Indoor Robot Localization Based on Wireless Sensor Networks

Long Cheng, *Student Member*, IEEE, Cheng-Dong Wu and Yun-Zhou Zhang, *Member*, IEEE

Abstract — *An effective indoor localization method of hybrid RSSI/TDOA is proposed to reduce the big errors occurred during indoor RSSI localization and high cost paid by TDOA localization. It measures RSSI with iterative recursive weighted average filter, and polynomial model is obtained to fitting the RSSI measurement and to obtain polynomial model. Furthermore the hybrid RSSI/TDOA localization algorithm is employed. The experiment results show that the proposed method of iterative recursive weighted average filter will improve the accuracy of RSSI localization on the condition of lower computation complexity, and the achieved localization is more accurate in the polynomial fitting than in the log-normal shadowing model. Moreover, the indoor location accuracy in the experiment is approximate 0.5 meter that satisfies the precision requirement of indoors location precision.*[1].

Index Terms — Wireless sensor networks, Indoor localization, Received signal strength index, Iterative recursive weighted average filter, Polynomial fitting.

I. INTRODUCTION

Localization is the one of key techniques in Wireless Sensor Networks (WSN). As a popular localization system, GPS (Global Positioning System) does not work indoors. A WSN-based indoor position system is proposed in the paper. It is hoped that the proposed system will be applied effectively to the wide areas such as robotic navigation and health care area.

Location estimation is a key issue for robots [1]. The classic methods to estimate the indoor location are time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength index (RSSI). TOA method measures travel times of signals between nodes; however synchronization error can significantly affect ranging error. TDOA method locates by measuring the signals' arrival time difference between anchor nodes and unknown node. It is able to achieve high ranging accuracy, but extra hardware is required and more energy is consumed. The angles between unknown node and a number of anchor nodes are used in the AOA method to estimate the location. As an inexpensive approach, RSSI has established the mathematical model on the basis of path loss attenuation with distance, and it requires relatively low configuration and energy. Indoor environments are particularly challenging for radio-based localization, because effects such as reflection, diffraction and scattering, make signal to characterize location more difficult. For RSSI-based localization is simple and the cost of implementation is much cheaper than TOA and AOA-based methods, it is suitable to employ in the WSN.

Based on the previous analysis, we will show that combinations of RSSI and TDOA measurements can lead to accurate location estimation in this paper. Filtering algorithm is applied first, and it is designed to fit WSN node with lower computational complexity. Polynomial fitting algorithm raises next. At last maximum likelihood is adopted to estimate and calculate the position. And the Cramer-Rao bound (CRB) is computed to estimate RSSI-based location. The accuracy of the proposed method is estimated in experiments.

II. RELATED WORKS

RSSI-based localization techniques have drawn considerable research interest. The performances between RSSI-based method and TDOA-based method are compared in [2] by experiments and their pros and cons are discussed in detail. Statistical method and artificial neural network method are proposed in [3] for distance measure based on RSSI value. The experiments demonstrate that the most important factor for distance estimation is to choose a transmission power according to the relevant distance; however, the method put forward has high computation complexity which is difficult to calculate in WSN node. Min-Max algorithm is proposed in [4] to detect and compensate measurement error. This algorithm overcomes the large attenuation measurement error for inbuilding wireless applications. It has low complexity in calculation and its localization accuracy is aimed at about 5 meters. An environment-adaptive method is proposed in [5] that is tolerant to parameter variations caused by environmental variations. The results of experiments show that proposed methods are more accurately than the existing localization system as time increases. It needs larger scale communication and induces WSN node lifetime that possesses limited energy. The accuracy of location is about 2 meter. A sigma-point Kalman smoother (SPKS)-based location and tracking algorithm is proposed in [6] for RSSI-based indoor positioning and tracking. Comparing with extend Kalman filter; SPKS algorithm is superior in localization accuracy under the same computational complexity. A transmit-power adaptive localization algorithm is proposed in [7] based on particle filtering for sensor networks assisted by multiple transmit-power

[1] This work was supported in part by National Natural Science Foundation of China under Grant No. 60874103; Station Key Laboratory of Robotics under Grant No. RLO200913.

The authors are with the School of Information Science and Engineering, Northeastern University, Shenyang 110819, China (e-mail: chenglong2000_0@yahoo.com.cn).

