation power (dBm) at the distance of 1 m, β is the path loss exponent, d_{ij} is the Euclidean distance between the i th training point and j th AP, and v represents the measurement noise. $G + P_j - L_j$ is always represented by one symbol and is called the received power at the distance of 1 m in other studies. To analyze the feature of the differential operation, we use three symbols to represent each factor here. The dynamic indoor environment always causes the change of parameters L_j and β , and the change of these parameters incur the change of the R_{ij} . As for different types of device, the receiver gain G is different, and thus the change of device causes the change of R_{ij} , as well.

The differential RSS is calculated as

$$R_{ij} - R_{im} = (P_j - P_m) - (L_j - L_m) - 10\beta(\log_{10} d_{ij} - \log_{10} d_{im}) + \bar{v}, \quad (4)$$

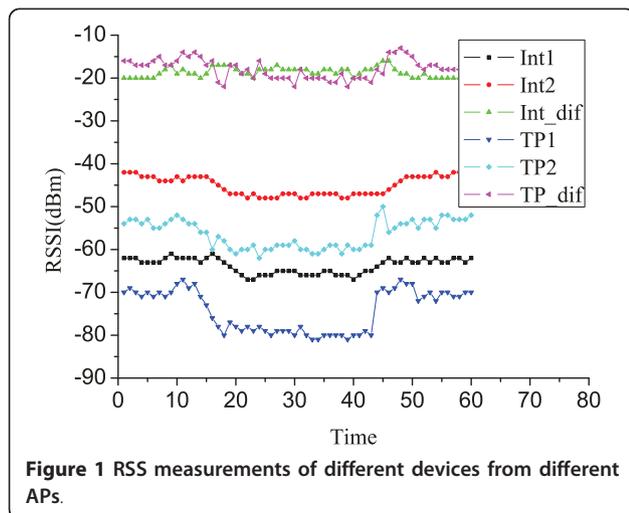
where $P_j - P_m$ is a constant which does not change with environment. While L_j and L_m change with the environment, they always offset to the same direction.

Consequently, the change of $L_j - L_m$ is not significant compared with the change of L_j and L_m . As for 10β ($\log_{10} d_{ij} - \log_{10} d_{im}$), since $\log_{10} d_{ij} - \log_{10} d_{im}$ is less than $\log_{10} d_{ij}$ and $\log_{10} d_{im}$, the change must be insignificant, too. From Equation 4, we can see that the term G is eliminated in the expression. Therefore, the differential RSS scheme is immune to the dynamic indoor environment, and can solve the problem caused by different receiver gains of multi-devices.

To validate the above theoretical analysis, we placed two different types of mobile devices at the same location and collected RSS measurements from two APs located at different places. We used an Intel 4965AGN wireless card and a TP-LINK TL-WN322G wireless card to gather RSS. There is a door between the wireless cards and APs, and we closed the door in the time instant 15-45. We define Int1 and Int2 as the RSS measurements, respectively, from AP1 and AP2 by 4965AGN, TP1 and TP2 as the RSS measurements by TL-WN322G, Int_dif as the differential signal of Int1 and Int2, and TP_dif as the differential signal of TP1 and TP2. Figure 1 demonstrates that the change of the differential RSS is quite insignificant compared with the change of RSS. It can also be seen that while the difference of the RSS measurements from the same AP with different devices is remarkable, the difference of differential RSS measurements is almost the same. The average differences between Int1 and TP1, Int2 and TP2 are 10.5 and 11.3, respectively, while that between Int_dif and TP_dif is only 0.8.

System architecture

The system flow of the proposed differential radio map-based localization system is plotted in Figure 2, where x_t is the current estimated location information, y_t is the current observation, $p(x_{t-1} | y_{t-1})$ is the posterior PDF



estimation of time instant $t - 1$, $p(x_t | y_{t-1})$ and $p(x_t | y_t)$ are the prior and posterior PDF estimations of time instant t , respectively.

The localization system follows the framework of Bayesian filter [12,13] and estimates the posterior PDF of the location recursively conditioned on all the measurements, y_1, \dots, y_t . The essential of the Bayesian filter is the prediction process and observation update process, which are defined as follows:

$$p(x_t | y_{t-1}) = \int p(x_{t-1} | y_{t-1}) p(x_t | x_{t-1}) dx_{t-1}, \quad (5)$$

$$p(x_t | y_t) = \frac{p(y_t | x_t) p(x_t | y_{t-1})}{\int p(y_t | x_t) p(x_t | y_{t-1}) dx_t}, \quad (6)$$

where the term $p(x_t | x_{t-1})$ represents the motion model, which describes the motion of the mobile device, and $p(y_t | x_t)$ represents the observation likelihood model, which describes the likelihood of observing a differential RSS measurement vector y_t at a location x_t . We describe the detailed models in the next section.

Implementation of the algorithm

This section first gives a brief introduction of the PF algorithm, and then defines the motion model and observation model in detail.

PF algorithm for localization and tracking

Bayesian filter algorithms [24] have achieved great success in handling the localization and tracking problem through the sequential estimation of target's state, cooperation with the movement modeling, prior distribution prediction, and posterior distribution estimation. Among these Bayesian filter algorithms, the PF algorithm [12,13] has emerged as a popular choice because of its unique ability in dealing with the complex non-Linear and non-Gaussian estimation problem. For these reasons, we adopt the PF algorithm for localization in this article. The PF algorithm approximates the probability distribution of the estimated target with several weighted particles, and deals with the sequential estimation by carrying out a series of particle-propagating operations. Let $\{x_t^i, w_t^i | i = 1, \dots, N\}$ denote a particle set, where x_t^i is a sample of x_t with associated normalized weight w_t^i . Then, the posterior PDF $p(x_t | y_t)$ can be approximated as

$$p(x_t | y_t) \approx \sum_{i=1}^N w_t^i \delta(x_t - x_t^i), \quad (7)$$

where $\delta()$ is the Dirac delta function. Suppose we have the proposal distribution $q(x_t | x_{t-1}, y_t)$, then the predicted location x_t^i can be generated based on the

