A Novel Robust Tracking Algorithm in Cluttered Environments for Distributed Sensor Network

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Tracking has attracted much attention over the past few years, particularly in the field of distributed sensor network. The most challenging issue is nonline of sight (NLOS) problem in cluttered environments such as indoor or urban areas since the presence of NLOS errors lead to severe degradation in the tracking performance. In this paper, we propose a novel robust tracking algorithm to mitigate the measurement noise and NLOS error. The robust localization method is firstly employed to estimate the positions of the mobile node with different subgroups. Then the residual test method is used to remove the larger localization error. Finally, the modified Kalman filter is introduced to improve the tracking accuracy. Simulation results show that the proposed algorithm can track the mobile node and estimate the position with relatively higher accuracy in comparison with existing methods.

1. Introduction

Due to the rapid development of the distributed sensing and wireless communication technologies, the distributed sensor network has emerged as a promising solution for a wide range of applications, such as habitat monitoring, energy management, and military initiatives [1]. The sensor node has the ability to collect, process, and store measurement information, as well as to communicate with other nodes via the wireless communication. Tracking technologies, which are designated to estimate the trajectory of a mobile object (or mobile node), have attracted much attention in recent years because of the increasing demand on location based services [2]. The tracking schemes estimate the position of the mobile object based on measured signals from the beacon nodes.

A number of tracking measurement methods have been widely studied with various types of signal measurements, including time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength (RSS) [3–5]. TOA measurement method relies on the travel time of signal between mobile node and beacon nodes, but this method is affected by the synchronization error seriously. TDOA method measures the signals’ arrival time difference between beacon nodes and mobile node. This method needs extra hardware configuration. As an inexpensive approach, RSS has established the mathematical model on the basis of path loss attenuation with distance. AOA method depends on the direction of propagation of a radio frequency wave incident on the antenna array. In this paper, any of the ranging measurements can be used in the proposed algorithm.

If the line of sight (LOS) propagation environment exists between the mobile node and beacon node, a high tracking accuracy can be achieved when the traditional Kalman filter is employed. However, for tracking in indoor or urban areas, where there may be no direct path between the mobile node and beacon node, the signal measurements include an error due to the excess path length traveled because of reflection or diffraction, which is termed the nonline of sight (NLOS) error [6]. The NLOS error degrades the robustness and accuracy of tracking system. Mitigation of the NLOS error in the tracking problem has received much attention.

In this paper, we propose a robust tracking algorithm in NLOS environment.

Following are the primary contributions of this paper.

1. The proposed algorithm does not need the statistical models or prior information on NLOS channel conditions.
The proposed algorithm does not require the identification of LOS and NLOS and it is independent of the physical layer used to perform ranging.

Our approach is robust against the NLOS error.

The rest of the paper is organized as follows. Section 2 introduces the related works. And Section 3 provides the system model. We will introduce our proposed algorithm in Section 4. Some simulation results will be presented in Section 5. The conclusions are given in Section 6.

2. Related Works

Several methods have been proposed to deal with the NLOS problem. Generally, these methods can be categorized into three different types.

The first type of methods uses all the available LOS and NLOS measurements. In [7], the authors proposed a Kalman based interacting multiple model (IMM) smoother to mitigate the NLOS error. The mode probabilities of the propagation conditions can be calculated and updated by a likelihood function. Then the Kalman based IMM algorithm is used to combine the estimation results of the two parallel Kalman filters with corresponding mode probabilities. In [8, 9], the authors proposed extended Kalman based IMM with data fusion method and fuzzy based IMM smoother, respectively. Chen [10] proposed a residual weighting algorithm which uses the sum of squared residuals of a least squares estimation as the indicator of the accuracy of calculated node coordinates. All possible combinations of the measurements are used and the least square estimator is employed to estimate the location. Finally the estimated location is computed as a weighted combination of these intermediate estimates. Hammes et al. [II] proposed a robust extended Kalman filter based on robust semiparametric estimators for tracking. In [12], the authors proposed an NLOS mitigation algorithm for tracking in mixed LOS/NLOS environment. This method is a combination of hard and soft decision approach; that is, the large outliers are discarded and other results are weighted with different probabilities. In [13], the authors presented an iterative algorithm for robust position estimation in harsh LOS/NLOS environments.

