The NLOS Localization Algorithm Based on the Linear Regression Model of Extended Kalman Filter

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***Abstract*—The location of the mobile node is an important issue in wireless sensor network (WSN). In WSN area, the NLOS (Non-line-of-sight) propagation of signal is ubiquitous and has a significant influence on the localization accuracy. Based on the Linear Regression Model of Extended Kalman Filter (EKF), the beacon node status is identified and the distance residuals is produced in this paper. Then the H-Infinity filter algorithm is used to filter the NLOS distance measurement values. Finally the maximum likelihood localization method is used to locate the position. Simulation results demonstrate that the proposed algorithm have a higher localization accuracy than other methods in different environments and have strong robustness in terms of inhibit NLOS errors.**

***Index Terms*—wireless sensor network, mobile localization, non line of sight, extended Kalman filter, H-infinity filter**

I. Introduction

Mobile node localization plays a significant role in WSN area [1], [2]. The common methods to estimate the distance are Angle of Arrival (AOA), Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Received Signal Strength (RSS) [3]. Most of the researchers assume that the signal propagation between the mobile node and the beacon nodes is Line of Sight (LOS). However, the direct propagation signal between the beacon nodes and the mobile node may be blocked in practical environment. The non-line-of-sight (NLOS) signal propagation is ubiquitous due to the diffraction and reflection.

Methods for identifying negative impact from NLOS mainly fall into two major categories: the identifying methods based on hypothesis test and the identifying methods with non-parameter. Borras *et al.* [4] proposed a double hypothesis test so as to identify the status of NLOS distance measurement. This method is a hypothesis test with parameters based on the standard deviation of NLOS distance measurement is bigger than that of LOS distance measurement, which also requires the NLOS errors should follow the Gaussian distribution. Then they identify the condition of the distance measurement with likelihood-ratio test. Venkatraman and Caffery *et al.* [5] identify the condition of the propagation signal with several test methods including inspecting the abnormal value and normality of observed data. They only need to know the priori knowledge to demonstrate that NLOS distance measurement does not follow the Gaussian distribution. Gezici *et al.* [6] proposed a non-parameter method to discriminate the status of base station. In consideration of the difference between the known distance error distribution and NLOS error distribution, this method defines a metric to describe the diversity and identify the status of propagation signals by the threshold value. Yu *et al.* [7] proposed a non-parameter hypothesis testing method, they structure the ratio of LOS and NLOS through Generalized Likelihood Ratio and identify the condition by using the Neyman-Pearson criterion. Based on the residual weight, Wang *et al.* [8] proposed an improved algorithm which uses the ratio between the propagation weight of mobile nodes and beacon nodes. Then they achieve he localization with strong robustness. Hammes *et al.* [9] proposed a robust tracking and localization algorithm to solve the NLOS error problem.

The identification algorithm based on hypothesis test with known parameters always need a great amount of priori knowledge and historical data. Thus the method usually apply to a specific environment, which makes it poor in portability. Few researches studied on the identification method with non-parameter hypothesis test. They only need little priori knowledge and the algorithm is independent on historical data so as to apply to the varieties environment. The algorithm has the better portability and practicability. The proposed algorithm is the unknown the parameters of NLOS error method and is able to identify the propagation signal without the NLOS error distributions and its parameters. We firstly utilizes EKF linear model to produce distance residuals. Then we use the H-Infinity filter algorithm to filter the NLOS distance measurement values. Finally, using the maximum likelihood localization method to finish the localization.

The rest of the paper is organized as follows: In Section II, we introduce the architecture of the localization algorithm. Section III derived the proposed method for NLOS environment. In Section IV, simulation results are presented. The conclusions are given in Section V.

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II. Architecture of Proposed Algorithm

There are mainly two ways to solve the NLOS propagation problem [10]. The first way is to mitigate the measurement noise. The researchers need to weak the adverse influences caused by NLOS errors. Then they use the weaken NLOS distance measurement values to finish the localization. The second way is to identify the channel conditions. They identify the status of the distance measurement value. After they obtain all the distance measurement value, then they can use the classic algorithm to solve the localization problem if there are more than 3 LOS distance measurement values. NLOS mitigating methods have better perform better when they are able to restrain NLOS errors in a great way, while NLOS identifying methods achieve a better result when they identify distance measurement value status in a more accurate way. In this paper we mainly identify the NLOS status and mitigate the NLOS error to finish the localization. We only use the standard deviation of distance measurement error and we needn't to know the distribution of the NLOS error. Fig. 1 shows that the architecture of proposed algorithm. The proposed algorithm is described as follows:

Averaging: We obtain the many distance measurements and the measuring frequency is higher than localization frequency. Therefore we should average the distance measurements.

