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A Robust Vector Matching Localization Approach Based on Multiple Channels SSD Fingerprinting of Zigbee Networks

Xiansheng Guo[1, 2, *], Lei Chu[1], Baocang Li[1], Baogen Xu[2], Qun Wan[1], and Yijiang Shen[3]

Abstract—We present a robust multiple-channel vector-matching localization approach (MCVM) based on signal strength difference (SSD) fingerprinting of ZigBee Network. Compared with some existing algorithms, our presented approach has threefold advantages: firstly, far fewer numbers of received signal strength (RSS) measurements and reference nodes are needed; secondly, it shows more robustness to the fluctuation of RSS; thirdly, it requires low time-consuming signal strength collection surveys in the location space. We demonstrate the performances of our algorithm experimentally using different numbers of channels, reference nodes and training points. The Cramér-Rao Low Bound (CRLB) of SSD is derived in order to compare the performance of the different localization methods addressed. The experimental results show the efficacy of our proposed approach.

1. INTRODUCTION

Localization is one of the essential modules of many mobile wireless applications. Although Global Positioning System (GPS) works extremely well in outdoor environment, it does not perform effectively in indoor environments due to the disability of GPS signals to penetrate in-building materials [2, 3, 6]. Therefore, indoor localization has gained growing interest from a wide range of applications in recent years.

In the last decade, indoor localization techniques which use RSS fingerprinting are widely adopted for their cost-effectiveness [1, 7]. However, RSS fingerprinting has some disadvantages, for example, building a fingerprinting database is a huge burden for its intensive in time and labor. And RSS value is vulnerable to environment influence and is observed to differ significantly across different devices' hardware even under same wireless conditions [4, 8]. To eliminate the fluctuation of RSS, a signal strength difference (SSD) fingerprinting has been proposed in WLAN environment [5, 10]. Compared with the RSS fingerprinting, SSD fingerprinting shows better performance in robustness and accuracy.

ZigBee is a wireless networking standard that is aimed at remote control and sensor applications with low data rates and needing low power consumption [11]. It has been applied in many home and industrial applications, including lighting control, remote reading of electric meters, wireless smoke detecting, medical sensing and monitoring, building automation, etc.. The biggest benefit is that ZigBee network can offer multiple channels communication ability [9]. As described in [13], the 2.4 GHz physical layer of ZigBee supports 16 channels between 2.4 and 2.4835 GHz with ample channel spacing 5 MHz aimed at easing transmit and receive filter requirements, which is summarized in Table 1. Therefore, we can capture the diversity of frequency response of indoor multiple channels to obtain the robust localization performance if we adopt the multiple channels measurement simultaneously.

Considering the aforementioned advantages, we first derive a multiple channel SSD fingerprinting from multiple channels RSS measurements of ZigBee network. Based on the multiple channel SSD

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* Corresponding author: Xiansheng Guo (xsguo@uestc.edu.cn).
[1] Department of Electronic Engineering, University of Electronics Science and Technology of China, Chengdu, Sichuan 611731, China.
[2] TONGFANG Electronic Science and Technology CO., LTD., Jiujiang, Jiangxi 332007, China. [3] Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China.

Table 1. The channel frequencies of 2.4 GHz ZigBee physical layer.

Channel number	Channel central frequency (MHz)
$k = 11, 12, \ldots, 26$	$2405 + 5 \times (k - 11)$

fingerprinting, a robust localization algorithm, named multiple-channel vector-matching localization approach (MCVM), is addressed. Compared with some existing algorithms, MCVM is more robust to the fluctuation of RSS with high accuracy and low time-consuming. To show the superiority of our proposed algorithm, the Cramér-Rao Low Bound (CRLB) of multiple-channel SSD is derived for the convenience of comparison.

