

Research Article

An Indoor Mobile Localization Strategy for Robot in NLOS Environment

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This paper deals with the problem of localization of mobile robot in indoor environment with mixed line-of-sight/nonline-of-sight (LOS/NLOS) conditions. To reduce the NLOS errors, a prior knowledge-based correction strategy (PKCS) is proposed to locate the robot. This strategy consists of two steps: NLOS identification and mitigation. We propose an NLOS identification method by applying the statistical theory. Then we correct the NLOS errors by subtracting the expected NLOS errors. Finally, the residual weighting algorithm is employed to estimate the location of the robot. Simulation results show that the proposed strategy significantly improves the accuracy of localization in mixed LOS/NLOS indoor environment.

1. Introduction

Indoor robot has been widely applied in health care, smart home, and emergency supporting. Location information is very important for mobile robot [1]. Due to the fact that GPS (Global Positioning System) does not work in indoor environment, so the indoor localization has motivated increased research interest. Since the Wireless Sensor Network (WSN) can be deployed quickly and flexible, so WSN is an effective application for indoor localization.

Recently, many indoor localization systems have been developed based on different wireless measurements: received signal strength (RSS) [2], time of arrival (TOA) [3], angle of arrival (AOA) [4], and time difference of arrival (TDOA) [5]. A mobile robot can estimate its location based on the wireless measurements with some beacon nodes whose locations are known prior. TDOA and AOA methods are energy-consuming resolution and they require extra hardware. TOA needs the high precision clock to achieve clock synchronization. So the above three methods are not suit for low configured sensor node. As an inexpensive approach, RSS has established the mathematical model on the basis of path loss attenuation with distance, and it requires relatively low configuration and energy. In this paper, we employ RSS localization method because of its characteristics. However, due to the complex indoor

environment where walls and other obstacles are present, the wireless channel will always be blocked. The NLOS environment causes the radio signal to propagate a longer path than the true distance between the beacon nodes and target (e.g., robot or unknown node) due to the reflection and diffraction. So it induces the degradation of the localization accuracy. Thus, indoor localization which is robust to the NLOS environment is required [6]. In the presence of obstacles, the major positioning errors are from the measurements errors and NLOS propagation errors. And the NLOS effect leads to large localization errors if we do not consider it in the localization method.

For the purpose of realizing robust localization in NLOS environment, we propose a localization method using RSS measurement. And this method consists of four steps: NLOS identification, NLOS correction, Kalman filter, and residual weighting algorithm.

Several previous works have been investigated the localization algorithm in NLOS environment. The localization methods in NLOS environment can be categorized as non-parametric method and parametric method. For the non-parametric method, Chen [7] proposes a residual weighting algorithm to alleviate the NLOS errors in the location estimate. This method employs the least squares on all possible combinations of distance measurements and then calculates the final position as a weighted combination of

these intermediate estimates. The computational complexity of this method grows exponentially with the number of measurements. A robust multilateration algorithm [8] is introduced in NLOS environment. This algorithm is robust in comparison with traditional least squares multilateration. However, the performance of this method is severely affected by the number of NLOS measurements. Least squares support vector machine [9] classifier is employed to distinguish LOS/NLOS propagation and further mitigate the ranging errors in NLOS conditions. For the parametric method, the additive noise in the range measurement is characterized by different noise distributions corresponding to LOS and NLOS errors. In [10], Borrás et al. propose a binary hypothesis test method to identify the NLOS measurements. In [11], Mazuelas et al. propose a prior NLOS measurements correction method to correct the measurements from NLOS propagation. Most of above works focus on the UWB system. But this system is not suit for WSN which consists hundreds of sensor nodes in the monitoring field.

Since the relatively low configuration and cost, RSS-based localization techniques have drawn considerable research interest [12]. An environment-adaptive method is investigated [13] that is tolerant to parameter variations caused by environmental variations. A sigma-point Kalman smoother (SPKS) based location and tracking algorithm is proposed [14] for RSSI-based positioning and tracking. However, all of the above methods only consider the LOS environment. Fewer papers investigate the RSS-based localization method in NLOS environment.

In this paper, we firstly investigate the RSS-based NLOS identification method using the recorded measurements. Then the ratio of NLOS present in the record of measurements and the expectation of the NLOS errors are used to mitigate the NLOS errors. Kalman filter is employed to improve the estimated range. Finally, we use the residual weighting algorithm to estimate the location of the robot.

This paper is organized as follows. In Section 2, we introduce range estimation model. NLOS identification, NLOS mitigation, and localization method are presented in Section 3. Some simulation results present in Section 4. The conclusions are given in Section 5.

