A Localization Algorithm Based on NLOS Identification with Improved VB-AKF

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Abstract. As a research hotspot, wireless sensor network (WSN) has a wide range of application prospect. The non-line of sight (NLOS) localization is one of the most basic techniques. In order to mitigate the NLOS influence and increase the localization accuracy, we propose an improved VB-AKF algorithm in this paper. Firstly, the propagation state of the signal is identified. Then, for the LOS and NLOS mix environments, we reduce the NLOS error by changing the attenuation coefficient. And the maximum likelihood (ML) method is used for localization. Finally, the simulation results show that our method can effectively obtain higher localization accuracy.

1. Introduction
With the rapid development of communication technology, WSN has been widely applied to many fields[1]. Obtaining accurate positional information is the basics to all these applications. In the LOS environment, we can gain the accurate position easily. However, the presence of NLOS propagation and complex environment decrease location accuracy greatly. Therefore, it is of great significance to deliberate the mobile localization methods in the NLOS environment[2].

In recent years, the mobile localization algorithms in NLOS environment can be summarized into two categories. The first class of methods is to depend on all available LOS and NLOS measurement information. In [3], a NLOS mobile location algorithm based on probability data association is proposed. And the algorithm has high location accuracy and good robustness in different environments. In [4], a NLOS location algorithm based on likelihood matrix correction is proposed. The distance is filtered and estimated by KF and HF methods, and the location is determined by the ML method.

The second class of methods includes the NLOS identification and NLOS error mitigation. In [5], a KF algorithm based on variable mean is proposed. The propagation condition is identified by hypothesis test, and KF algorithm with variable mean is used when the measurements are under NLOS environment. Furthermore NLOS error is suppressed by data association method. In [6], a method based on K-means clustering and improved SA algorithm is proposed, which is able to effectively reduce the NLOS error and has low complexity.

Although some progress have made in NLOS localization, but most of them need to foresee the parameters of NLOS error. In practice, the NLOS error model is usually unknown. To solve the problem, we propose an improved VB-AKF algorithm. First, the propagation condition is identified. Then the NLOS error is mitigated by changing the attenuation coefficient of VB-AKF algorithm. Finally, the position of the moving target can be determined by ML method.
2. **Construct the measurement model**

$N$ beacon nodes and one mobile node are randomly deployed. The coordinates of $N$ beacon nodes are $\theta_1, \theta_2, \ldots, \theta_N \left( \theta_i = \left[ x_i, y_i \right] \right)$. The coordinate of the mobile node at time $k$ is $\left( x(k), y(k) \right)$. In this paper the TOA based ranging method is selected.

### 2.1. Range model

At time $k$, the real distance between the unknown node and the $i$th beacon node is:

$$d_i(k) = \sqrt{(x(k) - x_i)^2 + (y(k) - y_i)^2}$$  

(1)

In the LOS environment, the measurement is only affected by the environmental noise, and the measurement distance between the $i$th beacon node and the mobile node at time $k$ is:

$$\hat{d}_i(k) = d_i(k) + n_i(k)$$

(2)

where $n_i(k)$ is the noise with zero mean and variance $\sigma_i^2$.

In the NLOS environment, the existence of obstacles will cause NLOS error. Therefore, the measurement distance between the $i$th beacon node and the mobile node at time $k$ is:

$$\hat{d}_i(k) = d_i(k) + n_i(k) + n_{\text{NLOS}}$$

(3)

where $n_{\text{NLOS}}$ is the NLOS error and the mean value of $n_{\text{NLOS}}$ is always positive.

### 2.2. System model

The state vector of the $i$th beacon node is defined as:

$$X_i(k) = \left[ d_i(k), \dot{d}_i(k) \right]^T$$

(4)

where $\dot{d}_i(k)$ is the speed of the mobile node relative to the $i$th beacon node.

In this paper, it is assumed that the mobile node moves at a constant speed, and the equation of state is:

$$X_i(k) = F \cdot X_i(k - 1) + v_i(k - 1)$$

(5)

where $F = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix}$, $T_s$ is the sampling period and $v_i(k - 1)$ is the process noise.