Contributed Paper
Manuscript received 05/29/11
Current version published 09/19/11
Electronic version published 09/19/11.
0098 3063/11/$20.00 © 2011 IEEE

information. This algorithm takes advantage of information from the ongoing wireless communication links to calculate the estimated position of sensor nodes. And simulation results suggest that the localization accuracy is improved with the increasing number of particles. The two-step indoor location estimation method based on RSSI in wireless senor networks is proposed in [8]. This method first estimate the environment parameters for signal propagation model by least-squares method, then using minimum mean squares error approach to estimate the location of the target node. Experimental results reveal that the approach can achieve high location estimation accuracy with low computation complexity. Wireless localization under various cases of multiple antennas is investigated in [9]. The experiment results indicate that the performance of accuracy and stability can be improved when using multiple antennas, and adding additional antennas helps average out small-scale environment effects.

III. INFRASTRUCTURE AND METHODOLOGY

In this section, the testbed infrastructure is described, and the involved methodologyies are: 1) iterative recursive weighted average filter for RSSI measurement; 2) polynomial fitting of RSSI and range; 3) the maximum likelihood estimate for localization and Cramer-Rao bound (CRB) for RSSI-based localization estimation.

A. Infrastructure of Testbed

Figure 1 depicts the floor plan of experimental site, where the floor size is 7m×9m. We deploy two types of nodes: ZigBee (RSSI) node and TDOA node. ZigBee nodes, as show in Figs.2(a), employ a 2.4 GHz low power radio chip, and observe RSSI values. The antennas have an omnidirectional pattern. Our system is based on a ZigBee communication, and all the communication is complied with the ZigBee protocol (IEEE 802.15.4). We also use TDOA node, as show in Figs.2 (b) to measure TDOA values. The robot, as show in Figs.2 (c), carries embedded processor, ZigBee node, and TDOA node. As shown in Fig.1, we deploy six ZigBee nodes and one TDOA node in the field. There are wifi and bluetooth devices in the building.

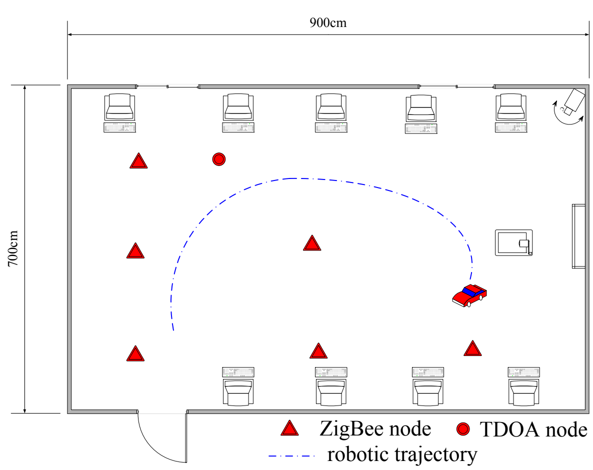
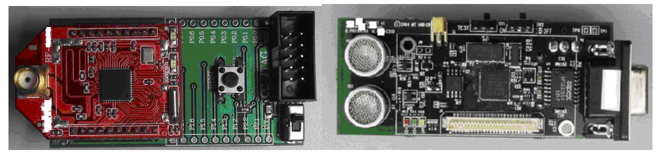
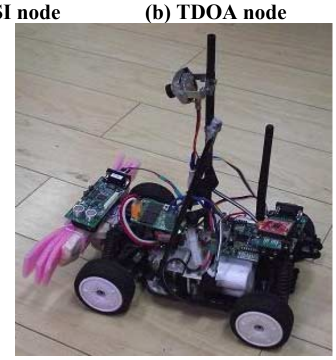


Fig.1 System deployment and robotic trajectory on the floor plan



(a) RSSI node (b) TDOA node



(c) The robot

Fig.2 The nodes and the robot

WSN nodes have limited energy that are mostly consumed during communication, thus wireless communication should be restricted. Beacon nodes are bounded in certain place and constant replacing batteries will add cost, but robot, acting as the unknown node, is easy to charge. Therefore, in the proposed system, unknown nodes send data package in certain transmitted power (0dBm) and beacon nodes possess sleep/awake mechanism in order to save energy. When beacon node received 50 packages, it filters on the average of RSSI measurement and the result is transmitted to base station, in where the result is converted into range information to calculate localization. This mechanism extends lifetime of sensor network.

