A Propagation Condition Identification and Non-Line of Sight Error Mitigation Algorithm in Wireless Sensor Network

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Abstract. Node localization is one of key technologies in wireless sensor networks (WSN). In practice, the occlusion of obstacles often leads to large non-line-of-sight (NLOS) error. Therefore, the misidentification of LOS (line-of-sight)/NLOS conditions can seriously reduce the accuracy of localization algorithms in WSN. In this paper, we propose a novel localization algorithm based on hypothesis testing method, which combines the NLOS condition identification algorithm and the extended Kalman filter method to mitigate the NLOS error. Moreover, we introduce the false alarm rate $f_a$ to fuse the estimated values in the LOS/NLOS condition to obtain more accurate results. The simulations demonstrate that the proposed algorithm can effectively reduce the influence of NLOS error and improve the localization accuracy.

1. Introduction

Wireless sensor network is a self-organizing network system. It is proposed to collaborative perception, collect and process information of the objects in the coverage of network and send them to the observers. In most cases, the location information is important for wireless sensor networks. Monitoring data will be meaningless without node location information.

The accuracy of positioning algorithms mostly relies on the line-of-sight (LOS) propagation of certain signals[1,2]. In complex environments such as buildings or special places, the signal propagation path is usually blocked by obstacles, which causes serious decline of positioning accuracy[3]. In order to solve this problem, many positioning methods that dedicated to eliminate non-line-of-sight (NLOS) error have been proposed, such as various modified Kalman filter[4,5], particle filtering[6,7], RSSI (Received Signal Strength Indication) localization and some other algorithms[8,9]. The advantage of EKF is that we do not need to know NLOS threshold which is quite difficult to decide in varying environment. However, the presence of noises may cause error in the LOS/NLOS condition determination. A cooperative localization method is designed to deal with NLOS propagation condition. The time-of-arrival (TOA), angle-of-arrival (AOA), and RSSI measurement are also described in detail. This method obtains accurate location information[10].

In this paper we propose a propagation condition identification algorithm based on hypothesis testing method. The false alarm rate is introduced to integrate with the extended Kalman filter to mitigate the localization error effectively. The reminder of this paper is organized as follows: in Section 2, we introduce the measurement model and illustrate hypothesis testing method. The propagation condition identification algorithm and the location algorithm are proposed in Section 3. The simulation results are presented in Section 4, In Section 5, we draw the conclusion and summarize the principal aspects of this paper.
2. System and measurement model description

2.1. Establishment of measurement model
The distance measurement between mobile node (MN) and static nodes (SN) can be represented as:

\[ R_i = \begin{cases} \ d_i + n_i, & \text{LOS} \\ \ d_i + n_i + n_{\text{NLOS}}, & \text{NLOS} \end{cases} \]  \tag{2.1}

where \( d_i \), \( n_i \) and \( n_{\text{NLOS}} \) are the true distance between \( i \)-th SN and MN, the measurement noise that obeys Gaussian distribution \( N(0, \sigma_i^2) \), the NLOS error which is respective with measurement noise, \( n_{\text{NLOS}} \) obeys \( N(\mu_{\text{NLOS}}, \sigma_{\text{NLOS}}^2) \) \( \sigma_i^2 < \sigma_{\text{NLOS}}^2 \).

RSS logarithm-normality model can be represented as:

\[ PL = PL_0 + 10n \log_{10} \left( \frac{d_i}{d_0} \right) + S \]  \tag{2.2}

where \( PL_0 \) is the signal strength under reference distance \( d_0 \), in this paper, \( d_0 = 1 \), \( n \) is path loss coefficient, \( S \) is error that is generated by shadow effect. In LOS condition, \( S \) obeys Gaussian distribution of zero-mean, i.e. \( S \sim N(0, \sigma_L^2) \). In NLOS condition, \( S \) has larger standard deviation, i.e. \( S \sim N(0, \sigma_N^2) \) and \( \sigma_L^2 < \sigma_N^2 \).

Measurement equation is:

\[ Z_i(k) = \begin{bmatrix} R_i(k) \\ PL_i(k) \end{bmatrix} = \begin{bmatrix} d_i(k) \\ PL_0 + 10n_0 \log_{10} \left( \frac{d_i(k)}{d_0} \right) + \frac{n_i}{S_k} \end{bmatrix} = g(X_i(k)) + v_k(k) \]  \tag{2.3}

where \( g(X_i(k)) = \begin{bmatrix} d_i(k) \\ PL_0 + 10n_0 \log_{10} \left( \frac{d_i(k)}{d_0} \right) \end{bmatrix} \), \( v_k(k) = \frac{n_i}{S_k} \) \tag{2.4}

2.2. A brief introduction to hypothesis testing
The hypothesis testing method can distinguish the current state by establishing the likelihood ratio function. Because the NLOS error and the measurement error obey different distributions, the prior probability of measurement error and the probability distribution function of measurement value under different circumstances can be established.