The second type of methods firstly identifies the signal propagation condition and then mitigates the NLOS error. These methods need the statistical models or prior information on NLOS error. In [14], the authors proposed a technique to determine the propagation condition between the mobile node and beacon node via the TOA and AOA measurements. In [15], the authors proposed an improved Rao-Blackwellized particle filter method to estimate the LOS/NLOS sight conditions by particle filtering using the optimal trial distribution. Then the decentralized extended Kalman filter method is applied to analytically compute the location. Ke and Wu [16] proposed a low complexity identification method based on innovation vectors. In [17–19], the authors proposed NLOS identification method such as hypothesis test, likelihood ratio test, and statistical analysis methods, respectively. If the identification is correct, the accuracy can be achieved. But there is always the possibility of wrong identification.

The third type of methods is termed pattern matching method. Since the NLOS error introduces some problems for fingerprinting method, only powers and delays of paths are taken into account. The Doppler information was taken into account since it had the effect of mitigating the NLOS error [20]. In [21], the authors proposed a method which combined with fingerprinting-geolocation and neural networks to overcome the NLOS error. This method provided better propagation characteristics of the wireless signal, in addition to a better interpretation of the signature parameters due to the neural networks. In [22], the authors proposed a hybrid method which followed a Levenberg-Marquardt based iterative algorithm to reduce the NLOS error. And the arrangement of reference nodes method was also introduced to create a fingerprinting database.

3. System Model

In this section, we firstly introduce the measurement model. Then we describe the state model.

3.1. Measurement Model. The distributed sensor networks compose of three node types: mobile node, base station, and beacon nodes in two-dimensional region. The mobile node whose location is unknown can collect the data from beacon nodes and convert the measurement into distance. It estimates the location through the tracking algorithm. The beacon nodes are fixed in the known locations. There are N beacon nodes and one mobile node in the field. The location of mobile node at time k is \( X^m(k) = [x^m(k), y^m(k)]^T \), \( k = 1, \ldots, K \); the position of the ith beacon node is \( X_i = [x_i, y_i]^T \), \( i = 1, \ldots, N \). The measured distance between mobile node and ith beacon node at time \( k \) is modeled as

\[
\tilde{d}_i(k) = d_i(k) + n_i(k) + b_i(k),
\]

where

\[
d_i(k) = \|X^m(k) - X_i\| = \sqrt{(x^m(k) - x_i)^2 + (y^m(k) - y_i)^2}.
\]

is the true distance between the mobile node and ith beacon node at time \( k \). \( n_i(k) \) and \( b_i(k) \) represent the measurement noise and the NLOS error. The \( n_i(k) \) is modeled as an independent and identically distributed zero mean white Gaussian noise with variance \( \sigma^2_n \). The probability distribution is shown as

\[
f_{n_i}(x) = \frac{1}{\sqrt{2\pi\sigma^2_n}} \exp \left( -\frac{x^2}{2\sigma_n^2} \right).
\]

The NLOS error \( b_i(k) \) is modeled as

\[
b_i(k) = \begin{cases} 
0, & \text{LOS} \\
q_i(k), & \text{NLOS},
\end{cases}
\]

where \( q_i(k) \) is a nonnegative bias and its probability distribution is generally unknown beforehand.
3.2. State Model. The state at time $k$ is defined as the vector:

$$X(k) = [x(k), y(k), \dot{x}(k), \dot{y}(k)]^T,$$

(5)

where $[x(k), y(k)]^T$ corresponds to the coordinates of the mobile node, $[\dot{x}(k), \dot{y}(k)]^T$ are the corresponding velocities.

The state vector with random acceleration can be modeled as:

$$X(k) = \Phi X(k-1) + w(k-1),$$

(6)

where the state transition matrix is $\Phi = \begin{bmatrix} I_2 & \Delta t I_2 \\ 0 & I_2 \end{bmatrix}$, $\Delta t = t(k) - t(k-1)$ is the sampling period, and $I_2$ denotes the $2 \times 2$ identity matrix. The random process noise $w(k-1)$ is a white zero mean Gaussian noise with covariance matrix $Q(k-1)$.