In order to avoid beacon nodes causing errors in RSSI measurement during robot's movement, the following mechanism is employed. Unknown nodes constantly send data packages (packet length is 30byte) in each position and filtered results will be delivered to base station to carry on localization calculation when beacon nodes receives 50 packages. After base station has received all data form beacon nodes, the commands of stopping send package are delivered to unknown nodes. Then base station orders robot to move to next position when localization calculation is complete. Meanwhile unknown nodes are notified to send new data packages again.

For the variety of indoor environment, error may occur if the model uses fixed parameter to describe the relation of RSSI-distance. In this paper, the parameter is defined in RSSI-distance function: one RSSI-distance data set $\Psi = \langle (P_1, d_1), \cdots, (P_M, d_M) \rangle$ is measured indoors, (P_i, d_i) means that RSSI measurement of the receiving node is P_i when distance between transmission and receiving nodes is d_i, M refers to the measuring times and by employing polynomial fitting and measured data setting Ψ, RSSI-distance function is presented as $d = f(P)$.

Supposing that there are N beacon nodes indoors, RSSI value of the jth data package at time t in the ith node is $P_{ij}(t), (i = 1, \ldots N; j = 1, \ldots 50)$. After 50 data packages are received, the average RSSI is calculated as $\hat{P}_i(t) = \sum_{j=1}^{50} P_{ij}(t) \Big/ 50$. Following that, iterative recursive weighted average filter(IRWAF) is used inside nodes to offer filtered results （$\widetilde{P}_i(t)$） to base station where estimates distance by built function $d = f(P)$ and localization can be calculated.

The flow chart of localization algorithm is as follows:

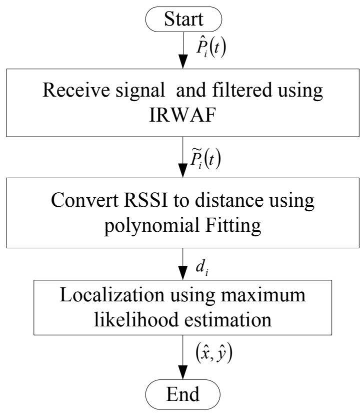


Fig.3 The flow chart of localization

B. *Iterative Recursive Weighted Average Filter*

Due to the complexity of indoor environment, the RSSI-range relation is unstable [10]. It is easy to cause big error if measurement data is applied to range directly. To reduce computation of base station, filtering algorithm is carried on within beacon nodes where contain low-power microcontroller and usually present low computational power and memory capabilities. Consequently the research about filtering method with low complexity is significant. This paper presents iterative recursive weighted average filter to RSSI measurement, which has high computational smoothness, needs fewer computing power and storage space, and fits nodes contains limited resources. The Pseudo-code of the algorithm is as follows:

Input: $\hat{P}_i(t-2)$, $\hat{P}_i(t-1)$, $\hat{P}_i(t)$ **Output:** $\widetilde{P}_i(t)$

1. Initialization: $\text{Filter1}(1) = \hat{P}_i(1)$; $\text{Filter2}(1) = \hat{P}_i(1)$;

$\text{Filter3}(1) = \hat{P}_i(1)$;

2. If (t==2)

3. $\text{Filter1(t)} = \beta_1 \hat{P}_i(t-1) + \beta_2 \hat{P}_i(t)$;

4. $\text{Filter2(t)} = \beta_1 \text{Filter1}(t-1) + \beta_2 \text{Filter1}_i(t)$;

5. $\text{Filter3(t)} = \beta_1 \text{Filter2}(t-1) + \beta_2 \text{Filter2}(t)$;

6. Else

7. $\text{Filter1(t)} = \beta_3 \hat{P}_i(t-2) + \beta_4 \hat{P}_i(t-1) + \beta_5 \hat{P}_i(t)$;

8. $\text{Filter2(t)} = \beta_3 \text{Filter1}(t-2) + \beta_4 \text{Filter1}(t-1) + \beta_5 \text{Filter1}(t)$;

9. $\text{Filter3(t)} = \beta_3 \text{Filter2}(t-2) + \beta_4 \text{Filter2}(t-1) + \beta_5 \text{Filter2}(t)$;

10. End

11. Output: $\widetilde{P}_i(t) = \text{Filter3}(t)$;

12. Where $\langle \beta_1, \beta_2, \beta_3, \beta_4, \beta_5 \rangle$ is the weighted coefficient.

Figure 4 illustrates comparison result of presented filtering methods and particle filter algorithm.