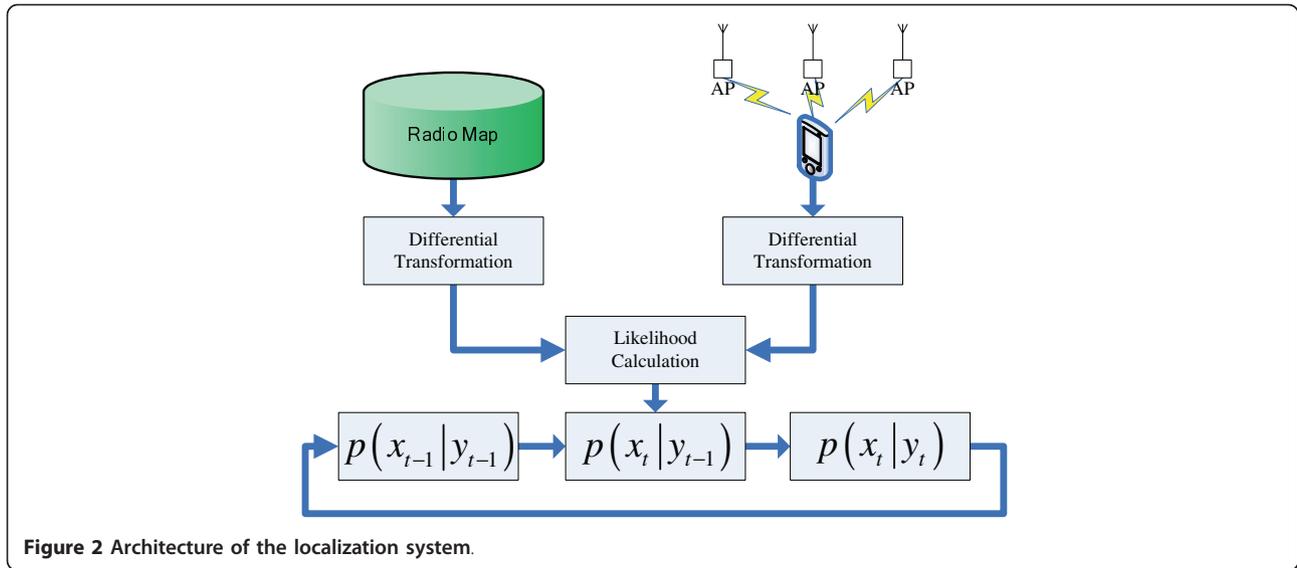


Figure 2 Architecture of the localization system.

previous location x_{t-1}^i and the latest observation y_t as follows:

$$x_t^i \sim q(x_t^i | x_{t-1}^i, y_t), \quad i = 1, \dots, N. \quad (8)$$

and w_t^i is given by

$$w_t^i \propto w_{t-1}^i \frac{p(y_t | x_t^i) p(x_t^i | x_{t-1}^i)}{q(x_t^i | x_{t-1}^i, y_t)}. \quad (9)$$

Most articles in the literature define the proposal distribution as $q(x_t | x_{t-1}, y_t) = p(x_t | x_{t-1})$, which only considers the motion model and neglects the latest observation y_t . For simplicity, we follow this scheme. Interested readers could find out the methods of designing advanced proposal distribution in [25]. Now, the question is how to define the motion model $p(x_t^i | x_{t-1}^i)$ and the observation likelihood model $p(y_t | x_t^i)$ for the particles.

Motion model

Speaking in general, the motion model of the mobile devices in the indoor environment is untraceable, and the velocity and direction of the mobile device are hard to estimate. In [19], Ferris et al. used a voronoi graph to aid the motion prediction. Although the performance of the prediction is improved, it needs detailed floor plan of the building which is impractical and inconvenient. Jin et al. [26] adopted dead reckoning sensors to make prediction, which needs the additional expensive sensors. Based on the principle of making the system as universal as possible, we define the motion model purely based on the historical motion information. We consider only two-dimensional localization, and the extension to the three-dimensional scenario is straightforward. The

two-dimensional location state x_t can be represented by (X_t, Y_t) . Suppose the location states of the previous two time instants are, x_{t-2} and x_{t-1} , the predicted velocity \hat{v}_t and direction $\hat{\alpha}_t$ of the mobile device can be estimated as follows:

$$\hat{v}_t = \min \left(\sqrt{(X_{t-1} - X_{t-2})^2 + (Y_{t-1} - Y_{t-2})^2}, v_{\max} \right), \quad (10)$$

$$\hat{\alpha}_t = \arctan \left(\frac{Y_{t-1} - Y_{t-2}}{X_{t-1} - X_{t-2}} \right), \quad (11)$$

where v_{\max} is the velocity threshold of the mobile device and generally set as $1m/s$. The motion model of the particles can be written as

$$\begin{bmatrix} X_t^i \\ Y_t^i \end{bmatrix} = \begin{bmatrix} X_{t-1}^i + v_t^i \cos(\alpha_t^i) \Delta t + n_t \\ Y_{t-1}^i + v_t^i \sin(\alpha_t^i) \Delta t + n_t \end{bmatrix}, \quad (12)$$

where n_t is the noise, $v_t^i \in [0.6\hat{v}_t, 1.4\hat{v}_t]$, $\alpha_t^i \in \left[\hat{\alpha}_t - \frac{\pi}{6}, \hat{\alpha}_t + \frac{\pi}{6} \right]$. The new particles are generated in the fan-shaped area. Meanwhile, to cope with the circumstance such as the swerve of the mobile device, we randomly select 80% particles that participate in the prediction defined by Equation 12, and let the rest 20% particles randomly move in the circular area, with the last estimation as center and v_{\max} as radius.