2. Range Estimation Model

The robot carries a sensor node which is used to communicate with the beacon nodes in the WSN. The beacon nodes emit signal continually. The robot estimates the distance between beacon node and the robot through received signal strength. The most widely applied signal propagation model is the log-normal shadowing model. The received signal strength of the robot from m th beacon node [15] is

$$PL_m = PL_0 - 10n_{\text{los/nlos}} \log_{10} \left(\frac{d_m}{d_0} \right) + S_{\text{los/nlos}} \quad (1)$$

where PL_0 is the received signal strength at reference distance of d_0 meters. d_0 is assumed to be 1 m, and n is the path loss exponent. Generally line-of-sight of indoor environment shows n around 1.6 to 1.8, and around 4 to 6 in the presence

of obstacles. $S_{\text{los}} \sim N(0, \sigma_{\text{los}}^2)$ is the LOS measurement noise modeled as zero mean white Gaussian with variance σ_{los}^2 . $S_{\text{nlos}} \sim N(\mu_{\text{nlos}}, \sigma_{\text{nlos}}^2)$ is the measurement noise in NLOS environment. And $\sigma_{\text{nlos}} > \sigma_{\text{los}}$. These parameters could be obtained in an environment through simulation or experiment. $d_m = \sqrt{(x_m - x)^2 + (y_m - y)^2}$ is the true distance between the m th beacon node and the robot. (x_m, y_m) is the coordinate of m th beacon node, and (x, y) is the position of the robot.

From (1), the estimated range between the m th beacon node and the robot can be expressed as

$$\begin{aligned} \hat{d}_m &= 10^{(10n_{\text{los/nlos}} \log_{10} d_m + S_{\text{los/nlos}}) / 10n_{\text{los/nlos}}} \\ &= d_m \cdot 10^{S_{\text{los/nlos}} / 10n_{\text{los/nlos}}} \\ &= d_m + (10^{S_{\text{los/nlos}} / 10n_{\text{los/nlos}}} - 1) d_m. \end{aligned} \quad (2)$$

We can approximately obtain that [16] $N_{\text{los}} = (10^{S_{\text{los}} / 10n_{\text{los}}} - 1) d_m \sim N(0, \sigma_1^2)$ under LOS environment, and $N_{\text{nlos}} = (10^{S_{\text{nlos}} / 10n_{\text{nlos}}} - 1) d_m \sim N(\mu_2, \sigma_2^2)$ under NLOS environment.

So the estimated range can be rewritten as

$$\hat{d}_m = d_m + N_{\text{los/nlos}}. \quad (3)$$

Based on this range estimation model, we investigate NLOS identification when the obstacles present and propose a prior knowledge-based correction strategy (PKCS) to mitigate NLOS errors. The proposed method can be used to localize the mobile robot in indoor environment. This strategy will improve the localization accuracy.

3. NLOS Identification and Mitigation

The propagation conditions can change from LOS to NLOS when the robot is moving in the indoor environment. The NLOS propagation generally leads to a positive bias in the estimation range and causes a serious error in location estimation. So we should firstly identify the propagation conditions and then to mitigate the NLOS errors.

We make the following assumptions in the study. There are M beacon sensors and one robot in the field. The beacon nodes emit radio signal which attenuates inside the area under observation. The intensity of a signal emitted omnidirectionally. The robot receives the radio and estimates the distance between the beacon node and the robot according to (3).

In this section, we propose a strategy for robot localization in NLOS environment. We firstly employ the polynomial fit to smooth the measurements, and then the average deviation between the smoothed curve and measurements and the standard deviation of the LOS noise are used to identify the NLOS measurements. Secondly, we estimate the NLOS ratio in the measurements to determine which measurements contain the NLOS errors, and then mitigate the NLOS measurements errors through subtracting the expectation of NLOS errors. Kalman filter is introduced to

improve the estimated range. Finally we use the residual weighting (Rwgh) algorithm to estimate the location of the robot. The flowchart of the proposed algorithm is given in Figure 1.

3.1. NLOS Identification. In order to identify the NLOS measurements, we consider the historical measurements from each beacon node individually. Based on the measurements of beacon node during a period of time and the standard deviation of the LOS noise, we determine whether the measurements contain the NLOS errors. We select a short period of time t_1-t_N , N is the number of sampled measurements from the m th beacon node, and the environment parameters are constant in the period. The estimated distance between the m th beacon node and the robot at time t_i is called $\hat{d}_m(t_i)$. The standard deviation of the measurements of m th beacon node can be expressed as [17]

$$S = \sqrt{\frac{1}{N} \sum_{i=1}^N [\hat{d}_m(t_i) - E(\hat{d}_m(t_i))]^2}. \quad (4)$$

We can determine that the data have affected by NLOS if the standard deviation is much larger than the standard deviation of the LOS noise. But the value of $E(\hat{d}_m(t_i))$ is unknown, so we will employ a smooth version of the measurement records which we have stored to estimate the value of $E(\hat{d}_m(t_i))$. For this purpose, we will use a smooth cubic regression of the measurements. The polynomial fit is used to estimate the deviation of the measurements. p_m is the third-order polynomial that best fits the available measurements minimizing its curvature. The third-order polynomial fulfills the objective of estimating the value of $E(\hat{d}_m(t_i))$ with a high accuracy.