The measurement equation is defined as

$$Z(k) = HX(k) + v(k).$$

(7)

Since measurement equation is linear, the observation model is defined as $H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$. $v(k)$ is the observation noise which is assumed to be zero mean Gaussian white noise with covariance $R(k)$.

### 4. Tracking in NLOS Environment

#### 4.1. General Concept. In this subsection, we describe the details of the proposed algorithm. The flowchart of the proposed algorithm is illustrated in Figure 2. Firstly, we group the measurements and use the robust localization method to estimate the position of the mobile node. We use the residual test method to remove the larger localization error. Finally, the Kalman prediction and fusion based Kalman update are used to improve the localization accuracy.

#### 4.2. Grouping and Robust Localization. We construct $C_N^{N-1} = N$ different subgroups of measurements together with the coordination of the corresponding beacon nodes to localize the position of mobile node. The $i$th measurement squared at time $k$ can be expressed as

$$\tilde{d}_i^2(k) = (x^m(k) - x_i)^2 + (y^m(k) - y_i)^2 + 2d_i(k) v_i + v_i^2,$$

(8)

where $v_i = n_i(k) + b_i(k), i = 1, \ldots, N - 1$.

Equation (8) can be rewritten as

$$\tilde{d}_i^2(k) - B_i = -2x^m(k) x_i - 2y^m(k) y_i + A + \tilde{v}_i,$$

(9)

where $B_i = x_i^2 + y_i^2, A = (x^m(k))^2 + (y^m(k))^2$, and $\tilde{v}_i = 2d_i v_i + v_i^2$.

The linear model at time $k$ is given by

$$\Psi = S \hat{\theta} + \tilde{v},$$

(10)

where,

$$\Psi = \begin{bmatrix} \tilde{d}_1^2(k) - B_1 \\ \vdots \\ \tilde{d}_{N-1}^2(k) - B_{N-1} \end{bmatrix},$$

(11)

$$S = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \vdots & \vdots & \vdots \\ -2x_{N-1} & -2y_{N-1} & 1 \end{bmatrix}, \quad \tilde{v} = \begin{bmatrix} \tilde{v}_1 \\ \tilde{v}_2 \\ \vdots \\ \tilde{v}_{N-1} \end{bmatrix}.$$
If all the propagation conditions are LOS, the conditional probability density function of measurements can be obtained as

$$F(d, \theta) = \prod_{i=1}^{N-1} f_n(d_i \mid \theta),$$

where $f_n(x) = (1/\sqrt{2\pi\sigma_i^2}) \exp(-x^2/2\sigma_i^2)$. The log of the joint conditional probability density function is

$$I(\theta) = \ln F(\hat{d}, \theta) = \sum_{i=1}^{N-1} f_n(\hat{d}_i \mid \theta).$$

The Fisher information matrix $J$ can be expressed as [24]

$$J = \begin{bmatrix} J_{xx} & J_{xy} \\ J_{yx} & J_{yy} \end{bmatrix},$$

where $J_{xx} = E(\partial^2 l(\theta)/\partial x^2) = (1/\sigma^2) \sum_{i=1}^{N-1} ((x^m - x_i)^2 / d_i^2)$,

$$J_{yy} = E\left(\frac{\partial^2 l(\theta)}{\partial y^2}\right) = \frac{1}{\sigma^2} \sum_{i=1}^{N-1} \frac{(y^m - y_i)^2}{d_i^2},$$

$$J_{xy} = E\left(\frac{\partial^2 l(\theta)}{\partial x \partial y}\right) = \frac{1}{\sigma^2} \sum_{i=1}^{N-1} \frac{(y^m - y_i)(x^m - x_i)}{d_i^2}.$$  

The Cramer-Rao lower bound matrix is defined as the inverse of the Fisher information matrix:

$$\text{CRLB} = E\left[ (\hat{\theta} - \theta)(\hat{\theta} - \theta)^T \right] \geq J^{-1}.$$

The $(1,1)$ and $(2,2)$ elements of $J^{-1}$ are indicated as $B_x$ and $B_y$. For $j$th localization result, the residual test factor can be defined as [25]

$$\omega_{x,j}^2 = \frac{[\hat{x}_j^m - x^m]^2}{B_{x,j}},$$

$$\omega_{y,j}^2 = \frac{[\hat{y}_j^m - y^m]^2}{B_{y,j}},$$

where $x^m$ and $y^m$ are the true coordination of the mobile node.