Observation likelihood model

In order to calculate the likelihood of the particles at arbitrary locations, the first thing that should be solved is to fulfill the radio map with the ability of representing the RSS measurements at arbitrary locations. The radio map defined by Equation 1 is a discrete map, and only

the RSS fingerprints of the training points are recorded. We adopt a linearization technique to predict RSS measurements at arbitrary locations. Within each of the square training cells, we use a hyperplane to approximate the RSS measurements of every AP. The 3D plane equation includes (x, y, r) coordinate, where (x, y) is the 2D location, and r is RSS measurement. The equation is defined as

$$a_x \times x + a_y \times y + a_r \times r = c, \quad (13)$$

where a_x , a_y , and a_r are the coefficients of the plane equation, and c is a non-zero constant and set as 1 in this article. The RSS measurements of the four vertices and their locations are known, therefore, they can be used to calculate the coefficients of the hyperplane equation. Suppose the locations of the four vertices are (x_1, y_1) , (x_2, y_2) , (x_3, y_3) , and (x_4, y_4) , the mean values of the RSS measurements from one AP are r_1 , r_2 , r_3 , and r_4 . We have a constraint matrix in the following form:

$$A \cdot B = C, \quad (14)$$

where

$$A = \begin{bmatrix} x_1 & y_1 & r_1 \\ x_2 & y_2 & r_2 \\ x_3 & y_3 & r_3 \\ x_4 & y_4 & r_4 \end{bmatrix}, \quad B = \begin{bmatrix} a_x \\ a_y \\ a_r \end{bmatrix}, \quad C = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}. \quad (15)$$

The coefficients of the hyperplane equation can be solved with the least square algorithm as $B = (A^T A)^{-1} A^T C$, where $()^{-1}$ and $()^T$ represent the matrix inverse and transpose, respectively. After building the hyperplane equation for every AP in each of the square training cells, the mean value of RSS fingerprint at an arbitrary location can be calculated with Equation 13, and the average value of the four vertices' covariance is set as the covariance of the location.

For the particle x_t^i , we first judge which training cell it belongs to and calculate the RSS fingerprint vector based on the hyperplane equation, and then, we transform the RSS fingerprint vector and the current, observed RSS measurement vector to their differential form. Suppose the differential fingerprint for the j th AP is $N(\bar{\mu}_{ij}, \bar{\sigma}_{ij}^2)$, the observed differential RSS measurement from the j th AP is \bar{o}_j , then the likelihood for the j th AP is $N(\bar{o}_j; \bar{\mu}_{ij}, \bar{\sigma}_{ij}^2)$. Suppose the RSS measurements from different APs are independent, the observation likelihood can be expressed as

$$p(y_t | x_t^i) = \left(\prod_{j=1}^n N(\bar{o}_j; \bar{\mu}_{ij}, \bar{\sigma}_{ij}^2) \right)^{1/n}, \quad (16)$$

where n is the number of detected APs. The exponent $1/n$ is used to smooth the likelihood so as to avoid the occurring of overconfident estimate. We calculate the observation likelihood values for all the particles and adopt $w_{t-1}^i p(y_t | x_t^i)$ as the new particle weight, and then, normalize it to ensure the summation of weights is equal to 1.

With the normalized weighted particle set $\{x_t^i, w_t^i | i = 1, \dots, N\}$, the location estimation x_t can be calculated as $x_t = \sum_{i=1}^N x_t^i w_t^i$. To avoid the occurrence of degeneration problem, we adopt the adaptive systematic resample method [25] for further optimizing the quality of the particles. The outline of our differential radio map-based Bayesian localization (DRMBL) algorithm is summarized in Table 1.

Experimental evaluation

In this section, we start by giving a detailed presentation of our testbed. Then, we evaluate the proposed improvement strategies under different conditions. For simplicity and comparison, the deterministic fingerprint-based RADAR algorithm adopts the weighted k -nearest neighbor technique, abbreviated as KNN, and the algorithm that adopts probabilistic fingerprint localization technique is abbreviated as PL. Furthermore, to evaluate the effectiveness of our differential strategy, the differential strategy is also applied to the KNN and PL algorithms. We define the improved algorithms as DRMKNN and DRMPL, respectively.

Experiment setup

To evaluate the performance of our algorithm, we performed realistic experiment on the second floor of the Electronic Information building of Dalian University of

Table 1 DRMBL algorithm

1. Initialization: $t = 0, 1$	Adopt the estimation of RADAR as the initial estimation.
2. While ($t > 1$) do	
2.1 Prediction update	
A. Estimate the velocity and direction using Equations 10 and 11	
B. Make prediction using Equation 12	
2.2 Observation update	
A. Calculate the observation likelihood function of each particle with Equation 16	
B. Calculate the normalized weight for each particle	
2.3 Adopt the weighted mean of the particles as the current location estimation	
2.4 Resample, if necessary	
End	

Technology. The layout of the floor is shown in Figure 3, and a scene of training is illustrated in Figure 4. The deployment area has a dimension of 72×29 meters. The TP-LINK TL-WR340G₊ APs are adopted, and there are six detectable APs on the floor. We use an IBM ThinkPad X60 laptop with Windows XP operating system as the mobile device. A TP-LINK TL-WN322G wireless card is adopted to gather RSS in the radio map building phase, and a 4965AGN card and a TL-WN322G wireless card are used in the localization phase. Unless otherwise specified, we adopted the data collected by 4965AGN in the following evaluations. We designed the software for collecting RSS based on the NDIS Miniport [27].

The radio map has 164 locations along the corridor and 70 locations inside the room. We placed the training points 1.2 m apart and collected 10 samples at each point with a time interval of 1 s. The default parameters for the algorithms are as follows: the parameter k of KNN is 4, and the number of particles used in the DRMBL is 1000.

Evaluation results

Figure 5a demonstrates the comparison of the cumulative distribution function (CDF) of the localization error when using a TL-WN322G wireless card which is the same as that used in the training phase; the DRMBL algorithm outperforms other algorithms and its average

localization error decreases by 13% compared with KNN. The average localization errors of DRMKNN and DRMPL algorithms decrease by 4% and 3.7%, respectively, when comparing with KNN and PL algorithms. Figure 5b shows the localization error when using an Intel 4965AGN wireless card. It can be seen that the performances of DRMBL, DRMKNN, and DRMPL algorithms are nearly the same as that of Figure 5a, while the performance of KNN and PL algorithms drops dramatically. These results show the effectiveness of our improvement strategies, and indicate that the differential method is generic and can be applied to other localization algorithms to improve their accuracy.

Table 2 summarizes the detailed results. It can be seen that comparing with KNN and PL algorithms, the average error of DRMBL decreases by more than 26% and 22%, respectively. With our differential strategy, the average errors of DRMKNN and DRMPL decrease by more than 18% and 10%. However, it should be mentioned that the maximum errors of DRMKNN and DRMPL increases, respectively, by 35% and 36%. This is because when the RSS measurements from the reference AP incur from severe noise, the differential operation may bring noise to the differential RSS vector, which incurs the increase of localization error. Hence, the selection of reference AP is of vital importance.