2. PROBLEM FORMULATION

2.1. Signal Propagation Model of Indoor Environment

Suppose that $P(d)$ and $P(d_0)$ denote the received signal strengths at an arbitrary distance d and a close-in reference distance d_0 from the transmitter, respectively. From the log-normal shadowing model [14], we have

$$P\left(d\right)|_{\mathrm{dBm}} = P\left(d_0\right)|_{\mathrm{dBm}} - 10\alpha \log\left(\frac{d}{d_0}\right) + n|_{\mathrm{dB}}\,, \tag{1}$$

where α defines the path loss component. The noise n is a Gaussian random variable with mean 0 and variance σ^2, i.e., $n \sim N(0, \sigma^2)$. Based on the assumption above, the RSS signal model can be simplified as

$$r = \left.\frac{P\left(d\right)}{P\left(d_0\right)}\right|_{\mathrm{dB}} = -10\alpha \ln\left(\frac{d}{d_0}\right) + w|_{\mathrm{dB}}\,, \tag{2}$$

where $w \sim N(0, \eta^2)$ and $\eta = \frac{\sigma}{\ln(10)}$. Provided that $d_0 = 1\,\mathrm{m}$, (2) leads to

$$r = -10\alpha \ln\left(d\right) + w. \tag{3}$$

For the sake of simplicity, we define the received signal strength (RSS) at the lth reference node in the pth channel as

$$r_{p,l}^{\mathrm{RSS}} = f_{p,l}^{\mathrm{RSS}}\left(\mathbf{x}\right) + w_{p,l}^{\mathrm{RSS}}, \tag{4}$$

where $\mathbf{x} = [x, y]^T$ is the unknown position to be estimated. And $f_{p,l}^{\mathrm{RSS}}(\mathbf{x})$ is a known nonlinear function with respect to $\mathbf{x}$ with the following expression

$$f_{p,l}^{\mathrm{RSS}}\left(\mathbf{x}\right) = -\alpha_{p,l} \ln \mathbf{d}, \tag{5}$$

with $\mathbf{d} = [d_1, d_2, \ldots, d_L]^T$ and $d_l = \|\mathbf{x} - \mathbf{x}_l\|_2 = \sqrt{(x - x_l)^2 + (y - y_l)^2}$. Here $\mathbf{x}_l = [x_l, y_l]^T$ ($l = 1, 2, \ldots, L$) is the location of the lth reference node. Then the basic object of indoor localization is to estimate $\mathbf{x}$ from some noised measurements r.

2.2. Bayesian Based Localization Methods

2.2.1. RSS Based Localization Method

As depicted in [12, 15, 16], this method considers localization as a classification problem. Assume that there are n location candidates $\{p_1, p_1, \ldots, p_n\}$. The vector of signal strength readings r over κ reference nodes can be defined as $r = [\lambda_1, \lambda_2, \ldots, \lambda_\kappa]^T$ with $\lambda_j = [r_{j,1}^{\mathrm{RSS}}, r_{j,2}^{\mathrm{RSS}}, \ldots, r_{j,L}^{\mathrm{RSS}}]^T$ and L is the total number of RSS samples at location p_i. The samples obtained from single channel and multiple channels are used form single channel RSS fingerprinting and multiple channels RSS fingerprinting. Accordingly, Bayesian based localization methods using RSS fingerprinting can be classified into two categories: Bayesian based localization methods using single channel RSS fingerprinting (Bayes (RSS)) and Bayesian based localization methods using multiple channels RSS fingerprinting (Bayes (M-RSS)). The online stage, the following decision rule can be obtained:

Choose p_i if $\Pr(p_i|r) > \Pr(p_j|r)$, for $i,\ j = 1,\ 2,\ \ldots, n.\ j \neq i$.
Here, $\Pr(p_i|r)$ denotes the probability that the mobile node is in location p_i, given that the average received signal vector is r. Also assume that $\Pr(p_i)$ is the probability that the mobile node is in location p_i. The given decision rule is based on *posteriori* probability. Using Bayes' formula, and assuming that $\Pr(p_i) = \Pr(p_j)$ for $i,\ j = 1,\ 2,\ \ldots,\ n$, we have the following decision rule based on the likelihood that $\Pr(r|p_i)$ is the probability that the signal vector r is received, given that the mobile node is located in location p_i:

Choose p_i if $\Pr(r|p_i) > \Pr(r|p_j)$, for $i,\ j = 1,\ 2,\ \ldots,\ n.\ j \neq i$, where $\Pr(r|p_i)$ is defined as

$$\Pr\left(r|p_i\right) = \prod_{l=1}^{\kappa} \Pr\left(\overline{\lambda_j}|p_i\right), \tag{6}$$

with $\overline{\lambda_j} = \frac{1}{L}\sum_{l=1}^{L} r_{j,l}^{\mathrm{RSS}}$.