Residual generation: After getting the mean distance measurement value of each beacon node, we use the EKF linear model to generate the residuals.

H-Infinity filter: We use the H-Infinity filter algorithm to filter the residuals from step (2). Then we compose a new distance vector.

Localization: Using the new distance vector that we get from the step (3) as the current measured vector and applying the maximum likelihood localization method to finish the localization.

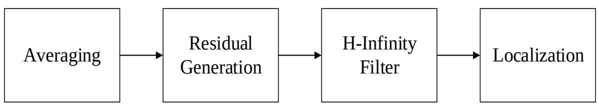

Figure 1. Architecture of proposed algorithm

III. Mobile Node Localization Algorithm

A. System Model

We deploy *N* beacon nodes and one mobile node in this paper. The coordinate of the beacon nodes are represented as $C_i = [x_i, y_i]^{\mathrm{T}}, i = 1, 2, ..., \mathrm{N}$. The beacon nodes transmit the signal and the mobile node receive it.

In LOS propagation environment, the measured distance between the mobile node and the *i*-th beacon node at the time *t* is:

$$r_t^i = d_t^i + n_i, i = 1, 2, ..., \mathrm{N} \tag{1}$$

where, d_t^i is the real distance between the mobile node and the *i*-th beacon node at the time *t*, n_i is the measurement noise error, which obeys Gaussian distribution whose mean is zero and standard deviation is σ_i .

In NLOS propagation environment, the measured distance between the mobile node and the *i*-th beacon node at the time *t* is:

$$r_t^i = d_t^i + n_i + e_{NLOS}, i = 1, 2, ..., \mathrm{N} \tag{2}$$

where e_{NLOS} is the NLOS error and independent with n_i . In different kinds of environment, e_{NLOS} could obey exponential distribution, Gaussian distribution or uniform distribution.

B. Extended Kalman Filter Algorithm and Linear Model

We deploy *N* beacon nodes in the WSN and the acceleration of the mobile node is uniform. The position of the mobile node can be calculated by the TOA measured values of *N* beacon nodes during the localization process. And g TOA measured values can be produced by each beacon node based on the idea of the high-frequency base station localization [11]. The mean distance vector between the mobile node and beacon nodes at the time t is:

$$\bar{\mathbf{r}}_t = \frac{1}{\mathrm{g}} \sum_{j=1}^{g} \mathbf{r}_t^j \tag{3}$$

where *g* is the times of the distance measurement that beacon nodes can complete during localization process; $\mathbf{r}_{\mathrm{t}}^j$ is the *j*-th distance vector which the beacon nodes measure at time *t* in the localization process.

As the measurement equation is nonlinearity, we need to process it with the linearization method. To get the residual value, we convert the standard EKF to the linear regression model of the EKF. Then the state equation and measurement equation are:

$$\begin{bmatrix} \mathbf{E}_4 \\ \mathbf{H}_t \end{bmatrix} \boldsymbol{\theta}_t = \begin{bmatrix} \mathbf{A}\hat{\boldsymbol{\theta}}_{t-1} \\ \bar{\mathbf{r}}_t - \mathbf{h}(\hat{\boldsymbol{\theta}}_t^-) + \mathbf{H}_t \hat{\boldsymbol{\theta}}_t^- \end{bmatrix} + \boldsymbol{\zeta}_{\mathrm{t}} \tag{4}$$

where $\mathbf{E}_4$ is the 4×4 matrix, $\mathbf{H}_t$ is the Jacobi matrix, $\boldsymbol{\theta}_t$ is the state vector of the mobile node at time t, $h_i(\boldsymbol{\theta}_t)$ is the vector which composed by the Euclidean distances between the mobile node and the *i*-th beacon node, $\boldsymbol{\zeta}_t$ is the residual vector.