To evaluate the performance of our DRMBL algorithm under different conditions, we studied the sensitivity of

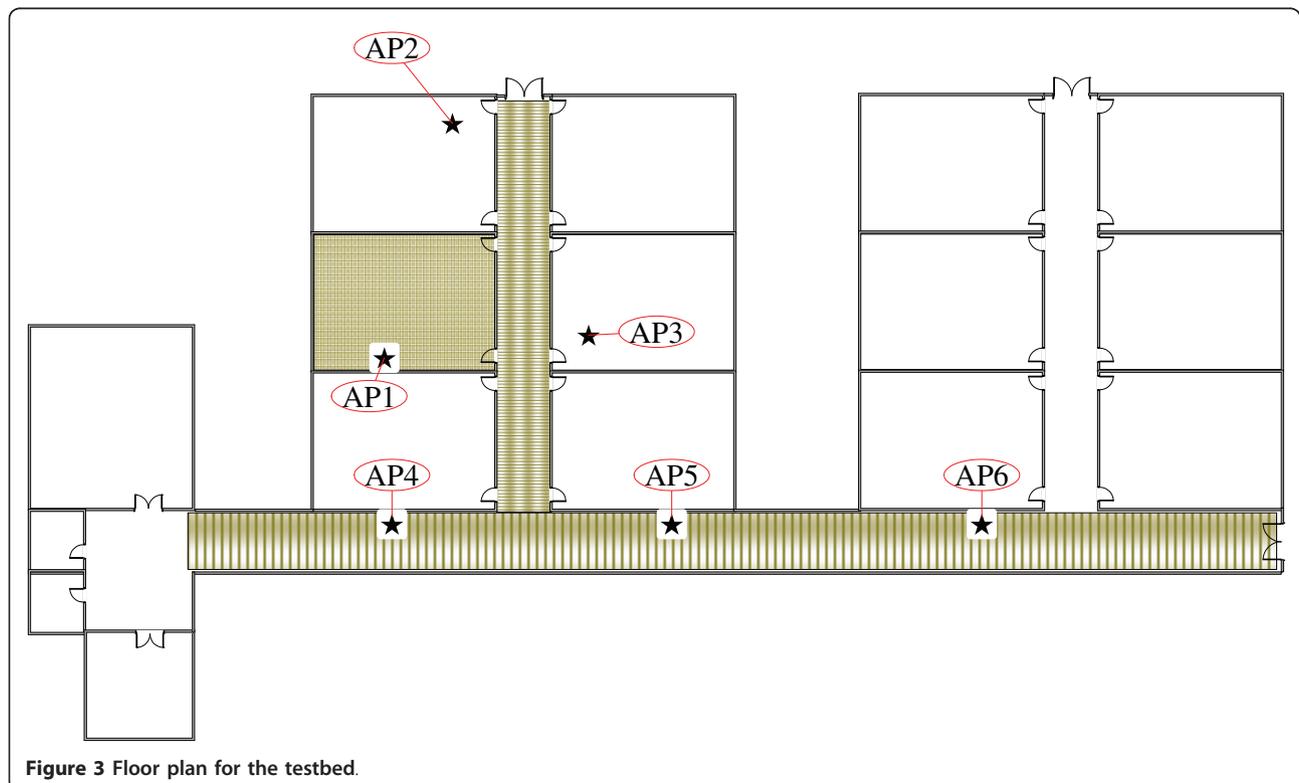


Figure 3 Floor plan for the testbed.