2.2.2. SSD Based Localization Method

The RSS is sensitive to changes in the model and performs poorly in the presence of model error. In order to eliminate the effects of variations, SSD based localization methods are proposed [5, 8]. Essentially, post-process the training data to be the difference in average signal strength $(\overline{\lambda_\delta} - \overline{\lambda_\beta})$ for every pair of reference nodes δ and β. Bayesian based localization methods using SSD fingerprinting can also be divided into two categories: Bayesian based localization methods using single channel SSD fingerprinting (Bayes (SSD)) and Bayesian based localization methods using multiple channels SSD fingerprinting (Bayes (M-SSD)). Tao identified that a weighting scheme where the conditional probability of each difference in signal strength is added to the probability for that location gives the best accuracy [5]. The weights are computed as follow

$$W\left(p_i\right) = \sum_{\delta=1}^{\kappa-1}\sum_{\beta=\delta+1}^{\kappa} \Pr\left(\left(\overline{\lambda_\delta} - \overline{\lambda_\beta}\right)|p_i\right). \tag{7}$$

Once the weights have been calculated for each p_i, we choose the position with the largest weight as the position estimate.

3. ROBUST LOCALIZATION APPROACH

3.1. Multiple-Channel Vector-Matching Localization Approach (MCVM) Based on the RSS Fingerprinting

The procedure of our proposed MCVM localization approach based on the multiple channels RSS fingerprinting (MCVM (M-RSS)) is shown as follow. At off-line training stage, we can model the world as a finite position space $\{p_1,\ p_2,\ \ldots,\ p_n\}$ with κ data recorders (reference nodes). For each training point, the raw RSS vector data obtained from the full 16 channels at the ρth reference node can be defined as $\overrightarrow{r_{i_\rho}^{\mathrm{RSS}}}$. Then repeating data recording process N times. The measurements $[\overrightarrow{r_{i_\rho,1}^{\mathrm{RSS}}},\ \overrightarrow{r_{i_\rho,2}^{\mathrm{RSS}}},\ \ldots,\ \overrightarrow{r_{i_\rho,N}^{\mathrm{RSS}}}]^T$ are stored in a database as a fingerprinting. At the online localization stage, after obtaining the RSS vector $\overrightarrow{r_{\rho}^{\mathrm{RSS}}}$ at the blind node, we match the vector to the fingerprinting. The variables $\psi_{i,\rho}$ are defined to estimate the location and

$$\psi_{i,\rho} = \min_j \left(\left\|\overrightarrow{r_{i_\rho,j}^{\mathrm{RSS}}} - \overrightarrow{r_{\rho}^{\mathrm{RSS}}}\right\|_2\right), \quad j = 1, 2, \ldots, N, \tag{8}$$

where $\|\|_2$ denotes ℓ_2-norm. Our position estimation($\mathrm{PE}_{\text{M-RSS}}$) is computed from

$$\mathrm{PE}_{\text{M-RSS}} = \min_i \left(\prod_{\rho=1}^{\kappa}\left(\psi_{i,\rho}\right)\right). \tag{9}$$

That is to say, we choose the position with the smallest value as our location estimate. If multiple locations are obtained, we choose the centroid of these locations as our location estimate.