According to Eq.(2) and (3), the measurement equation in LOS and NLOS condition can be shown as:

$$Z_i(k) = \hat{d}_i(k) = d_i(k) + n_i(k)$$

(6)

$$Z_i(k) = \hat{d}_i(k) = d_i(k) + n_i(k) + n_{\text{NLOS}}$$

(7)

3. **Proposed method**

### 3.1. Algorithm structure

In VB-AKF algorithm, attenuation coefficient $\rho_i$ represents the correlation degree of the measurement noise variances between two adjacent times. If the propagation condition is the same as before, $\rho_i = 1$; else $\rho_i = \rho_m$ ($0 < \rho_m < 0.5$).

The system structure of the proposed algorithm is shown in Figure 1. First, the state and the covariance matrix are calculated using the Kalman prediction, and then the propagation condition is identified. If the propagation condition is the same as the previous time, $\rho = 1$; else $\rho = \rho_m$. And the parameters are updated to estimate the mean and variance of the measurement noise. Finally the ML method is used to determine the position.
Kalman Prediction
NLOS Identification

\[ \hat{X}_i(0|0) = \begin{bmatrix} \hat{d}_i(0),1 \end{bmatrix}^T \]

and the Kalman prediction equations are:

\[ \hat{X}_i(k|k-1) = F \cdot \hat{X}_i(k-1) \]
\[ P_i(k|k-1) = F \cdot P_i(k-1) \cdot F^T + Q_i(k-1) \]

3.2. Propagation state identification

In this paper, the likelihood ratio test method is used to detect the propagation state. If the propagation state is LOS, the measurement distance of the \(i\)th beacon node and the probability density function can be expressed as:

\[ f_{LOS}(\hat{d}_i) = \frac{1}{\sqrt{2\pi} \sigma_i} \exp\left(-\frac{(\hat{d}_i - \mu_{LOS})^2}{2\sigma_i^2}\right) \]

If the propagation state of the signal is NLOS, the measurement distance and the probability density function of the \(i\)th beacon node can be expressed as:

\[ f_{LOS}(\hat{d}_i) = \frac{1}{\sqrt{2\pi} (\sigma_i^2 + \sigma_{NLOS}^2)} \exp\left(-\frac{(\hat{d}_i - \mu_{NLOS})^2}{2(\sigma_i^2 + \sigma_{NLOS}^2)}\right) \]

We can establish the generalized likelihood ratio as follow:

\[ \lambda(k) = \frac{f_{LOS}(\hat{d}_i | E^i)}{f_{NLOS}(\hat{d}_i | E^i)} \]

If \(\lambda(k) > 1\), the current propagation state is LOS, else the current propagation state is NLOS.

3.3. Improved VB-AKF algorithm

The improved VB-AKF algorithm can realize continuous estimation of the state and measurement noise. The steps of the improved VB-AKF algorithm are as follows:

1. Parameter transformation

\[ \alpha_i(k|k-1) = \rho_i \cdot \alpha_i(k-1) \]
\[ \beta_i(k|k-1) = \rho_i \cdot \beta_i(k-1) \]

2. Parameter update

a. Setting initial value

\[ \hat{X}_i^{(0)}(k|k-1) = \hat{X}_i(k|k-1) \]
\[ P_i^{(0)}(k|k-1) = P_i(k|k-1) \]
\[ \alpha_i^{(0)}(k|k-1) = 1/2 + \alpha_i(k|k-1) \]
\[ \beta_i^{(0)}(k|k-1) = \beta_i(k-1) \]
b. Iterative computation

\[ \hat{R}^{(n)}(k) = \text{diag} \left( \beta(k) / \alpha(k) \right) \]

\[ K^{(n)}(k | k) = P^{(0)}(k | k - 1) H^T(k) \left( H(K) \cdot P^{(0)}(k | k - 1) \cdot H^T(k) + \hat{R}^{(n)}(k) \right)^{-1} \]

\[ \hat{X}^{(n)}(k | k) = \hat{X}^{(0)}(k | k - 1) + K^{(n)}(k | k) (z(k) - H(k) \cdot \hat{X}^{(0)}(k | k - 1)) \]  

\[ P^{(n)}(k | k) = P^{(0)}(k | k) - K^{(n)}(k | k) \cdot H^T(k) \cdot P(k | k - 1) \]

\[ \beta^{(n)}(k | k, i) = \beta^{(0)}(k | k - 1) + \frac{1}{2} \left( Z_i(k) - H_i(k) \cdot \hat{X}_i^{(n)}(k | k) \right)^2 + \frac{1}{2} \left( H_i(k) \cdot P(k | k) \cdot H_i^T(k) \right) \]

c. Final value of parameter

\[ \beta(k | k - 1) = \beta^{(N)}(k | k - 1) \]

\[ \hat{x}(k | k) = \hat{x}^{(N)}(k | k) \]

\[ P(k | k) = P^{(N)}(k | k) \]  