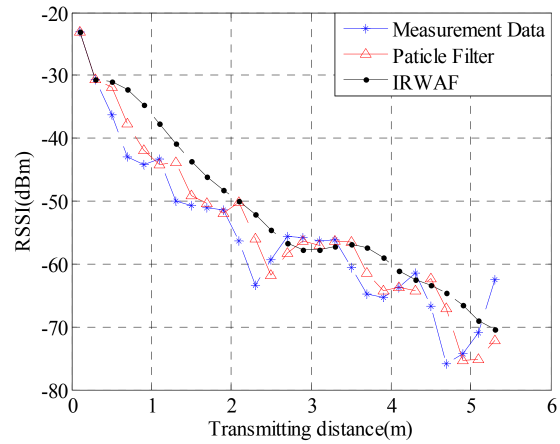


Fig.4 Comparison with different filtering algorithms

Figure 4 shows that comparing with particle filter algorithm, presented filtering method exhibits smoother curve, more stable RSSI-range relation and better effect on noise suppression.

C. *Parameter Estimation of Polynomial Fitting*

(1) Estimation of fitting coefficient

The most widely applied signal propagation model is the log-normal shadowing model [11]:

$$P(d)_{[dBm]} = P(d_0)_{[dBm]} - 10n\log\left(d \big/ d_0\right) + X_0 \tag{1}$$

Where $P(d_0)$ is the path loss at reference distance of d_0 meters. d_0 is assumed to be 1m, and n is the path loss exponent. $X_0 \sim N(0,\sigma^2)$ is the RSSI measurement noise modeled as zero mean white Gaussian with variance σ^2. The log-normal model can not fully characterize the relationship between RSSI data and distance [12]. It can also be concluded from figure 2 that the transmission of indoor wireless signal is not merely monotonous curve, and big errors can be made in distance estimation while the situation that P-d relation presents themselves as log in Equation (1). Due to different indoor environment, various transmission models of indoor wireless signal are adopted to fit various situation, a set of indoor data is measured in the paper and corresponding transmission model is found which improve the precision of the following localization calculation.

The polynomial fitting of channel model can be described as,

$$d = f(P) = \alpha_0 + \alpha_1 P + \alpha_2 P^2 + \ldots + \alpha_m P^m + \omega \tag{2}$$

Where P is received RSSI value. d is the distance between transmitter and receiver. $\alpha = [\alpha_0, \alpha_1, \ldots, \alpha_m]^T$ is the fitting coefficient. m is the order of the polynomial fitting, $\omega \sim N(0,\sigma^2)$ is the is Gaussian random variable with zero mean and σ^2 variance.

The ith measurement is $(P_i, d_i), (i = 1, \ldots n)$:

$$d_i = f_i(P_i) = \alpha_0 + \alpha_1 P_i + \alpha_2 P_i^2 + \ldots + \alpha_m P_i^m + \omega_i$$

The most favorable estimation of parameter α is through least square which leads to the least errors as follows:

$$\hat{\alpha} = \left(\mathrm{P}^T \mathrm{P}\right)^{-1} \mathrm{P}^T D \tag{3}$$

where,

$$D = \left[d_1, d_2, \ldots, d_n\right]^T, \mathrm{P} = \begin{bmatrix} 1 & P_1 & \cdots & P_1^m \\ 1 & P_2 & \cdots & P_2^m \\ \vdots & \vdots & \vdots & \vdots \\ 1 & P_n & \cdots & P_n^m \end{bmatrix}$$

(2) Estimation the order of the polynomial fitting

In the polynomial fitting, the choice of its fitting order is crucial. Without loss of generality, this paper works on measurement fitting of m and m-1-order models. The residual sum of squares of the corresponding measurement as:

$$S_m = \sum_{i=1}^{n} \left(d_i - \hat{d}_m\right)^2 = \sum_{i=1}^{n} \left(d_i - P_m D\right)^2$$

$$S_{m-1} = \sum_{i=1}^{n} \left(d_i - \hat{d}_{m-1}\right)^2 = \sum_{i=1}^{n} \left(d_i - P_{m-1} D\right)^2$$

and $\frac{S_m}{\sigma_m^2} \sim \chi^2(n-m-1)$, $\frac{S_{m-1}}{\sigma_{m-1}^2} \sim \chi^2(n-m)$, assuming that polynomial fitting variance has no remarkable difference in significant level.