3.2. Multiple-Channel Vector-Matching Localization Approach (MCVM) Based on the SSD Fingerprinting

We propose a novel and robust fingerprinting generating approach based on the difference of RSS received from multiple channels of ZigBee networks. The main idea of multiple-channel vector-matching localization approach based on the multiple channels SSD fingerprinting (MCVM (M-SSD)) is demonstrated as follows: Firstly, multiple channels SSD can be obtained by computing the difference in signal strength for every pair of reference nodes i and j. Specifically,

$$r_{p,k}^{\mathrm{SSD}} = r_{p,i}^{\mathrm{RSS}} - r_{p,j}^{\mathrm{RSS}} = f_{p,i}^{\mathrm{RSS}}(\mathbf{x}) - f_{p,j}^{\mathrm{RSS}}(\mathbf{x}) + w_{p,i}^{\mathrm{RSS}} - w_{p,j}^{\mathrm{RSS}} = f_{p,k}^{\mathrm{SSD}}(\mathbf{x}) + w_{p,k}^{\mathrm{SSD}}, \tag{10}$$

where $i,\ j = 1,\ 2,\ \ldots,\ \kappa$; $k = 1,\ 2,\ \ldots,\ \binom{\kappa}{2}$; $p = 1,\ 2,\ \ldots,\ 16$. Here, $w_{p,k}^{SSD} \sim N(0, \eta_{p,i}^2 + \eta_{p,j}^2)$. So the noise measurement $r_{p,k}^{\mathrm{SSD}}$ shows more robustness to the fluctuation of $r_{p,l}^{\mathrm{RSS}}$ in (4). Secondly, the idea of MCVM approach based on the multiple channels SSD fingerprinting is proposed. Regarding the ith training point, the multiple channels SSD information can be expressed as $\overrightarrow{r_{i_k,j}^{\mathrm{SSD}}} = \overrightarrow{r_{i_\alpha,j}^{\mathrm{RSS}}} - \overrightarrow{r_{i_\beta,j}^{\mathrm{RSS}}}$ based on (10), where $\alpha = 1,\ 2,\ \ldots,\ \kappa-1$; $\beta = \alpha+1,\ 3,\ \ldots,\ \kappa$; $k = 1,\ 2,\ \ldots,\ \binom{\kappa}{2}$. At the blind node, similarly, the RSS measurements vector $\overrightarrow{r_\rho^{\mathrm{RSS}}}$ are recorded, then SSD information is formed as $\overrightarrow{r_k^{\mathrm{SSD}}} = \overrightarrow{r_\alpha^{\mathrm{SSD}}} - \overrightarrow{r_\beta^{\mathrm{SSD}}}$. For the purpose of location estimate, we define $\phi_{i,k}$ as

$$\phi_{i,k} = \min_j \left(\left\| \overrightarrow{r_{i_k,j}^{\mathrm{SSD}}} - \overrightarrow{r_k^{\mathrm{SSD}}} \right\|_2 \right). \tag{11}$$

The position estimation ($\mathrm{PE}_{\text{M-SSD}}$) can be given by

$$\mathrm{PE}_{\text{M-SSD}} = \min_i \left(\sum_{k=1}^{M} \phi_{i,k} \right), \quad M = \binom{\kappa}{2}. \tag{12}$$

As mentioned above, the position with the smallest value is chosen as our location estimate. If multiple locations are obtained, we choose the centroid of these locations as our location estimate.

3.3. Derivation of CRLB

The Cramér-Rao Low Bound (CRLB) of SSD is derived in order to compare the performances of the different localization methods addressed. The key in producing the CRLB is to construct the corresponding Fisher information matrix (FIM). The diagonal elements of the FIM inverse are the minimum achievable variance values [17]. Considering the measurement model of (3), the standard procedure to compute the CRLB is summarized using the following steps:

1 Compute the second-order derivatives of the logarithm of the measurement PDF with respect to $\mathbf{x}$, that is $\partial^2 \ln f(\mathbf{x})/(\partial\mathbf{x}\partial\mathbf{x}^T)$.

2 Take the expected value of $\partial^2 \ln f(\mathbf{x})/(\partial\mathbf{x}\partial\mathbf{x}^T)$ to yield $\mathbf{I}(\mathbf{x}) = E\{\partial^2 \ln f(\mathbf{x})/(\partial\mathbf{x}\partial\mathbf{x}^T)\}$, where $\mathbf{I}(\mathbf{x})$ denotes the Fisher information matrix (FIM).