Since the true position of the mobile node is unknown, we employ the localization results of $N$ measurements to replace it. We define $\omega_{xy,j} = \sqrt{\omega_{x,j}^2 + \omega_{y,j}^2}$. For $N$ subgroups, we can obtain $\omega = [\omega_{xy,1}, \omega_{xy,2}, \ldots, \omega_{xy,N}]$. We sort the vector $\omega$ from small to large; then we can obtain the new
Figure 3: (a) The influence function (left) and extremal function (right) of Huber estimation methods. (b) The influence function (left) and extremal function (right) of sinusoidal estimation methods.

vector \( \omega' = [\omega'_{xy,1}, \omega'_{xy,2}, \ldots, \omega'_{xy,N}] \), and the localization results \( [\hat{\theta}_1', \hat{\theta}_2', \ldots, \hat{\theta}_N'] \) are also sorted according to the order of \( \omega' \). Hence, the larger \( \omega'_{xy,i} \) is, the more probability that the localization result contains the NLOS error is. The former three localization results \( [\hat{\theta}_1', \hat{\theta}_2', \hat{\theta}_3'] \) are selected in the next subsection.

4.4. Kalman Prediction. The initialization of the Kalman filter is assumed to be \( \tilde{X}(0 | 0) = [\sum_{i=1}^{3} \hat{\theta}_1'(1)/3, \sum_{i=1}^{3} \hat{\theta}_1'(2)/3, 0, 0]^T \) and \( P(0 | 0) = I_4 \), which can be obtained by the robust localization method at time 0. We can obtain the predicted state and prediction covariance at time \( k \) as follows:

\[
\tilde{X}(k | k-1) = \Phi(k) \tilde{X}(k-1 | k-1),
\]

\[
P(k | k-1) = \Phi(k) P(k-1 | k-1) \Phi^T(k) + CQ(k) C^T,
\]

(22)

where \( C = I_2 \). Consider

\[
\tilde{Z}(k | k-1) = H \tilde{X}(k | k-1) .
\]

(23)

Since we obtain three estimated localization results, the measurement residual of Kalman filter is

\[
\gamma_i(k) = \tilde{\theta}_i'(k) - \tilde{Z}(k | k-1), \quad i = 1, 2, 3.
\]

(24)

4.5. Fusion Based Kalman Update. In Section 4.4, we obtain three measurement residuals of Kalman filter. In order to use all the useful information, we fuse all the measurement residuals in Kalman update step. The residual covariance is given by

\[
S(k) = CP(k | k-1) C^T + R(k).
\]

(25)

The optimal Kalman gain is employed to minimize the covariance \( E[\gamma(k)\gamma^T(k)] \) as follows:

\[
K(k) = P(k | k-1) C^T S^{-1}(k).
\]

(26)
The fusion factor is defined as
\[ \lambda_i(k) = \frac{\omega_{xy,j}}{\sum_{j=1}^{3} \omega_{xy,j}}. \] (27)

The fused state equation can be obtained as
\[ \hat{X}(k | k) = \hat{X}(k | k-1) + K(k) \sum_{i=1}^{3} \lambda_i(k) \gamma_i(k). \] (28)

The updated estimate covariance is calculated as
\[ P(k | k) = (I - K(k)H)P(k | k-1). \] (29)

5. Simulation Results

Simulation results are provided in this section to assess the performance of the proposed algorithm in cluttered environment. The size of the sensing field is 100 m × 100 m. There are five beacon nodes deployed in the field. We assume that the mobile node has the velocity of 1 m/s. The communication range of sensor node is 150 m. The measurement noise is modeled as a white random variable with zero mean and standard deviation \( \sigma_i \) (defaulted as 0.5 m). The NLOS error is modeled as Gaussian, exponential, or uniform distribution. The performance of the proposed algorithm is compared with the nonfilter, Kalman, and robust Kalman filters. The simulation results are obtained from 1000 Monte Carlo runs. To compare the performance of different algorithms, the tracking error is analyzed, which can be defined as
\[ \text{Tracking error} = \frac{1}{N \cdot K} \sqrt{\sum_{i=1}^{N} \sum_{k=1}^{K} \| X^m(k) - \hat{X}_i^m(k) \|.} \] (30)