Drawing from distribution of χ^2, it can be concluded that $\frac{R_m}{\sigma^2} = \frac{S_{m-1} - S_m}{\sigma^2} \sim \chi^2(1)$.

To verify variance of the two distributions, this paper adopts F distribution test and its distribution definition as follows: $F = \dfrac{S_{m-1} - S_m}{S_m / (n-m-1)}$.

Selecting significant level $\lambda = 0.01$ and finding critical value F_λ of F distribution that degrees freedom equals 1 and (n-m-1), if $F < F_\lambda$, it is m-1-oder polynomial fitting model to be chosen and otherwise it is m-order. Third-order polynomial fitting is chosen in the paper after rounds of calculation of measured data.

D. Localization Estimate

(1) Maximum likelihood estimate

Let the position of beacon node in TDOA be (x_0, y_0), the position of beacon node in RSSI be $\langle (x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N), \rangle$ and the position of unknown node be $X = [x, y]^T$.

$$X = \left(A^T A\right)^{-1} A^T B \tag{4}$$

Where, $A = 2\begin{bmatrix} (x_0 - x_1) & (y_0 - y_1) \\ (x_0 - x_2) & (y_0 - y_2) \\ \vdots & \vdots \\ (x_0 - x_N) & (y_0 - y_N) \end{bmatrix}$

$$B = \begin{bmatrix} \tilde{d}_1^2 - \tilde{d}_0^2 - \left(x_1^2 + y_1^2\right) + \left(x_0^2 + y_0^2\right) \\ \tilde{d}_2^2 - \tilde{d}_0^2 - \left(x_2^2 + y_2^2\right) + \left(x_0^2 + y_0^2\right) \\ \vdots \\ \tilde{d}_N^2 - \tilde{d}_0^2 - \left(x_N^2 + y_N^2\right) + \left(x_0^2 + y_0^2\right) \end{bmatrix}$$

(2) The Cramer-Rao bound analysis of RSSI location estimation

The log-normal shadowing model:

$$P(d)_{[dBm]} = P(d_0)_{[dBm]} + 10n \log\left(d / d_0\right) + X_0$$

The conditional probability density function of i-th node is shown in (5).

$$f_{P_i}(P_i \mid \theta) = \frac{10}{\ln 10 \cdot P_i \sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2}\gamma\left(\log\frac{d_i^2}{\hat{d}_i^2}\right)^2\right] \tag{5}$$

$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}$, (x, y) is the position of unknown node, (x_i, y_i) is the position of the i-th node, $\hat{d}_i = d_0 (P_0 / P_i)^{1/n}$, $\gamma = (10n / (\sigma \ln 10))^2$.

The conditional probability density function of RSSI measurements can be obtained from [13]:

$$F(p, \theta) = \prod_{i=1}^{N} f_{p_i}(P_i | \theta) \tag{6}$$

$l(\theta) = \ln F(p, \theta) = \sum_{i=1}^{N} \ln\left(f_{P_i}(P_i \mid \theta)\right)$, F is Fisher Information Matrix (FIM). $F = \begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix}$

Where, $c_{11} = -E\left(\frac{\partial^2 l(\theta)}{\partial x^2}\right)$, $c_{22} = -E\left(\frac{\partial^2 l(\theta)}{\partial y^2}\right)$, $c_{12} = -E\left(\frac{\partial^2 l(\theta)}{\partial x \partial y}\right)$

The Cramer-Rao bound of RSSI is expressed in Equation (7).

$$\Delta^2 = E\left[(x - \hat{x})^2 + (y - \hat{y})^2\right] \geq \frac{c_{11} + c_{22}}{c_{11} c_{22} - c_{12}^2} \tag{7}$$

Where $(\hat{x}, \hat{y})$ is the estimated position of the unknown node.