3 The CRLBs for $\mathbf{x}$ are given by $[\mathbf{I}^{-1}(\mathbf{x})]_{1,1}$ and $[\mathbf{I}^{-1}(\mathbf{x})]_{2,2}$ respectively.

Considering our SSD model (10), $\mathbf{I}_{\mathrm{SSD}}(\mathbf{x})$ can be computed as

$$\mathbf{I}_{\mathrm{SSD}}(\mathbf{x}) = \left[\frac{\partial f_{p,k}^{\mathrm{SSD}}(\mathbf{x})}{\partial \mathbf{x}} \right]^T \mathbf{C}^{-1} \left[\frac{\partial f_{p,k}^{\mathrm{SSD}}(\mathbf{x})}{\partial \mathbf{x}} \right], \tag{13}$$

where $\mathbf{C}$ denotes the covariance matrix of the noise w. The CRLB is determined according to above steps and can be expressed as

$$\mathrm{CLRB}_{\mathrm{SSD}}(x) = \left[\mathbf{I}_{\mathrm{SSD}}^{-1}(\mathbf{x})\right]_{1,1} + \left[\mathbf{I}_{\mathrm{SSD}}^{-1}(\mathbf{x})\right]_{2,2}. \tag{14}$$

4. EXPERIMENTAL STUDY

We describe our experiment testbed in Section 4.1 and then introduce the establishing procedure of the fingerprinting database in Section 4.2. Lastly, we show our experiment findings to demonstrate the efficacy of our proposed approach.

4.1. Testbed Layout

Our testbed layout is shown in Fig. 1. The testbed locates inside the laboratory of our academy that span over an area of nearly 200 m^2. In Fig. 1, hollow circle dots indicate training points and the bigger pentagram denote reference nodes which may be used in the different experiments.

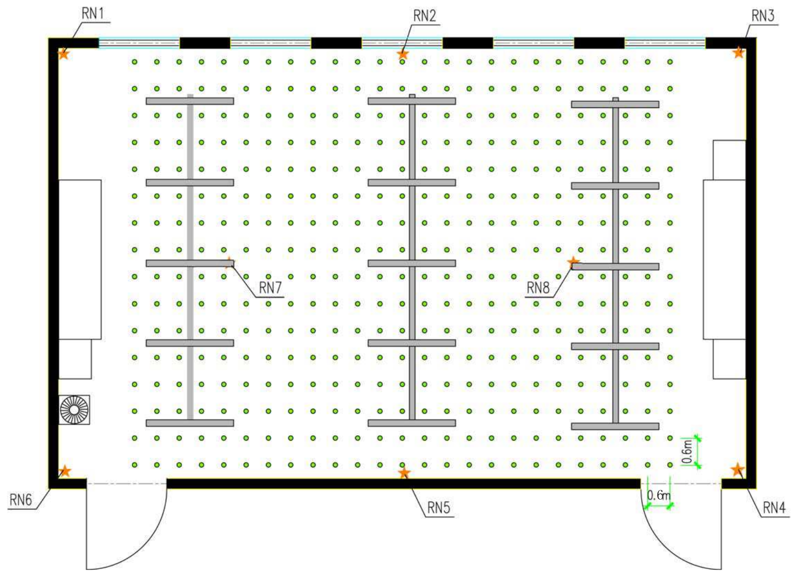

Figure 1. The geometry of our testbed.

4.2. Establishing Fingerprinting Database

In our location system, three essential network equipments required for localization are described as follows:

1) Gateway node: A node that is connected to a computer and configures and monitors the mobile nodes and reference nodes. The nodes at a known location can be seen in Fig. 2.
2) Reference nodes (RN): The nodes at known locations can be seen from Fig. 2.
3) Mobile nodes, namely, the training point. In the offline phase, it is used to record Received Signal Strength (RSS) between the training point and the reference nodes while during the online localization phase, it can act as the blind node.

4.3. Data Collection

As shown in Fig. 1, we have set up a total of 400 training points and 8 reference nodes. Training points (Smaller green open circles) are approximately uniformly distributed in the testbed. They are all kept in the height of 1.5 m (as can be seen from Fig. 2) from the ground in the experiment. and the blind nodes were selected randomly during the online localization phase.