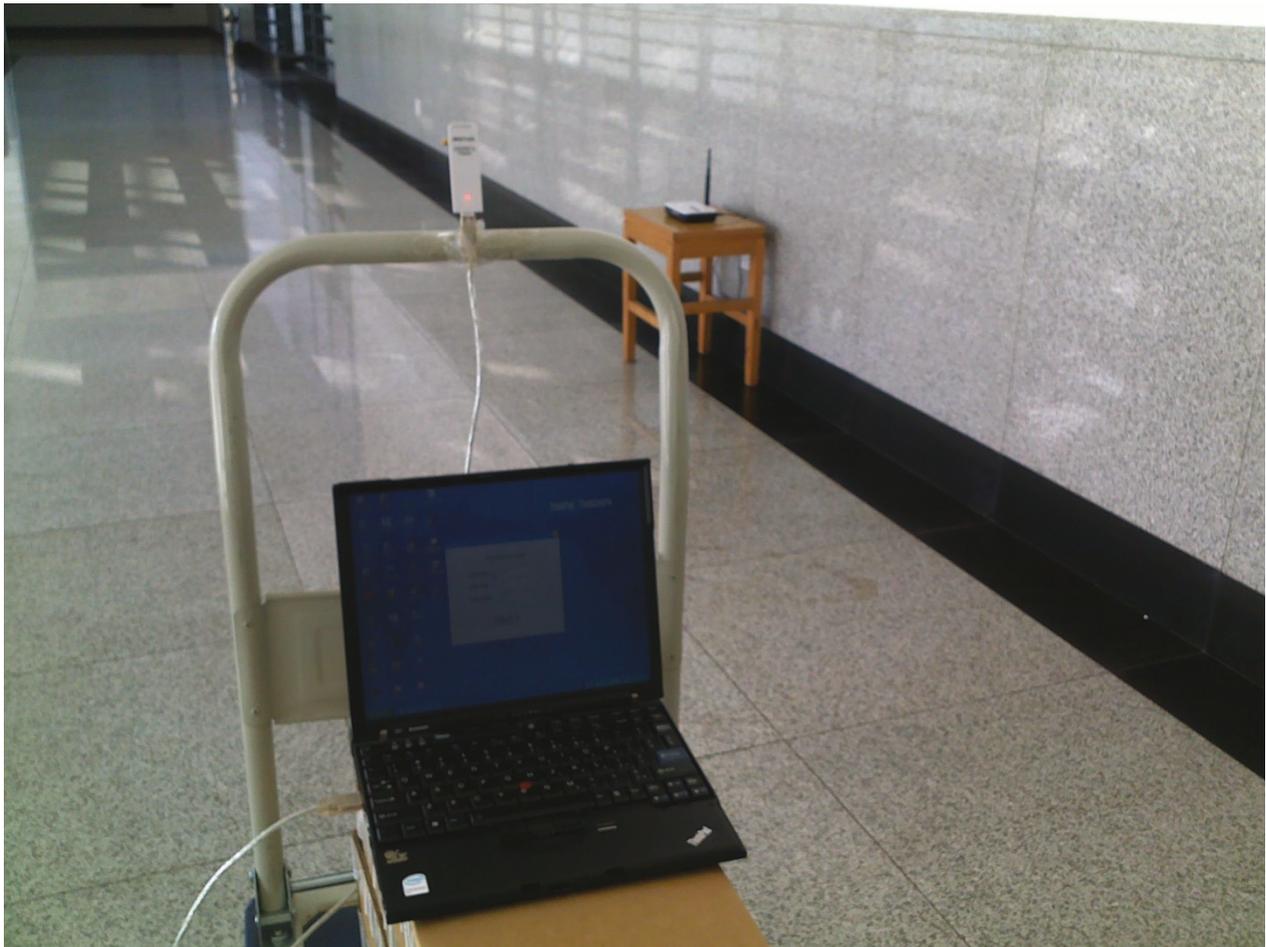


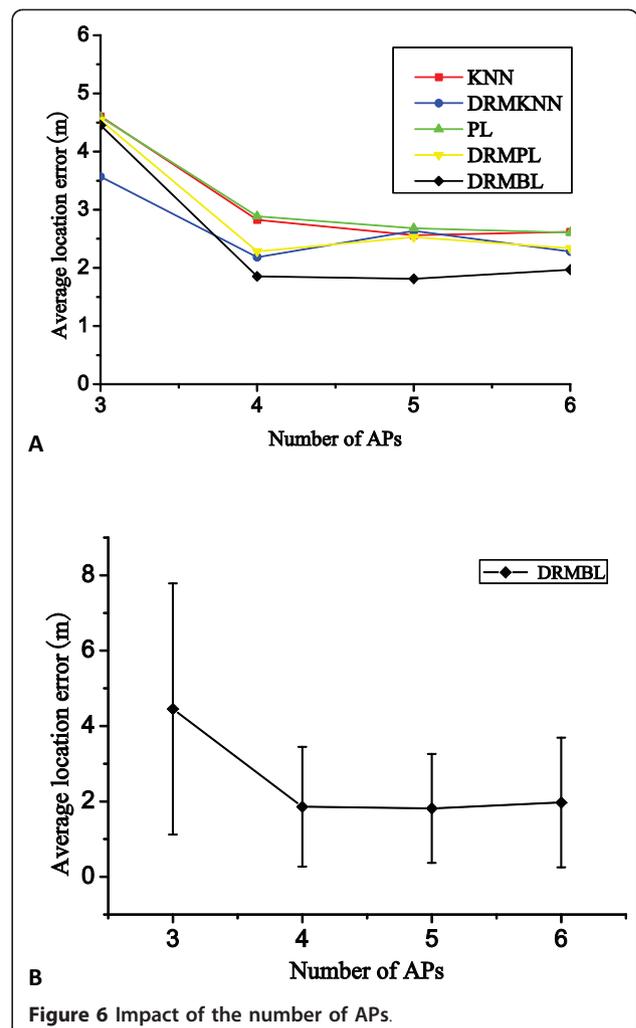
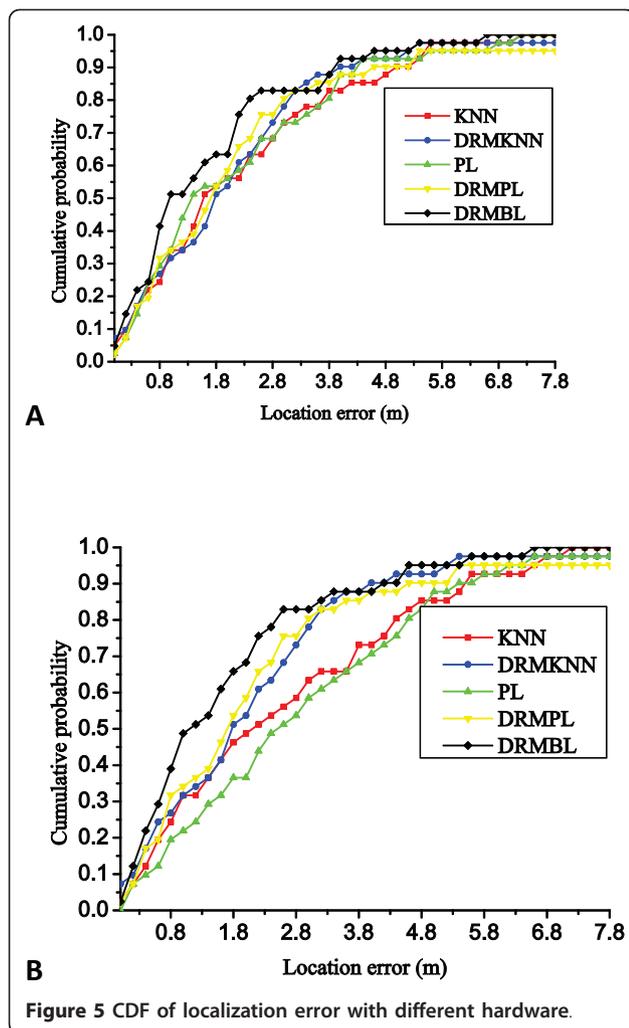
Figure 4 A scene of training.

the algorithm to the number of APs and radio map spacing. Figure 6a illustrates that the average localization error decreases gradually with the increase of the number of APs, and a relatively stable condition can be achieved when the number of APs is greater than 4. In Figure 6b, the error bars represent the standard deviation. It demonstrates nearly the same character as that of average error. It can be seen from Figure 7 that the accuracy decreases and standard deviation increases gradually with the increase of radio map spacing. However, the DRMBL algorithm still achieves average error of 2.56 m at the radio map spacing of 9.6 m. It can be learned from Figure 7a that the performances of DRMKNN and DRMPL drop dramatically with the increase of radio map spacing; because with the decrease of the number of training points, the RSS measurement from the reference AP may be far away from any training points, which introduces noise to the differential RSS vector.

Essentially speaking, our DRMBL algorithm is a PF algorithm, and the performance of PF algorithm

depends largely on the number of particles adopted in the algorithm. We evaluated the algorithm using different number of particles. Figure 8 illustrates that with the increase of the number of particles, the average error and its standard deviation decrease gradually. It can be seen that 100 particles are sufficient for the algorithm to achieve reasonable results.