IV. EXPERIMENTAL RESULTS

In this paper, 50 indoor positions are pre-measured to form the data set Ω. During the experiment, 30 measurements are chosen randomly to be the initial data group, and range function $d = f(R)$ is established and employed for distance estimation. We obtain the parameters of log-normal shadowing model as follows: through least square, initial data group Ψ is used to identify parameters in Equation (1) to estimates distance. The power of transmission node sets at 0dBm and there is no obstacle between transmission node and receiving one.

Figure 5 displays position error of unfiltered polynomial fitting method (NFPF), filtered polynomial fitting (FPF), log-normal shadowing model fitting (FF) and its comparison with Cramer-Rao bound (CRB) in different number of beacon nodes.

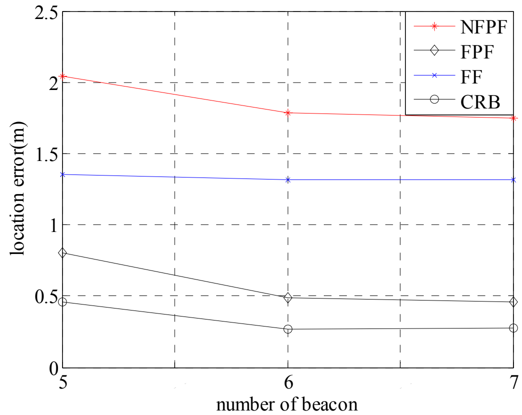


Fig.5 Localization error of comparing various number of beacon nodes

According to figure 5, NFPF has the biggest localization error which is about 1.5 meters; average localization accuracy of FPF is about 0.5 meter; localization error of FF is about 1 meter; Cramer-Rao bound of log-normal shadowing model fitting is about 0.4 and FPF's error curve closes most to Cramer-Rao curve. The existing RSSI localization system has the highest localization accuracy of 0.5 meter in favorable environment. The average localization error of FPF raised here is 0.5 meter. In the situation of low computational complexity, the proposed method produces better localization result.

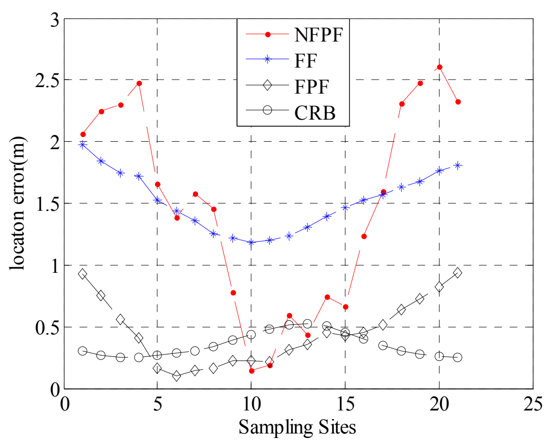


Fig.6 Localization error of comparing various sampling points

Figure 6 shows that when there are 6 beacon nodes (5 RSSI nodes and 1 TDOA node), the comparison of location error based on the 21 sampling sites by adopting three location algorithms between Cramer-Rao bound.

Figure 6 indicates that under the condition of 6 beacon nodes, the average Cramer-Rao bound of the 21 sampling sites is 0.34. In most sampling sites, the FPF algorithm presented here has the least localization error which is less than 1 meter. In certain position, FPF algorithm localization accuracy closes very much to Cramer-Rao bound which only based on RSSI. NFPF possesses the most localization error which is about 1 to 2 meters. And the error of FF is below 1.5 meters which is more than NFPF in most sampling sites.

V. Conclusion

WSN nodes have little computational functions and the errors may occur when applying log-normal shadowing model fitting method indoors, a WSN node-fit filtering method is proposed in the paper and on its basis the indoor polynomial fitting method is presented. This method restrains noise and stabilizes RSSI/range relation by employing proposed filtering. It also defines polynomial parameters through maximum likelihood estimation and statistical test method, and calculates hybrid RSSI/TDOA localization by least square and Cramer-Rao bound by log-normal shadowing model. Statistics of the experiments show that the method has lower computational calculation complexity, more close to Cramer-Rao bound, higher localization accuracy comparing with log-normal shadowing model fitting and unfiltered situation. Furthermore it is more suitable for indoor WSN localization application.