Make the equation (4) multiply with $\mathbf{D}_t^{-1}$ simultaneously both sides of the equation on the left, then the equation (4) can be rewritten as the linear least square regression model:

$$\widehat{\mathbf{r}}_t = \mathbf{M}_t \boldsymbol{\theta}_t + \mathbf{v}_t \tag{5}$$

We use the least square method to solve the equation (5) and then we get the state vector:

$$\widehat{\boldsymbol{\theta}}_t = \left(\mathbf{M}_t^{\mathrm{T}} \mathbf{M}_t\right)^{-1} \mathbf{M}_t^{\mathrm{T}} \widehat{\mathbf{r}}_t \tag{6}$$

C. H-Infinity Filter Algorithm

The H-infinity filter algorithm need not any statistics information [12], [13]. The standard EKF algorithm can be converted to the linear regression model of the EKF algorithm, we employ the H-infinity filter algorithm for the further processing.

The observation vector is defined as follow:

$$\hat{\theta}_t^- = \mathbf{L}\hat{\theta}_{t-1} \tag{7}$$

$$\mathbf{P}_t^- = \mathbf{L}\left(\mathbf{Q}_{t-1}\right)^{-1} - \beta^2\mathbf{I} \tag{8}$$

The update process is shown as:

$$\mathbf{K}_t = \left(\frac{1}{\beta}\mathbf{I} + \mathbf{J}\left(\mathbf{Q}_t\right)^{-1}\mathbf{H}_t^T\right)\left(\mathbf{I} + \mathbf{H}_t\left(\mathbf{Q}_t\right)^{-1}\mathbf{H}_t^T\right)^{-1} \tag{9}$$

$$\hat{\theta}_t = \mathbf{J}\hat{\theta}_t^- + \mathbf{K}_t(\delta - \mathbf{H}_t\hat{\theta}_t^-) \tag{10}$$

$$\mathbf{Q}_t = (\mathbf{J} - \mathbf{K}_t\mathbf{H}_t)(\mathbf{Q}_t)^{-1}(\mathbf{J} - \mathbf{K}_t\mathbf{H}_t)^T + \mathbf{K}_t\mathbf{K}_t^T \tag{11}$$

The output of H-Infinity filter is shown as:

$$d_H(t) = \mathbf{D}\hat{\theta}_t, \mathbf{D} = [1,0] \tag{12}$$

D. Localization

In this section, we introduce maximum likelihood localization method. The position of the beacon node is $[x_i, y_i]^{\mathbf{T}}, i = 1, 2, ..., \mathrm{N}$. The position of mobile node at time t is $[x_t, y_t]^{\mathbf{T}}, t = 1, 2, ..., t_n$. d_t^N is output by the proposed algorithm.

$$\begin{cases} \left(x_1 - x_t\right)^2 + \left(y_1 - y_t\right)^2 = \left(d_t^1\right)^2 \\ \vdots \\ \left(x_N - x_t\right)^2 + \left(y_N - y_t\right)^2 = \left(d_t^N\right)^2 \end{cases} \tag{13}$$

We can obtain the coordinate matrix of the mobile node as follows:

$$X = \left(A^T A\right)^{-1} A^T B \tag{14}$$

where

$$A = 2\begin{bmatrix} (x_1 - x_2) & (y_1 - y_2) \\ (x_1 - x_3) & (y_1 - y_3) \\ \vdots & \vdots \\ (x_1 - x_N) & (y_1 - y_N) \end{bmatrix}$$

$$B = \begin{bmatrix} d_t^2 - d_t^1 - \left(x_2^2 + y_2^2\right) + \left(x_1^2 + y_1^2\right) \\ d_t^3 - d_t^1 - \left(x_3^2 + y_3^2\right) + \left(x_1^2 + y_1^2\right) \\ \vdots \\ d_t^N - d_t^1 - \left(x_N^2 + y_N^2\right) + \left(x_1^2 + y_1^2\right) \end{bmatrix}$$

IV. Simulation Results

In this section, we analyze the performance of the proposed algorithm described in this paper through simulation. As shown in the Fig. 2, we deploy 8 beacon nodes in the 5m×7m room, mobile nodes move around a rectangle table in uniform velocity (long tables constitute the obstacles between nodes, which are not shown in this figure) following a rectangle trajectory. We compare the proposed method H-Infinity high-frequency extended Kalman filter (H-FKEF) with the high-frequency extended Kalman filter algorithm (FKEF). In each simulation case, 500 Monte Carlo runs are performed in the same parameters. The performance of the proposed algorithm is measured by Root Mean Square Error (RMSE) and Cumulative Distribution Function (CDF):

$$RMSE_t = \sqrt{\frac{1}{MC}\sum_{j=1}^{MC}(x_j(t) - \hat{x}_j(t))^2 + (y_j(t) - \hat{y}_j(t))} \tag{15}$$

where $(x_j(t), y_j(t))$, $(\hat{x}_j(t), \hat{y}_j(t))$ describes the true and the estimated position of mobile node at time t for the *j*-th Monte Carlo run, respectively.