The filtering distance of the \( i \)th beacon node is:

\[ \hat{d}_i(k) = G \cdot \hat{X}_i(k | k) \]

3.4. Maximum likelihood localization method

Set the position of the mobile node at time \( k \) as \( \mathbf{M}(k) = [x^M(k), y^M(k)]^T \), and we can establish the following equations:

\[ \begin{cases} 
(x_1 - x^M(k))^2 + (y_1 - y^M(k))^2 = (\hat{d}_1(k))^2 \\
\vdots \\
(x_N - x^M(k))^2 + (y_N - y^M(k))^2 = (\hat{d}_N(k))^2 
\end{cases} \]  

(19)

When \( A \) and \( B \) are as follows, the above equation can be converted to \( \mathbf{A} \cdot \hat{\mathbf{M}}(k) = \mathbf{B} \).

\[ \mathbf{A} = 2 \begin{bmatrix} 
(x_1 - x_2) & (y_1 - y_2) \\
\vdots & \vdots \\
(x_1 - x_N) & (y_1 - y_N) 
\end{bmatrix} \]  

(20)

\[ \mathbf{B} = \begin{bmatrix} 
(\hat{d}_2(k))^2 - (\hat{d}_1(k))^2 - (x_2^2 + y_2^2) + (x_1^2 + y_1^2) \\
\vdots \\
(\hat{d}_N(k))^2 - (\hat{d}_1(k))^2 - (x_N^2 + y_N^2) + (x_1^2 + y_1^2) 
\end{bmatrix} \]  

(21)

The position of the mobile node can be estimated as:

\[ \hat{\mathbf{M}}(k) = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{B} \]  

(22)

4. Simulation results

In this section, the effectiveness of the proposed algorithm is verified by simulation experiments. We compare the proposed method with the KF method and the RKF method, and the simulation results are obtained by 500 Monte Carlo experiments.

Figure 2 shows the localization results for the proposed method. It illustrates that the localization errors of KF algorithm and RKF algorithm are large due to the influence of NLOS error, and the
The proposed algorithm is superior to KF algorithm and RKF algorithm. The average localization errors of KF, RKF and the proposed algorithm are 0.7717m, 0.6325m and 0.3300m.

Figure 2. Localization errors at different points

Figure 3. Mean of NLOS versus location error

Figure 3 shows the relationship between the mean value of NLOS error and mean localization error of TOA. It illustrates that the average localization errors of the three algorithms increase with the increase of $\mu_{\text{N}}$. KF algorithm and RKF algorithm are greatly affected, but the proposed method is influenced little. Therefore, the proposed method has better robustness, and has the highest location accuracy compared with the other two algorithms.

5. Conclusion

In order to reduce the influence of NLOS propagation and improve the localization accuracy, an improved VB-AKF algorithm is proposed in this paper. In complex propagation conditions, the location accuracy can be effectively improved by changing the attenuation coefficient. The simulation results show that the proposed algorithm can effectively reduce the NLOS error, which is better than KF and RKF algorithm.

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References

[1] Sharma, G., Kumar, A. (2018) Improved DV-Hop localization algorithm using teaching learning based optimization for wireless sensor networks. Telecommunication Systems, 67: 1-16.
[2] Gwo, J. J., Gwo J. H. (2019) Optimal Path Planning for a Biomedical Combined WSN System via RSSI and LQI. Wireless Personal Communications, 108: 957-976.
[3] Yu, X., Hu, N. (2016) A Novel NLOS Mobile Node Localization Method in Wireless Sensor Network. In: International Conference on Communications. Chengdu. pp. 541-549.
[4] Cheng, L., Wu, C. (2013) Indoor Mobile Localization in Wireless Sensor Network under Unknown NLOS Errors. International Journal of Distributed Sensor Networks, 1: 59-64.
[5] Yu, X., Ji, P., Wang, Y. (2017) Mean Shift-Based Mobile Localization Method in Mixed LOS/NLOS Environments for Wireless Sensor Network. Journal of Sensors, 6: 1-8.
[6] Cheng, L., Wu, X. (2017) A non-line of sight localization method based on k-means clustering algorithm. In: 7th IEEE International Conference on Electronics Information and Emergency Communication. pp. 465-468.