At m th beacon node, the measurements are smoothed as

$$p_m(t_i) = \sum_{k=1}^3 b_m(k) t_i^k. \quad (5)$$

So the standard deviation of the measurements can be rewritten as

$$S = \sqrt{\frac{1}{N} \sum_{i=1}^N [\hat{d}_m(t_i) - p_m(t_i)]^2}. \quad (6)$$

Because the NLOS errors are uncorrelated in time, so the measured data will have a significantly larger average deviation from the smoothed curve when the NLOS errors present. The algorithm requires comparison of the deviation S and the standard deviation of the LOS noise. If $S \gg \sigma_L$, then the measurements contain the NLOS errors. Otherwise the propagation path of the measurements is LOS.

3.2. NLOS Mitigation. When the NLOS is present, the measured data will deviate from the smoothed curve largely. In order to mitigate the NLOS errors, we must know which measurements are affected by NLOS. We firstly estimate the percentage of measurements in our records which are

corrupted by NLOS errors during the sample period. Then we determine which measurements are corrupted by NLOS errors. Finally, an NLOS mitigation algorithm is proposed in this subsection.

If the measurements are affected by NLOS,

$$\begin{aligned} (\hat{d}_{m,L}(t_i) - p_{m,L}(t_i)) &\sim N(\mu_L(K), \sigma_L^2(K)), \\ (\hat{d}_{m,N}(t_i) - p_{m,N}(t_i)) &\sim N(\mu_N(K), \sigma_N^2(K)), \end{aligned} \quad (7)$$

where L and N represent the measurements taken at time t_i coming from LOS and NLOS, respectively. K is the percentage of measurements corrupted by NLOS errors. So

$$\begin{aligned} NS^2 &= \sum_{i=1}^N [\hat{d}_m(t_i) - p_m(t_i)]^2 \\ &= \sum_{\text{los}} [\hat{d}_{m,L}(t_i) - p_{m,L}(t_i)]^2 \\ &\quad + \sum_{\text{nlos}} [\hat{d}_{m,N}(t_i) - p_{m,N}(t_i)]^2 \\ &= \sigma_L^2(K) \sum_{\text{los}} \left[\frac{\hat{d}_{m,L}(t_i) - p_{m,L}(t_i)}{\sigma_L(K)} \right]^2 \\ &\quad + \sigma_N^2(K) \sum_{\text{nlos}} \left[\frac{\hat{d}_{m,N}(t_i) - p_{m,N}(t_i)}{\sigma_N(K)} \right]^2 \\ &= \sigma_L^2(K) X + \sigma_N^2(K) Y. \end{aligned} \quad (8)$$

Since

$$\begin{aligned} \frac{\hat{d}_{m,L}(t_i) - p_{m,L}(t_i)}{\sigma_L(K)} &\sim N(\mu_L(K), 1), \\ \frac{\hat{d}_{m,N}(t_i) - p_{m,N}(t_i)}{\sigma_N(K)} &\sim N(\mu_N(K), 1). \end{aligned} \quad (9)$$

From (9), it can be seen that the X and Y follow noncentral chi-square distribution: $X \sim \chi_{(1-K)N, \lambda_1(K)}^{\text{NC}}$, $Y \sim \chi_{KN, \lambda_2(K)}^{\text{NC}}$, where $\lambda_1 = \sqrt{\sum_{\text{los}} \mu_L^2(K)}$, $\lambda_2 = \sqrt{\sum_{\text{nlos}} \mu_N^2(K)}$, NC means noncentral.

Therefore the expectation of the deviation can be presented as

$$\begin{aligned} E(S^2) &= \sigma_L^2(K) \left[(1-K) + \mu_L(K) \sqrt{\frac{1-K}{N}} \right] \\ &\quad + \sigma_N^2(K) \left[K + \mu_N(K) \sqrt{\frac{K}{N}} \right]. \end{aligned} \quad (10)$$

When the number of sample N is large, (10) can be rewritten as:

$$E(S^2) = (1-K) \sigma_L^2(K) + K \sigma_N^2(K). \quad (11)$$

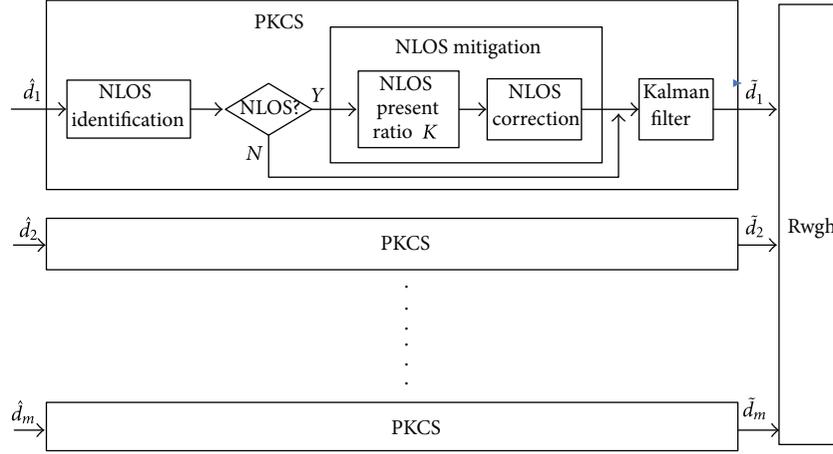


FIGURE 1: The architecture of the proposed algorithm frame.