Figure 9 demonstrates the tracking effect of our DRMBL algorithm. A mobile device is moving in the deployment area, its motion trace covers straight corridor with excellent AP signal coverage and corner with noisy and feeble AP signal. In Figure 9a, the blue "L" shape line is the ground truth trace, and the black trace is the estimated one. We can see that, in the corridor, the tracking performance is very good; however, in the corner, the estimation error increases remarkably. For clarity, we mark the poor estimations with red stars and plot the detailed estimation errors in Figure 9b. From Figure 9, we can learn that one should pay special attention to the placement of APs to ensure that the radio signal could cover every corner in the deployment area.



Discussion

We highlight some of the experience on the DRMBL algorithm, including the differential strategy, the density of training points, and the characteristic of the PF algorithm.

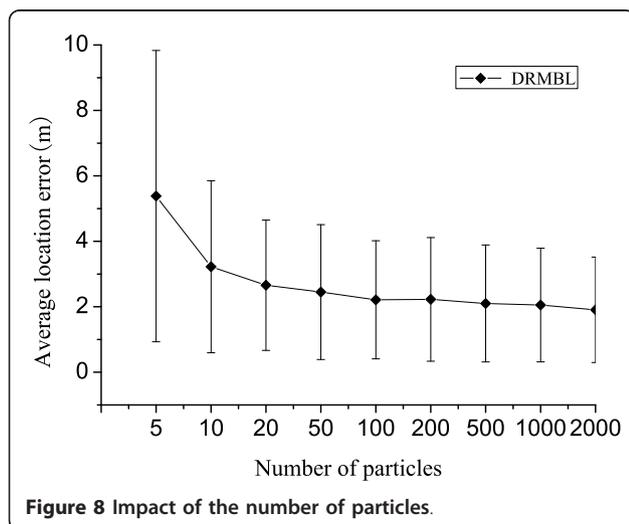
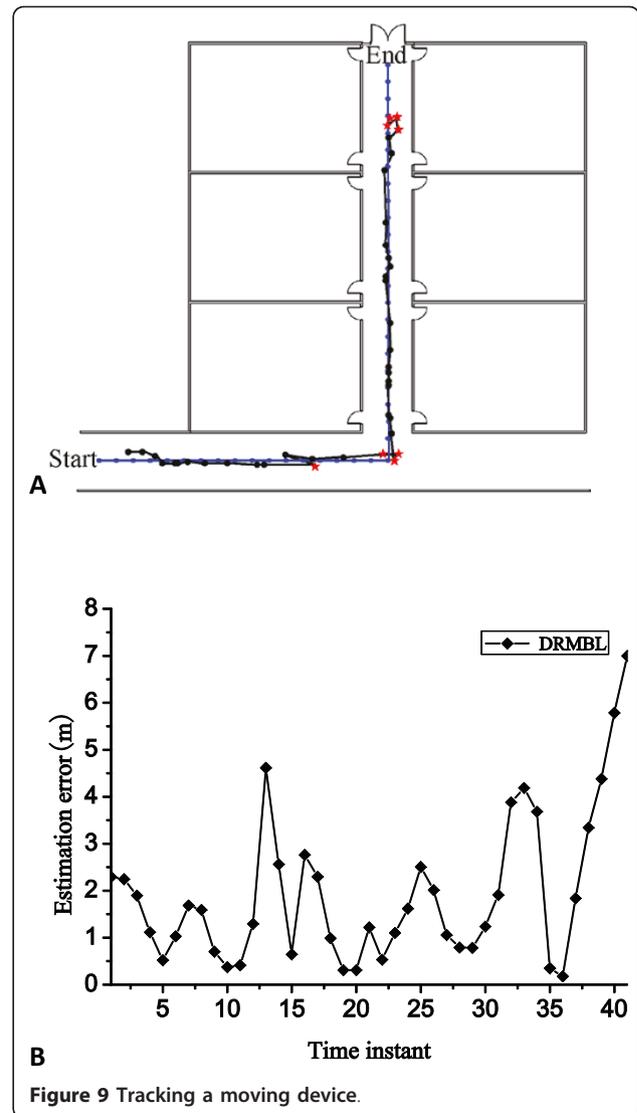
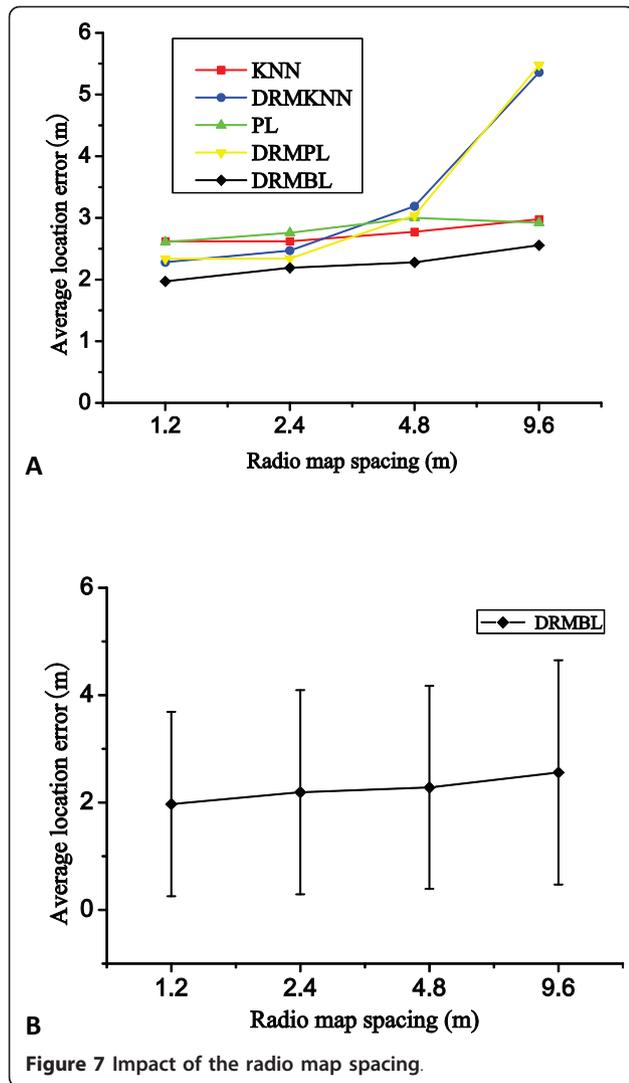
It should be mentioned that the differential strategy is generic. It can be adopted by any localization system as long as they use the RSS as measurement, such as WLAN, Zigbee, Bluetooth, and GSM-based systems. If N APs are detected, ideally there are C_N^2 pairs of differential RSS measurements. For simplicity, we select the