References

[1] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. Cambridge, MA: MIT Press, 2005.

[2] Hara S., Anzai D., "Experimental Performance Comparison of RSSI- and TDOA-Based Location Estimation Methods," *IEEE VTC,* 2008, PP.2651-2655.

[3] Awad A., Frunzke T., Dressler, F. "Adaptive Distance Estimation and Localization in WSN using RSSI Measures," *DSD 2007,* Vol.2, pp.471-478.

[4] Youngbae Kong; Younggoo Kwon; Gwitae Park. "Robust localization over obstructed interferences for inbuilding wireless applications," *IEEE Trans. on Consumer Electronics*, Vol.55, No.1, pp.105-111, Feb.2009.

[5] Hyo-Sung Ahn, Wonpil Yu, "Environmental-Adaptive RSSI-Based Indoor Localization," *IEEE Trans. on Automation Science and Engineering*,.Vol.6, No.4, pp.626-633, Oct.2009.

[6] Paul A.S., Wan E.A., "RSSI-Based Indoor Localization and Tracking Using Sigma-Point Kalman Smoothers," *IEEE J. of Selected Topics in Signal Processing*, Vol.3, pp.860-873, Oct.2009.

[7] Hongliang Ren, Meng M.Q.-H, "Power Adaptive Localization Algorithm for Wireless Sensor Networks Using Particle Filter," *IEEE Trans. on Vehicular Technology*, Vol.58, pp.2498-2508, Jun.2009.

[8] Yu-Yi Cheng, Yi-Yuan Lin, "A new received signal strength based location estimation scheme for wireless sensor network," *IEEE Trans. on Consumer Electronics*. Vol.55, No.3, pp.1259-1299, Aug.2009.

[9] Kleisouris K, Chen Y, Yang J, Martin R, "Empirical Evaluation of Wireless Localization When Using Multiple Antennas," *IEEE Trans. on Parallel and Distributed Systems*. Vol.99, pp.1-15, Nov.2010.

[10] Bosisio A.V., "RSSI-Based localization and tracking algorithm for indoor environments," *ICEAA, 2009*, pp.469–472.

[11] Saxena M., Gupta P., Jain B.N., "Experimental analysis of RSSI-based location estimation in wireless sensor networks," *COMSWA*, *2008*, pp.503–510.

[12] Patwari, N., Hero, A.O., III, Perkins, M., Correal, N.S., O'Dea, R.J., "Relative location estimation in wireless sensor networks," *IEEE Trans. on Signal Processing*. Vol.51 No.8, pp.2137-2148, Aug.2003.

[13] Catovic A., Sahinoglu Z., "The Cramer-Rao bounds of hybrid TOA/RSS and TDOA/RSS location estimation schemes," *IEEE Communications Letters*. Vol.8 No.10, pp.626-628, Oct.2004.

BIOGRAPHIES

Long Cheng received B.S. degree in automatic control from Qingdao University of Science and Technology, Qingdao, China, in 2008, the M.S. degree in pattern recognition and intelligent system from Northeastern University, Shenyang, China, in 2010. He is pursing the Ph.D. degree in pattern recognition and intelligent system from Northeastern University, Shenyang, China. His research interests include wireless sensor networks and distributed system. He is a student member of the IEEE.

Cheng-Dong Wu received M.S. degree in automatic control from Tsinghua University, Beijing, China, in 1988. He received Ph.D. degree in automatic control from Northeastern University, Shenyang, China, in 1994. From 1995 to 1997, he worked as a postdoctoral researcher in University of Wales, U.K. From 2001 to 2002, he worked as senior visiting professor in University of Bedfordshire, U.K. His current research interests include wireless sensor networks, home automation and robot.

Yun-Zhou Zhang received B.S. degree and M.S. degree in Mechanical and Electronic engineering from National University of Defense Technology, Changsha, China in 1997 and 2000, respectively. He received Ph.D. degree in pattern recognition and intelligent system from Northeastern University, Shenyang, China, in 2009. His research interests include distributed system, intelligent robot and wireless sensor networks. He is a member of the IEEE.