Establishing the database in accordance with the data measurements is introduced as follow. The database are kept in consistent with different experiments. For the single channel experiment, we obtain RSS data continuously from the 1st channel and collected 192 groups of data at each training point and blind node. For the multiple channel experiment, 12 groups of data were recorded from all the 16 channels and each group of data includes 16 RSS measurements. These data are stored into the PC and saved to a RSS-matrix $\mathbf{R}$. Then the RSS-matrix $\mathbf{R}$ is used to form the SSD-matrix $\mathbf{R}'$ according to (10). At the online localization phase, we collect a group of data at the mobile node, then they will be delivered to PC to help form the location estimation. Besides, we have a Graphical User Interface (GUI) in the PC which can help us to load the location field map and click on the training points in the map to be trained and located conveniently. We totally repeat the experiment 101 times during two days.

Figure 2. The reference nodes locations in our testbed.

4.4. Analysis of Experimental Results

4.4.1. Robustness Justification

In the first verification test we conducted 3 set of experiments. We first consider the case of different numbers of channel. In the course of collecting data, we repeat the process 192 times in the single channel experiment while 12 times for the 16 non-overlapping channel in order to keep the same size of the fingerprinting. Fig. 3 shows our vector matching localization approach based on multiple channel SSD Fingerprinting performs better than other methods. Considering of the same size of the fingerprinting, we can conclude that the multiple channel fingerprinting outstands the single one in time and labor.

Next, we test the influence of different number of reference nodes and training points on the performance of the approaches. In the experiments, only 5 RNs (1, 3, 4, 6, 7) were employed in one experiment while another considers just 100 training points. We compare the localization performance with the first experiment. Fig. 4 shows that a decrease in the RN number will result in performance variation. Our MSSD-based fingerprinting outperforms MRSS-based fingerprinting. This sufficiently demonstrates the robustness of our algorithm. Besides, Fig. 5 depicts the multiple channel localization

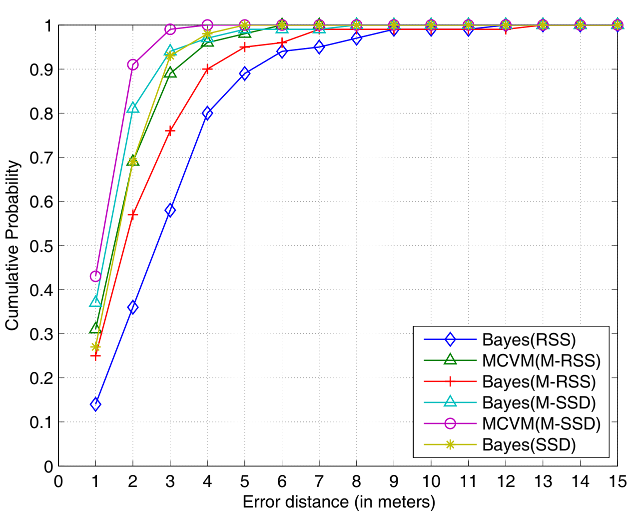

Figure 3. Comparison of error performance using different location fingerprinting.

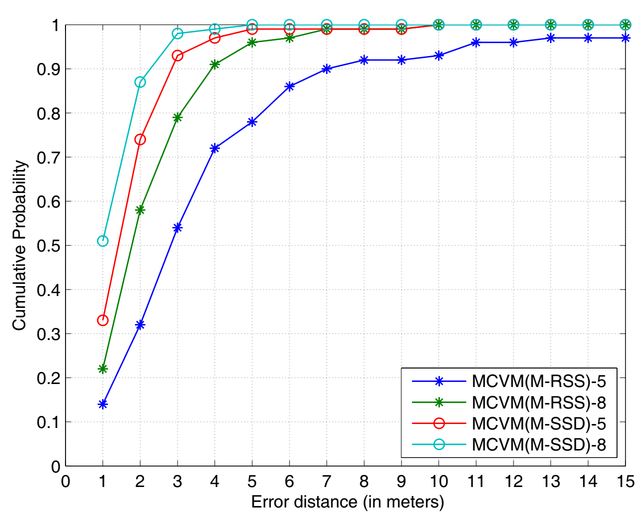

Figure 4. Multiple channel localization methods performance versus different RN numbers.