The variance of S^2 is given by

$$\text{Var}(S^2) = \frac{\sigma_L^4(K) \text{Var}(X) + \sigma_N^4(K) \text{Var}(Y)}{N^2}, \quad (12)$$

where $\text{Var}(X) = 2(1 - K)N + 4\mu_L(K)\sqrt{(1 - K)N}$ and $\text{Var}(Y) = 2KN + 4\mu_N(K)\sqrt{KN}$.

When N is relatively large, variance of S^2 is very small in (12). So we can assume that $S^2 \approx E(S^2)$. We can obtain S^2 as

$$S^2 \approx (1 - K)\sigma_L^2(K) + K\sigma_N^2(K). \quad (13)$$

Assume that $\sigma_L(K) \approx \sigma_1$, $\sigma_N(K) \approx \sigma_2$. σ_2 is much larger than σ_1 .

The percentage of measurements corrupted by NLOS errors is given by

$$K = \frac{S^2 - \sigma_1^2}{\sigma_2^2 - \sigma_1^2}. \quad (14)$$

Then we estimate which measurements are corrupted by NLOS errors after the percentage of measurements which have NLOS errors is obtained.

As we know, $P\{N_{\text{los}} > (3/2)\sigma_1\} = 0.0668$. It means that the probability of LOS errors which larger than one and half its standard deviation is very low. So the large errors are mainly from the NLOS environment. And we assume that $p = P\{N_{\text{mlos}} > (3/2)\sigma_1\}$, so the number of NLOS measurements is pNK. We sort the standard deviation of the measurements S from large to small. The largest pNK measurements may contain the NLOS errors. We calculate the mean of these standard deviations of the pNK measurements, and it can be expressed as M_{NLOS} . Since the NLOS errors are the positive bias. We correct the pNK measurements which contain the NLOS by subtracting the expected NLOS errors M_{NLOS} . The corrected range can be expressed as

$$\hat{d}'_m(q) = \hat{d}_m(q) - M_{\text{NLOS}}, \quad q = 1, \dots, \text{pNK}. \quad (15)$$

3.3. Kalman Filter. The KF is one of the popular filtering methods developed and it, as well as its descendants, has been the dominate filter type for the past 40 years. Most localization systems use Kalman filter for state estimation. Kalman filter produces optimal estimates when measurement noise is Gaussian and stationary. It can be executed within a computer and iteratively without any extensive modification or special hardware. We perform the Kalman filter for the measurements in LOS and the corrected measurements in NLOS. The state equation of m th beacon node under LOS/NLOS environment can be expressed as follows:

$$X_m(t_{i+1}) = F(\Delta t) X_m(t_i) + C w_m(t_i), \quad m = 1, \dots, M, \quad (16)$$

where $X_m(t_i)$ and $X_m(t_{i+1})$ are the state vectors at time t_i and t_{i+1} , respectively. Let the state vector be $X_m(t_i) = [d_m(t_i) \quad \dot{d}_m(t_i)]^T$, $m = 1, \dots, M$, where T denotes the transpose operator, and $d_m(t_i)$ represents the distance between the m th beacon node and the robot. $\dot{d}_m(t_i)$ denotes the velocity of the robot, where $w_m(t_i)$ is the process noise and follows zero mean independently and identically distributed Gaussian with variance σ_m^2

$$F(\Delta t) = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \quad C = \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix}, \quad (17)$$

where $\Delta t = 1$ is the sample period.

The measurement equation of sensor m under LOS/NLOS environment can be expressed as follows:

$$Z_m(t_{i+1}) = \hat{d}_m(t_{i+1}) = d_m(t_{i+1}) + N_{\text{los}}, \quad m = 1, \dots, M, \quad (18)$$

where \hat{d}_m is the corrected range according to (15) in NLOS or the measurements in LOS.

We can obtain the predicted state and prediction covariance as follows:

$$\begin{aligned}\widehat{X}_m(t_{i+1} | t_i) &= F(\Delta t) \widehat{X}_m(t_i | t_i), \\ P_m(t_{i+1} | t_i) &= F(\Delta t) P_m(t_i | t_i) F^T(\Delta t) + \sigma_m^2 C C^T, \\ \gamma_m(t_{i+1}) &= Z_m(t_{i+1}) - \widehat{Z}_m(t_{i+1} | t_i), \\ \widehat{Z}_m(t_{i+1} | t_i) &= G \widehat{X}_m(t_{i+1} | t_i),\end{aligned}\quad (19)$$

where \widehat{X}_m represents the estimate of state vector X_m , $\widehat{X}_m(t_{i+1} | t_i)$ is the predicted state estimate of state vector, $\widehat{X}_m(t_i | t_i)$ is the state estimate at the time t_i , $P_m(t_i | t_i)$ and $P_m(t_{i+1} | t_i)$ are the estimate and predicted covariance at the time t_i , respectively, and $\widehat{Z}_m(t_{i+1} | t_i)$ is the priori state estimate of measurement $Z(t_{i+1})$.