Table 2 Comparison of localization error

Algorithm	Median (m)	Average (m)	Stand deviation (m)	90% (m)	Max (m)
KNN	2.42	2.78	1.89	5.28	7.34
DRMKNN	1.97	2.28	1.85	4.19	9.95
PL	2.26	2.60	1.86	4.82	7.50
DRMPL	1.92	2.34	2.12	4.61	10.23
DRMBL	1.49	2.04	1.75	4.17	6.80

AP with the strongest RSS as the reference AP and select $N - 1$ differential RSS measurements relative to it according to Equation 2. Computational resources permitting, one can utilize all the differential measurements to improve the performance. The performance of the differential strategy is greatly affected by the reference AP. Therefore, the selection of the most appropriate reference AP is vital for the DRMBL algorithm. We have verified four criteria: AP with the strongest RSS, AP with the weakest RSS, AP with the minimum standard deviation, and AP with the maximum standard deviation. Table 3 illustrates that the criterion of selecting the AP with the strongest RSS is superior to others.

As has been seen from Figure 7a, one shortcoming of the differential strategy is that it requires dense training points. Our DRMBL algorithm solves this problem with continuous interpolation technique. When the differential strategy is adopted, we suggest that the interpolation technique could be used for generating some virtual training points. Figure 10 demonstrates the results of



DRMKNN and DRMPL with interpolation technique used in the radio maps of 4.8 and 9.6 m spacings.

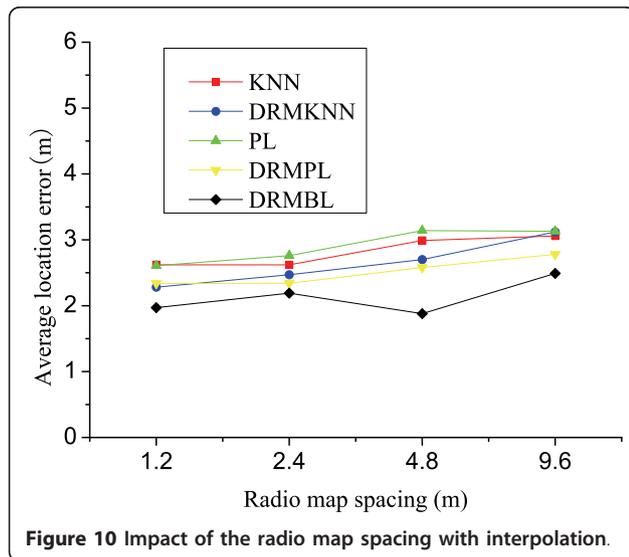
Moreover, with the essential similarity to PF algorithm, DRMBL deals with the location estimation problem by means of prediction and observation update process. In this article, we suppose that the algorithm knows nothing about the prior knowledge; if we have some prior information about the velocity or direction, the tracking accuracy will be improved significantly. Figure 11 demonstrates the localization error for tracking the same trace as that of Figure 9a while having prior velocity information. The estimation error is remarkably reduced, and the average localization error is only 1.17 m.

Conclusion

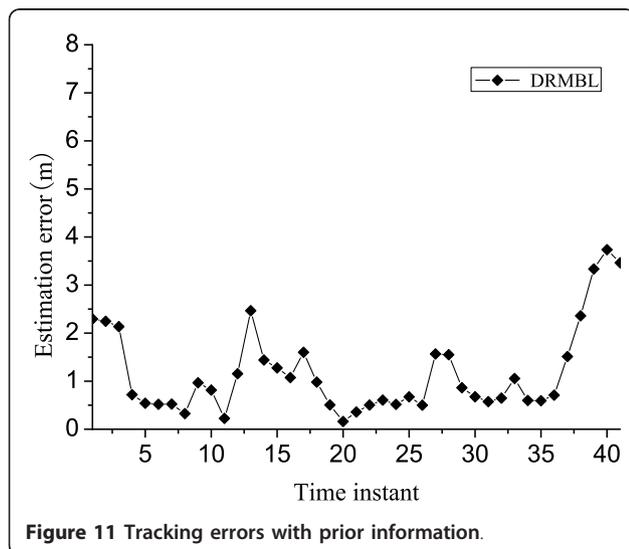
To address the problem of realizing accurate localization in complex dynamic environment in the WLAN which

Table 3 Comparison of the reference AP selection criterions

critierion	Median (m)	Average (m)	Stand deviation (m)	90% (m)	Max (m)
Strongest RSS	1.43	2.01	1.71	4.27	6.80
Weakest RSS	1.91	2.36	1.71	4.72	7.16
Minimum standard deviation	1.66	2.06	1.64	4.12	7.13
Maximum standard deviation	1.73	2.18	1.79	4.32	8.08



is made up of different types of devices, we proposed a novel DRMBL algorithm under the Bayesian framework. We proposed a differential strategy to overcome the common mode noise and a continuous interpolation technique to accurately realize the particle weight calculation. The experiments validated our proposed schemes, and revealed that DRMBL algorithm could



achieve reasonable localization results under challenging background conditions. The schemes proposed in this article are generic and could be adopted by other localization systems.

Abbreviations

CDF: cumulative distribution function; DRMBL: differential radio map-based Bayesian localization; GPS: global positioning system; PDF: probability distribution function; RSS: received signal strength; SDM: signal-distance map; WLAN: wireless local area network.

Acknowledgements

This study was supported by the National Natural Science Foundation of China under grant numbers 60871046 and the National Hi_Tech Research and Development 863 program of China under grant numbers 2008AA092701. The authors thank the constructive discussions with their group members during the writing of the article. The authors would also like to thank the reviewers for their useful suggestions and comments.

Author details

¹Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, No.2 Linggong Road, Ganjingzi District, Dalian, Liaoning Province 116024, People's Republic of China ²Institute of Industrial Science, The University of Tokyo, Tokyo, Japan

Competing interests

The authors declare that they have no competing interests.