One realization of the tracking and localization performance of the proposed algorithm is shown in Figure 4. The obstacles are randomly deployed. And we do not plot them in Figure 4. The NLOS error is modeled as normal distribution with mean \( \mu_{\text{NLOS}} = 3 \) m and standard deviation \( \sigma_{\text{NLOS}} = 8 \) m. In this figure, the symbols “△” denote the positions of the beacon node, and “.” and “∗” denote the true position and estimated position of mobile node. It can be seen that the proposed algorithm is able to accurately track and locate the mobile node.

The performance comparison with respect to tracking error in position is shown in Figure 5, and the simulation results suggest that the proposed algorithm performs better than nonfilter, Kalman, and robust Kalman filters. The proposed algorithm achieves higher accuracy since it could remove the larger tracking error and fuse the different results.

For Figures 6–8, the measurement noise is the Gaussian white noise with zero mean and standard deviation 0.5 m. The NLOS error is modeled as normal distribution; that is, \( q_i \sim N(3, 8^2) \). Figure 6 plots cumulative distribution function (CDF) of the tracking error. It can be observed that the tracking error of the proposed algorithm at 90% confidence level is less than 8 m. In the same condition, the nonfilter, Kalman, and robust Kalman methods are achieve at 17 m, 15 m, and 14 m, respectively. So the proposed algorithm achieves better performance than the other methods.

Figure 7 shows the impact of the standard variance of measurement noise on the localization accuracy. It can be observed that the tracking error increases as the standard variance of measurement noise increases. In all cases, the tracking error of the proposed method is smaller than other methods. And the proposed method’s improved effect decreases as the standard variance of measurement noise increases. The proposed method deteriorates when the standard variance of the measurement increases. Generally, the performance of the proposed method is better than other methods.
Figure 6: CDF of the Tracking error.

Figure 7: Tracking error versus standard variance of the measurement noise.

Figure 8: Tracking error versus standard variance of the NLOS error.

Figure 9: Tracking error versus the number of beacon nodes.

Figure 10: The number of beacon nodes.

The NLOS error obeys exponential distribution, namely, $\varphi_t \sim E(\mu)$; the parameter $\mu$ is defaulted as 5. Figure 9 shows the relationship between the tracking error and the number of beacon nodes. We can see that the number of beacon nodes has less effect on the number of tracking errors. And the proposed method gives the best performance.

As shown in Figure 10, the proposed method slightly outperforms other methods when the parameter $\mu$ is relatively small. This is because the NLOS effect is small when the parameter $\mu$ is small; in the other words, the measurement error is the dominant factor. With the increase of the parameter $\mu$, the tracking error of other methods increases dramatically, but the tracking error of the proposed method...
increases slowly. So the proposed method is relatively robust to the parameter $u$ in comparison with other methods.

For Figures 11-12, the NLOS error is modeled as uniform distribution, that is, $U(1, U_{\text{max}})$, and $U_{\text{max}}$ is defaulted as 8 m. And the measurement noise is the Gaussian white noise with zero mean and standard deviation 0.5 m. The plot CDF of the tracking error using the described error model is shown in Figure 11. It can be observed that the nonfilter method has similar performance in comparison with Kalman filter. This is because the ability of the Kalman filter to process the non-Gaussian noise is relatively low. And the proposed method outperforms other methods.

Figure 12 depicts the tracking error of the four methods versus different parameters $U_{\text{max}}$. It can be seen that the tracking error of the proposed method increases slower than the other three methods.

6. Conclusions

The NLOS propagation is the most common condition in indoor or urban area. In this paper, a novel tracking algorithm is proposed in cluttered environment (LOS and NLOS environments). The proposed method does not need to know the statistical models or prior information on NLOS channel conditions. It also does not require the identification of LOS and NLOS and it is independent of the physical layer used to perform ranging. Simulation results show that the performance of the proposed method significantly outperforms the other three methods.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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