In the LOS condition, the prior probability of the measurement error is \( P(H_0) \), and the probability density function of the measured value \( X \) is \( f(X|H_0) \). In the NLOS condition, the prior probability of the measurement error is \( P(H_1) \), and the probability density function of the measured value \( X \) is \( f(X|H_1) \). If the prior probabilities are known, the generalized likelihood ratio can be established, we can get:

\[ \frac{f(X|H_0)}{f(X|H_1)} \geq \frac{P(H_0)}{P(H_1)} \]  \tag{2.5}

3. Proposed method

3.1. Propagation condition detection and mitigation algorithm base on hypothesis testing
The proposed method considers the idea of Kalman filter and hypothesis. The flow chart of the algorithm is shown in Figure 1.
Figure 1. The architecture of the proposed algorithm

According to equation (2.2), the RSS’s probability density function is:

$$
f(S|d, H) = \begin{cases} 
(2\pi\sigma^2_{SL})^{-\frac{1}{2}} \exp \left(-\frac{PL_i - PL_0 - 10\log_{10}(\frac{d}{d_0})}{2\sigma^2_{SL}}\right), & H = H_0 \\
(2\pi\sigma^2_{SN})^{-\frac{1}{2}} \exp \left(-\frac{PL_i - PL_0 - 10\log_{10}(\frac{d}{d_0})}{2\sigma^2_{SN}}\right), & H = H_1 
\end{cases} \quad (2.6)
$$

where $H_0$ represents LOS measurement condition, $H_1$ represents NLOS measurement condition.

It is assumed that $PL(k)$ and $R(k)$ are measurement values under LOS, $f_0$ denotes probability of LOS propagation, $f_1$ denotes probability of NLOS propagation. If $d = R(k)$, the value of $f(S|d, H)$ can be calculated by (2.6). If $f_1 > f_0$. The propagation state is determined as LOS, otherwise it is NLOS. Hypothesis testing algorithm obtains identification propagation status and estimation probability of every condition.

Because the measurement equation is nonlinear, in this paper, adopting Taylor expansion to convert the nonlinear measurement equation into a linear equation:

$$
G_i = \begin{bmatrix}
\frac{\partial g(X_i)}{\partial x_i} \\
\frac{\partial g(X_i)}{\partial \ln d_0}
\end{bmatrix} = \begin{bmatrix}
1 & 0 \\
\frac{\ln 10}{d_0}
\end{bmatrix}
$$

(2.7)

Parameters in $G$ select different values according to different propagation environments. The Kalman gain is obtained by minimizing the following covariance

$$
\hat{X}_{i,i}(k+1|k+1) = \hat{X}_{i,i}(k+1|k) + K_{i,i}(k+1)\gamma_{i,i}(k+1) \quad (2.8)
$$

$$
P_{i,i}(k+1|k+1) = P_{i,i}(k+1|k) - K_{i,i}(k+1)S_{i,i}(k+1)K_{i,i}^T(k+1) \quad (2.9)
$$

Kalman filtering algorithm updates equation:

$$
\hat{X}_{i,i}(k+1|k+1) = \hat{X}_{i,i}(k+1|k) + K_{i,i}(k+1)\gamma_{i,i}(k+1) \quad (2.10)
$$

$$
P_{i,i}(k+1|k+1) = P_{i,i}(k+1|k) - K_{i,i}(k+1)S_{i,i}(k+1)K_{i,i}^T(k+1) \quad (2.11)
$$

where $K$ is Kalman gain.

3.2. Information fusion location algorithm based on maximum likelihood estimation

The estimated values of LOS and NLOS can be obtained through filtering in two different environments, then according to the estimated probability of the hypothesis testing, the values of the two filters are fused, taking into consideration the discriminant error of the hypothesis test, together with false alarm rate parameter $fa$, Kalman update equation after information fusion are represented as follows:

$$
f_{i,i}(k+1) = f_{i,i-1}(k) + (1 - fa) \cdot f_{i,i}(k) \quad (2.12)
$$

$$
\hat{X}_{i,i}(k+1) = \sum_{i=0}^{\hat{X}_{i,i}(k+1|k+1) - \hat{X}_{i,i}(k+1|k+1)} \quad (2.13)
$$

$$
P_{i,i}(k+1|k+1) = \sum_{i=0}^{\gamma_{i,i}(k+1|k+1) + \omega_{i}(k+1|k+1) \times \omega_{i}^T(k+1|k+1) \cdot f_{i,i}(k+1) \quad (2.14)
$$

where $\omega_{i}(k+1|k+1) = \hat{X}_{i,i}(k+1|k+1) - \hat{X}_{i,i}(k+1|k+1)$. Measurement distance after filtering:
\[ \tilde{d}_i(k + 1) = D \hat{X}_i(k + 1), D = [1, 0] \]  