Received: 24 November 2010 Accepted: 16 June 2011

Published: 16 June 2011

References

1. P Bahl, VN Padmanabhan, RADAR: an in-building RF-based user location and tracking system, in *Proceedings of the 19th IEEE International Conference on Computer Communications (INFOCOM '00)*, vol. 2, (Tel Aviv, Israel, March 2000), pp. 775–784
2. TP Deasy, WG Scanlon, Simulation or measurement: the effect of radio map creation on indoor WLAN-based localisation accuracy. *Wirel Personal Commun*, **42**(4), 563–573 (2007)
3. TC Tsai, CL Li, TM Lin, Reducing calibration effort for WLAN location and tracking system using segment technique, in *Proceedings of the IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC '06)*, vol. 2, (Taichung, Taiwan, June 2006), pp. 46–51
4. XY Chai, Q Yang, Reducing the calibration effort for probabilistic indoor location estimation. *IEEE Trans Mobile Comput*, **6**(6), 649–662 (2007)
5. B Philipp, Redpin-adaptive, zero-configuration indoor localization through user collaboration, in *Proceedings of the 1st ACM international workshop on Mobile entity localization and tracking in GPS-less environments (MELT '08)* (San Francisco, USA, September 2008), pp. 55–60
6. K Chintalapudi, AP Iyer, VN Padmanabhan, Indoor localization without the pain, in *Proceedings of the 16th Annual International Conference on Mobile Computing and Networking (MOBICOM '10)* (Chicago, USA, September 2010), pp. 173–184
7. Y Wu, JB Hu, Z Chen, Radio map filter for sensor network indoor localization systems, in *Proceedings of the 5th IEEE International Conference on Industrial Informatics (INDIN '07)* (Vienna, Austria, July 2007), pp. 63–68
8. M Youssef, A Agrawala, The Horus location determination system. *Wirel Netw*, **14**(3), 357–374 (2008)

9. YC Chen, JR Chiang, HH Chu, P Huang, AW Tsui, Sensor-assisted wi-fi indoor location system for adapting to environmental dynamics, in *Proceedings of the 8th ACM international symposium on Modeling, analysis and simulation of wireless and mobile systems (MSWiM '05)* (Montreal, Canada, October 2005), pp. 118–125
10. J Yin, Q Yang, LM Ni, Learning adaptive temporal radio maps for signal-strength-based location estimation. *IEEE Trans Mobile Comput*, **7**(7), 869–883 (2008)
11. SH Fang, TN Lin, A dynamic system approach for radio location fingerprinting in wireless local area networks. *IEEE Trans Commun*, **58**(4), 1020–1025 (2010)
12. A Doucet, S Godsill, C Andrieu, On sequential Monte Carlo sampling methods for Bayesian filtering. *Stat Comput*, **10**(3), 197–208 (2000)
13. PM Djuric, JH Kotecha, JQ Zhang, YF Huang, T Ghirmai, MF Bugallo, J Miguez, Particle filtering. *IEEE Signal Process Mag*, **20**(5), 19–38 (2003)
14. V Honkavirta, T Perala, S Ali-Loytty, R Piche, A comparative survey of WLAN location fingerprinting methods, in *Proceedings of the 6th Workshop on Positioning, Navigation and Communication (WPNC '09)* (Hannover, Germany, March 2009), pp. 243–251
15. F Seco, AR Jimenez, C Prieto, J Roa, K Koutsou, A survey of mathematical methods for indoor localization, in *Proceedings of the 6th IEEE International Symposium on Intelligent Signal Processing (WISP '09)* (Budapest, Hungary, August 2009), pp. 9–14
16. H Lim, LC Kung, JC Hou, HY Luo, Zero-configuration, robust indoor localization: theory and experimentation, in *Proceedings of the 25th IEEE International Conference on Computer Communications (INFOCOM '06)* (Barcelona, Spain, April 2006), pp. 1–12
17. M Hossain, HN Van, Y Jin, WS Soh, Indoor localization using multiple wireless technologies, in *Proceedings of the 4th IEEE International Conference on Mobile Adhoc and Sensor Systems (MASS '07)* (Pisa, Italy, October 2006), pp. 1–8
18. A Schwaighofer, M Grigoras, V Tresp, C Hoffmann, GPPS: a Gaussian process positioning system for cellular networks, in *Proceedings of the 7th Conference on Neural Information Processing Systems (NIPS '03)* (Whistler, Canada, December 2003), pp. 1–8
19. B Ferris, D Hahnel, D Fox, Gaussian processes for signal strength-based location estimation, in *Proceedings of the 2nd Robotics: Science and Systems (RSS '06)* (Philadelphia, USA, August 2006), pp. 1–8
20. D Madigan, E Einahrawy, RP Martin, WH Ju, P Krishnan, AS Krishnakumar, Bayesian indoor positioning systems, in *Proceedings of the 24th IEEE International Conference on Computer Communications (INFOCOM '05)*, vol. 2, (Miami, USA, March 2005), pp. 1217–1227
21. CT Huang, CH Wu, YN Lee, JT Chen, A novel indoor RSS-based position location algorithm using factor graphs. *IEEE Trans Wirel Commun*, **8**(6), 3050–3058 (2009)
22. H Wymeersch, J Lien, MZ Win, Cooperative localization in wireless networks. *Proc IEEE*, **97**(2), 427–450 (2009)
23. C Feng, WSA Au, S Valaee, ZH Tan, Compressive sensing based positioning using RSS of WLAN access points, in *Proceedings of the 29th IEEE International Conference on Computer Communications (INFOCOM '10)* (San Diego, USA, March 2010), pp. 1631–1639
24. D Fox, J Hightower, L Lin, D Schulz, G Borriello, Bayesian filtering for location estimation. *IEEE Pervas Comput*, **2**(3), 24–33 (2003)
25. AM Johansen, A Doucet, A note on auxiliary particle filters. *Stat Probab Lett*, **78**(12), 1498–1504 (2008)
26. YY Jin, M Motani, WS Soh, JJ Zhang, SparseTrack: enhancing indoor pedestrian tracking with sparse infrastructure support, in *Proceedings of the 29th IEEE International Conference on Computer Communications (INFOCOM '10)* (San Diego, USA, March 2010), pp. 668–676
27. The Code Project. http://www.codeproject.com/KB/IP/wlanscan_ndis.aspx

doi:10.1186/1687-1499-2011-17

Cite this article as: Wang et al.: Differential radio map-based robust indoor localization. *EURASIP Journal on Wireless Communications and Networking* 2011 **2011**:17.

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