$G = [1 \ 0]$, where G assigns different value according to different measurement mechanisms. Consider

$$S_m(t_{i+1}) = G P_m(t_{i+1} | t_i) G^T + Q_m, \quad (20)$$

where Q_m is the covariance matrix of measurement error. The Kalman gain is as follows:

$$K_m(t_{i+1}) = P_m(t_{i+1} | t_i) G^T S_m^{-1}(t_{i+1}). \quad (21)$$

Then we can obtain the updated state estimate and updated estimate covariance as follows:

$$\begin{aligned}\widehat{X}_m(t_{i+1} | t_{i+1}) &= \widehat{X}_m(t_{i+1} | t_i) + K_m(t_{i+1}) \gamma_m(t_{i+1}), \\ P_m(t_{i+1} | t_{i+1}) &= P_m(t_{i+1} | t_i) - K_m(t_{i+1}) G P_m(t_{i+1} | t_i).\end{aligned}\quad (22)$$

The ranging estimation in Kalman filter is expressed as:

$$\widetilde{d}_m(t_{i+1}) = D \widehat{X}_m(t_{i+1} | t_{i+1}), \quad D = [1, 0]. \quad (23)$$

3.4. Location Estimation. The outputs of Kalman filter are the estimated distances between the robot and beacon nodes. According to the estimated distances, we can locate the robot in the field. In this section, we introduce residual weighted localization method to estimate the location of the robot.

The Conventional Residual Weighting algorithm can be described as follows [7].

- (a) Make initialization with $n = M$, ($M > 3$). M is the number of sensor nodes, the beacon nodes form $Z = \sum_{i=3}^M C_M^i$ range measurement combinations. Each combination is represented by a beacon node index set $\{S_k | k = 1, 2, \dots, Z\}$.
- (b) For each beacon node index set, we employ the maximum likelihood method to estimate the location of the robot which can be represented as $\widehat{X}_k = [\widehat{x}_k, \widehat{y}_k]$. Then we compute the average of Res (residual) as follows:

$$\overline{\text{Res}}(\widehat{X}_k, S_k) = \frac{\text{Res}(\widehat{X}_k, S_k)}{\text{size}(S_k)}, \quad (24)$$

TABLE 1: Default parameter values.

Parameters	Default values
Number of sensor nodes (M)	6
Mean of the LOS noise (μ_L)	0
Mean of the NLOS noise (μ_N)	3
Standard variance of LOS noise (σ_L)	1
Standard variance of NLOS noise (σ_N)	5

where $\text{Res}(\widehat{X}_k, S_k) = \sum_{j \in S_k} (\widehat{d}_j' - \sqrt{(x_j - \widehat{x}_k)^2 + (y_j - \widehat{y}_k)^2})^2$ and (x_j, y_j) are the coordinate of j th beacon node.

- (c) Find the final estimated location of the robot as the weighted linear combination of the intermediate estimations from step (b). The weight is inversely proportional to $\overline{\text{Res}}$ of the estimation. Mathematically, we can get the estimated location of the robot as follows:

$$\widehat{X} = \frac{\sum_{k=1}^Z \widehat{X}_k (\overline{\text{Res}}(\widehat{X}_k, S_k))^{-1}}{\sum_{k=1}^Z (\overline{\text{Res}}(\widehat{X}_k, S_k))^{-1}}. \quad (25)$$

4. Performance Evaluation and Analysis

In this section, we evaluate the performance of the NLOS localization method described in the previous sections through simulations. Table 1 presents the default parameter values in the experiments. We consider a 200 m \times 160 m area with six beacon nodes, and the robot moves in the field. There are two obstacles in the field. In each simulation case, 2000 Monte Carlo runs are performed with the same parameters. The performance of the proposed algorithm is measured by average localization error as

$$\text{error} = \frac{1}{N_t} \sum_{i=1}^{N_t} \sqrt{(\widehat{x}_i - x)^2 + (\widehat{y}_i - y)^2}, \quad (26)$$

where $N_t = 2000$, (x, y) is the true location of the robot. $(\widehat{x}_i, \widehat{y}_i)$ is the estimated location of the robot at i th Monte Carlo trial.

In this section, we compare the proposed algorithms (PKCS-ML and PKCS-Rwgh) with the naïve ML and Rwgh algorithms. All of the four algorithms employ the Kalman filter to improve the estimated range.

In Figure 2, we compare the localization results between the Rwgh and PKCS-Rwgh algorithm. Figure 2(a) shows the sight state with respect to all the beacon nodes in sample points. We can see that the sight states vary with time. A mobile localization is shown in Figure 2(b). This figure compares the true trajectory between the estimated one obtained by Rwgh and another obtained by our method. The localization errors can be appreciated by looking at the lines that connect the true and the estimated positions. In Figure 2(c), we can obtain the detailed localization errors in each sample point. It can be observed that the proposed method has better performance in comparison with Rwgh in most of the sample points.