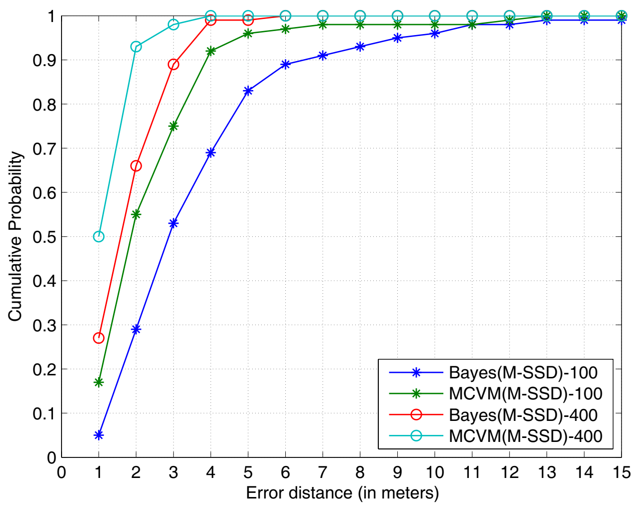

Figure 5. Multiple channel localization methods performance versus different training points numbers.

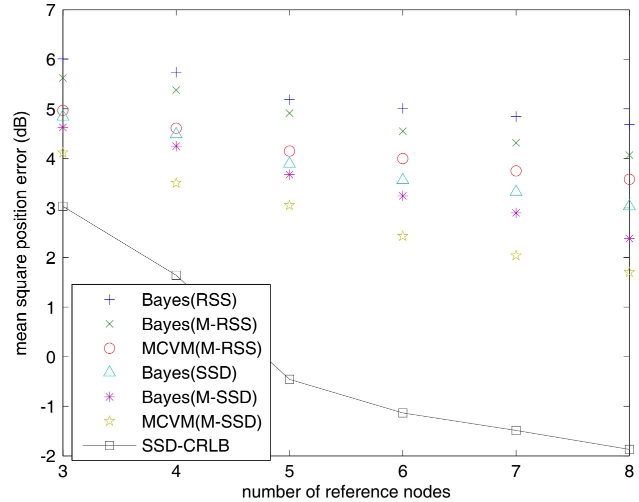

Figure 6. Mean square location error versus RN numbers for differ localization methods.

methods performance versus different training points numbers. Obviously, training points reduction will lead to deterioration of the localization performance. However, our MCVM method is less affected than the typical Bayes. The experimental results again give verification to the algorithm robustness.

4.4.2. Comparison of MCVM with Other Robust Fingerprintings Methods

We study the effect of the number of reference nodes on the mean square location error performance of our MCVM and other approaches. The number of RN is added successively from 3 to 8 (1, 3, 4, 6, 7, 8, 2, 5) in the testbed. The result is displayed in Fig. 6.

Six indoor localization approaches have been addressed in the paper. In the presence of zero-mean Gaussian measurement errors, the estimation performance of the MCVM outperforms other approaches. The performance of SSD-based approaches performs better than that of RSS-based approaches and multiple channel approaches exceed the singles. The MCVM approach based on the multiple channel SSD fingerprinting can provide the optimal localization accuracy. What's more, as for the localization methods mentioned in the article, we can conclude that when N is large (say $N \geq 6$), an increase in the number of reference nodes will not result in significant improvement of the localization accuracy in the real environment.

5. CONCLUSIONS

This paper presents a robust and effective indoor localization MCVM approach based on the multiple channel SSD fingerprinting. We verify its performance on platform cc2431. We do not use the RSS information directly, but associate the RSS information with the location information to construct the multiple channel location-SSD localization fingerprinting; we further study the impacts about different channel number as well as reference node numbers and training points numbers to the location error. We also theoretically deduce the CRLB of SSD in order to compare the performance of the different localization methods addressed in this paper. The research results show that the MCVM approach we proposed, yields satisfactory localization accuracy in the realistic settings.

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