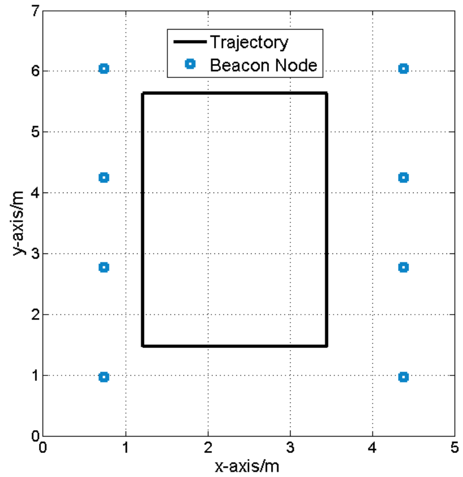

Figure 2. The schematic diagram of the deployment environment

The root mean square error for two algorithms is compared as shown in Fig. 3. We can observe the RMSE of the FEKF algorithms is large, but the localization accuracy of H-FEKF algorithm is higher than the FEKF algorithm. FEKF algorithm is sensitive to NLOS error, and it is easier to be affected by the NLOS error. In contrast, the localization performance of the H-FEKF algorithm is stable and the localization accuracy improves greatly.

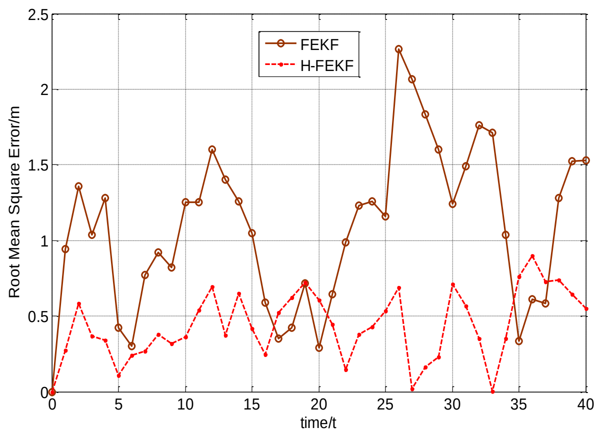

Figure 3. Comparison of root mean square error

Fig. 4 shows cumulative distribution function of localization error. It can be seen the localization error of the FEKF algorithms is 2.3m when the cumulative distribution function is close to 1, while the localization error of the H-FEKF algorithm is 1m. The 50-percentile of localization error of the FEKF, and H-FEKF algorithms are less than 0.4m and 1.2m. It can be seen the H-FEKF algorithm has the higher localization accuracy.

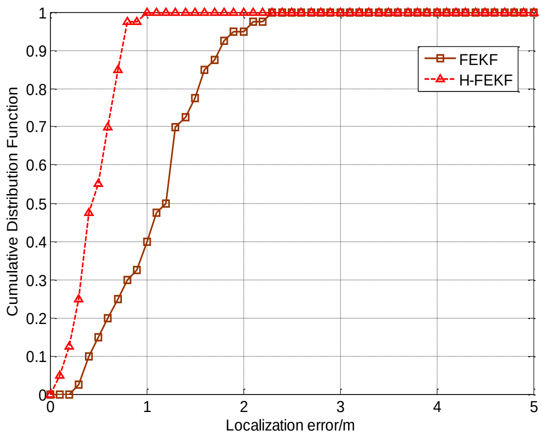

Figure 4. The cumulative distribution function of localization error

V. CONCLUSION

In this paper, a novel algorithm to identify the NLOS problem based on the EKF linear model and H-infinity filter algorithm is proposed. The EKF linear model is firstly utilized to produce distance residuals in this algorithm. Then the H-infinity filter algorithm is used to filter the NLOS distance measurement values. Finally, maximum likelihood localization method is used to finish the localization. The simulation results show that the proposed algorithm has a good inhibition effect on NLOS errors and have the higher localization accuracy in different environment than other methods.

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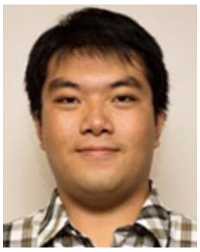

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