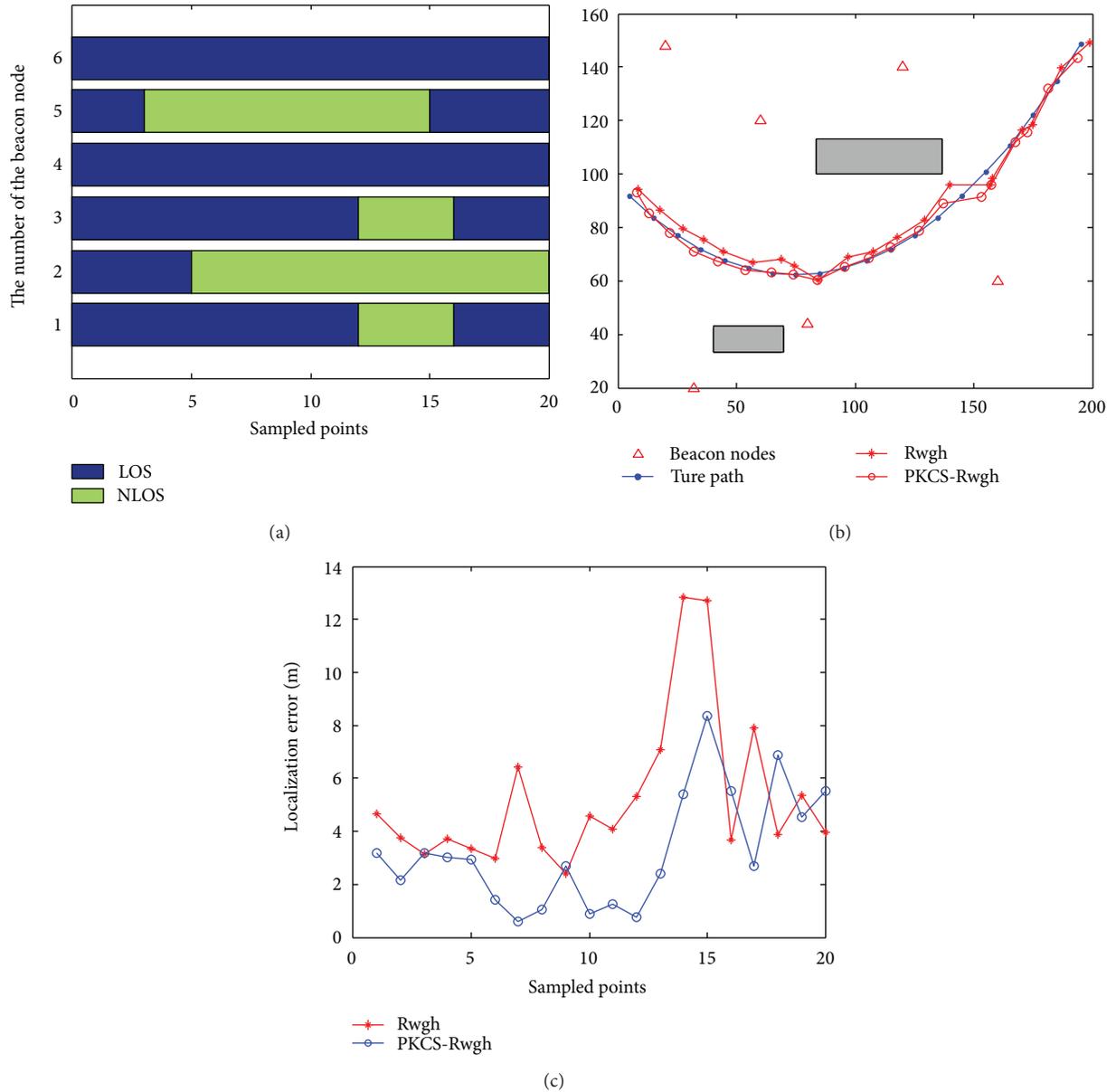


FIGURE 2: (a) The sight state in each sample point, (b) example of the mobile localization, (c) the localization errors in each sample point.

In Figure 3, the number of beacon nodes is varied from 4 to 8. The MLE and Rwhg methods with the prior knowledge-based correction strategy are called PKCS-MLE and PKCS-Rwhg, respectively. The results show that the effect of increasing the number of beacon nodes is higher using MLE method in comparison with the Rwhg method. However, the PKCS-MLE and PKCS-Rwhg methods have higher localization accuracy compared with MLE and Rwhg methods.

Figure 4 shows the average localization error versus the standard variance of LOS noise. The PKCS-MLE and PKCS-Rwhg methods demonstrate similar robustness against the standard variance of LOS noise. The localization errors of the MLE are always larger than 4 m and increase significantly as the standard variance of LOS noise increases. Due to

the PKCS, the performance of PKCS-MLE and PKCS-Rwhg methods outperforms the MLE and Rwhg methods.