Based on the measured value after filtering, the maximum likelihood estimation method is used for position estimation in this paper. It is assumed that SN coordinates are \([(x_1, y_1), \ldots, (x_N, y_N)]\), MN coordinate is \(X = [x, y]^T\). \(d_i\) is the measurement value after filtering by maximum likelihood estimation:

\[
X = (A^T A)^{-1} A^T \tilde{d}_i
\]  

where matrix A and B are

\[
A = \begin{bmatrix}
(x_1 - x_2) & (y_1 - y_2) \\
(x_1 - x_3) & (y_1 - y_3) \\
\vdots & \vdots \\
(x_1 - x_{N-1}) & (y_1 - y_{N-1})
\end{bmatrix}
\]

\[
B = \begin{bmatrix}
d_2^2 - \tilde{d}_1^2 - (x_2^2 + y_2^2) + (x_1^2 + y_1^2) \\
d_3^2 - \tilde{d}_1^2 - (x_3^2 + y_3^2) + (x_1^2 + y_1^2) \\
\vdots \\
d_{N-1}^2 - \tilde{d}_1^2 - (x_{N-1}^2 + y_{N-1}^2) + (x_1^2 + y_1^2)
\end{bmatrix}
\]

4. Simulation results

In this section, we use Matlab to simulate and verify the NLOS localization method based on hypothesis testing (KHT), and compare the proposed algorithm with the EKF (Extended Kalman Filter) algorithm. Figure 2 shows the deployment of nodes and obstacles. The default of the model parameters is shown in the Table 1.

Figure 2. The deployment of nodes and obstacles

Table 1. The default parameters in models

| Parameter | LOS conditions | NLOS conditions |
|-----------|----------------|-----------------|
| \(\sigma_{\text{ref}}\) | 3 \(\sigma_{\text{con}}\) | \(75\) \(\sigma_{\text{con}}\) |
| \(\rho_{\text{con}}\) | 0.2 \(\rho_{\text{con}}\) | \(97\) \(\rho_{\text{con}}\) |
| \(\sigma_{\text{ref}}\) | 2.5 \(\sigma_{\text{con}}\) | \(43.2\) \(\sigma_{\text{con}}\) |
| \(n_{\text{ref}}\) | 1.8 \(n_{\text{con}}\) | \(32.4\) \(n_{\text{con}}\) |
| \(P_{\text{ref}}\) | 40 \(P_{\text{con}}\) | \(37.330\) \(P_{\text{con}}\) |

The default parameters of the model are shown in the Table 1, in which “hard” represent the case of relatively large NLOS error, and “soft” represent the case of relatively small NLOS error.

Figure 3 shows the influence of different number of beacon nodes on localization error. We can see the mean localization error of the proposed algorithm is 2.76 meters, and the mean localization error of the EKF algorithm is 5.54 meters, the localization accuracy is higher than EKF about 51.06% in the environments which are strongly affected by NLOS error. In the environments which are weakly affected by NLOS error, the localization accuracy is higher than EKF about 35.4%. The experiments show that the proposed algorithm has a better performance compared with the EKF algorithm.
Figure 3. The number of beacon nodes and localization error

Figure 4 shows the localization error in strong and weak NLOS environments respectively. Through the Figure 4, we can see that the proposed algorithm has smaller localization error at most sampling points. The experiments show that the proposed algorithm has a better performance compared with the EKF algorithm in terms of robustness.

5. Conclusion

In this paper, we propose a novel NLOS error declined positioning algorithm based on hypothesis testing method. Firstly, we analyze the current research on NLOS condition verification positioning algorithm. Secondly, the algorithm verifies the propagation state effectively by using the RSSI measurement signals and different characteristics of signals in LOS and NLOS conditions. Finally, the hypothesis testing method is combined with Kalman filter to weaken the influence of NLOS error on localization accuracy. The simulation results show that the proposed algorithm can effectively reduce the influence of NLOS error and improve the localization accuracy.

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