To investigate the robustness of the proposed method, we evaluate it under different standard variances of NLOS noise. In Figure 5, it is obvious that the average localization error increases with the increment of standard variance of NLOS noise. We can see that the localization accuracy of PKCS-MLE is improved significantly in comparison with MLE. And the PKCS-Rwhg has 6.87% higher localization accuracy than Rwhg.

In Figure 6, we show the average localization error versus mean of NLOS noise. The accuracy of all methods is decreased with the increase of mean of the NLOS noise. We can see that the proposed method can significantly

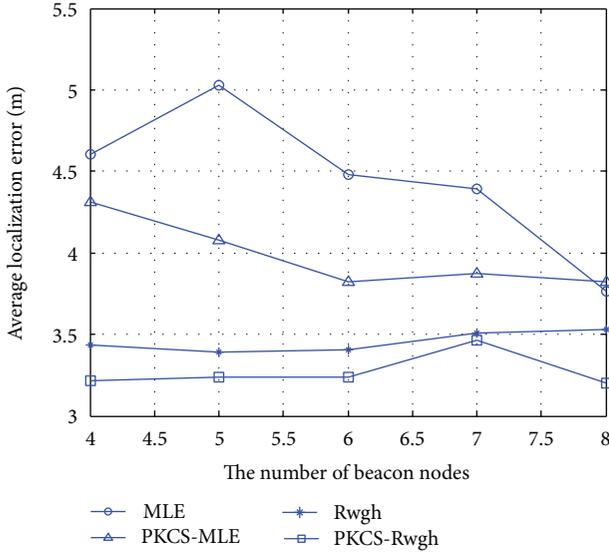


FIGURE 3: Average localization error versus the number of beacon nodes.

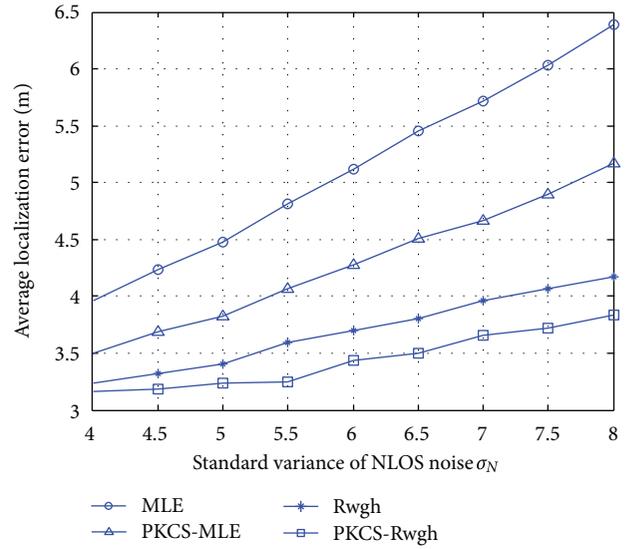


FIGURE 5: Average localization error versus the standard variance of NLOS noise.

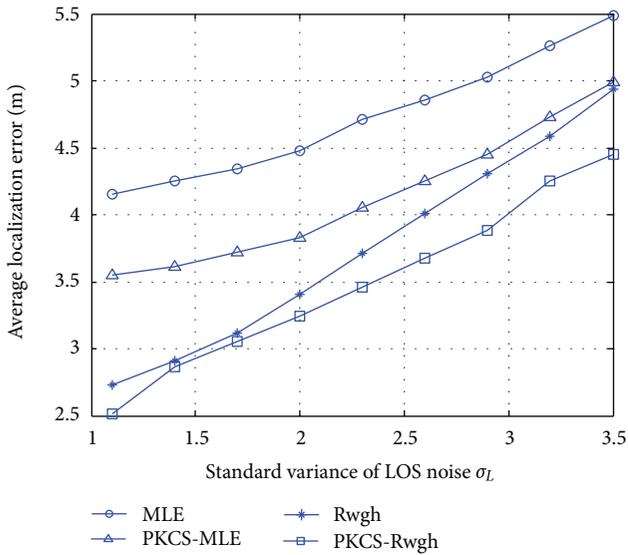


FIGURE 4: Average localization error versus the standard variance of LOS noise.

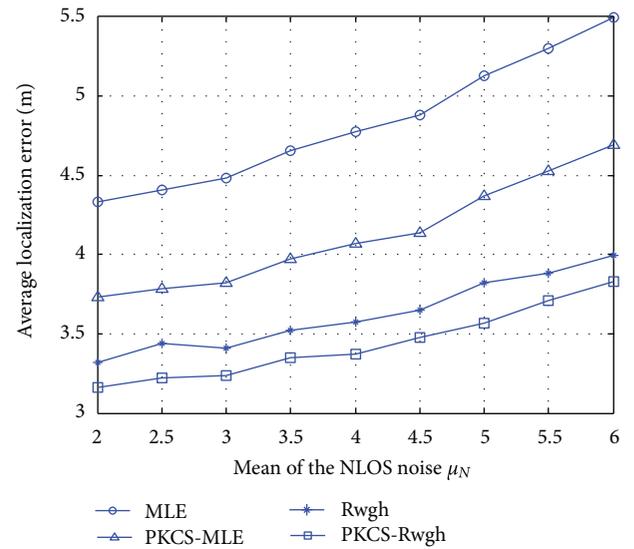


FIGURE 6: Average localization error versus the mean of NLOS noise.

improve the location estimation accuracy by subtracting the expectation of NLOS errors. And the average localization error of MLE and Rwgh methods are worse without prior knowledge-based correction strategy.

5. Conclusion

An NLOS correction approach has been proposed to locate the position of mobile robot in order to alleviate the NLOS errors which arise in clustering environment. We consider the prior knowledge of the errors to identify the NLOS and then remove the NLOS errors by subtracting the expectation

of NLOS errors. This method could mitigate the NLOS propagation effect. Simulation results show that the PKCS has much better performance than those methods without the correction method and significantly improves the localization accuracy.

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References

- [1] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*, The MIT Press, Cambridge, Mass, USA, 2005.
- [2] I. Amundson, J. Sallai, X. Koutsoukos, and A. Ledeczi, "Mobile sensor waypoint navigation via RF-based angle of arrival localization," *International Journal of Distributed Sensor Networks*, vol. 2012, Article ID 842107, 15 pages, 2012.
- [3] I. Güvenç and C. C. Chong, "A survey on TOA based wireless localization and NLOS mitigation techniques," *IEEE Communications Surveys and Tutorials*, vol. 11, no. 3, pp. 107–124, 2009.
- [4] Y. S. Lee, J. W. Park, and L. Baroll, "A localization algorithm based on AOA for ad-hoc sensor networks," *Mobile Information Systems*, vol. 8, no. 1, pp. 61–72, 2012.
- [5] Y. Weng, W. Xiao, and L. Xie, "Total least squares method for robust source localization in sensor networks using TDOA measurements," *International Journal of Distributed Sensor Networks*, vol. 2011, Article ID 172902, 8 pages, 2011.
- [6] J. Wang, Q. H. Gao, Y. Yu, H. Y. Wang, and M. L. Jin, "Toward robust indoor localization based on bayesian filter using chirp-spread-spectrum ranging," *IEEE Transactions on Industrial Electronics*, vol. 59, no. 3, pp. 1622–1629, 2012.
- [7] P. C. Chen, "A non-line-of-sight error mitigation algorithm in location estimation," in *Proceedings of the IEEE Wireless Communications and Networking Conference*, pp. 316–320, New Orleans, La, USA, 1999.
- [8] S. Nawaz and N. Trigoni, "Robust localization in cluttered environments with NLOS propagation," in *Proceedings of the IEEE 7th International Conference on Mobile Adhoc and Sensor Systems (MASS '10)*, pp. 166–175, San Francisco, Calif, USA, November 2010.
- [9] S. Maranò, W. M. Gifford, H. Wymeersch, and M. Z. Win, "NLOS identification and mitigation for localization based on UWB experimental data," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 7, pp. 1026–1035, 2010.
- [10] J. Borras, P. Hatrack, and N. B. Mandayam, "Decision theoretic framework for NLOS identification," in *Proceedings of the 48th IEEE Vehicular Technology Conference (VTC '98)*, pp. 1583–1587, May 1998.
- [11] S. Mazuelas, F. A. Lago, J. Blas et al., "Prior NLOS measurement correction for positioning in cellular wireless networks," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 5, pp. 2585–2591, 2009.
- [12] L. Cheng, C. D. Wu, and Y. Z. Zhang, "Indoor robot localization based on wireless sensor networks," *IEEE Transactions on Consumer Electronics*, vol. 57, no. 3, pp. 1099–1104, 2011.
- [13] H. S. Ahn and W. Yu, "Environmental-adaptive RSSI-based indoor localization," *IEEE Transactions on Automation Science and Engineering*, vol. 6, no. 4, pp. 626–633, 2009.
- [14] A. S. Paul and E. A. Wan, "RSSI-based indoor localization and tracking using sigma-point kalman smoothers," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 5, pp. 860–873, 2009.
- [15] M. Saxena, P. Gupta, and B. N. Jain, "Experimental analysis of RSSI-based location estimation in wireless sensor networks," in *Proceedings of the 3rd International Conference on Communication System Software and Middleware*, pp. 503–510, Piscataway, NJ, USA, January 2008.
- [16] S. Slijepcevic, S. Megerian, and M. Potkonjak, "Characterization of location error in wireless sensor networks: analysis and applications," in *Proceedings of the 2nd International Workshop on Information Processing in Sensor Networks*, pp. 593–608, Palo Alto, Calif, USA, 2003.
- [17] M. P. Wylie and J. Holtzman, "The non-line of sight problem in mobile location estimation," in *Proceedings of the 5th IEEE International Conference on Universal Personal Communications*, pp. 827–831, Cambridge, Mass, USA, October 1996.



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