Research Article

Target Tracking with NLOS Detection and Mitigation in Wireless Sensor Networks

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RN and SSR approaches are designed to detect NLOS propagation paths in this paper. When the NLOS propagation paths are detected, an estimation approach for the NLOS range errors is proposed by using residual-error decomposition. The approach can estimate the NLOS range errors quickly and effectively, even if there are multiple NLOS propagation paths. Combining the movement equation with observation position, the position of mobile target node can be tracked precisely with Kalman filter algorithm. Using the estimated NLOS range errors, we correct the localization result and modify Kalman filter to mitigate the NLOS propagations. The simulations demonstrate the validity with RN and SSR detection methods and analyze the impacts of NLOS range errors and number of NLOS anchor nodes. The estimated NLOS range errors are proved to be close to the true especially when the NLOS range errors are much bigger than LOS range errors. The simulation results show that the position of target node can be tracked precisely and effectively, when the NLOS mitigation is used to track the target node position with modified Kalman filter.

1. Introduction

Recent advances in wireless communications, microelectro mechanical systems, electronics, and distributed processing technology have enabled the deployment of large numbers of cheap and smart sensor nodes to construct wireless sensor networks (WSNs). Deployed in the monitoring region, a large number of sensor nodes form a multihop ad hoc network system through wireless communication. These networked sensors are able to process sensed data locally and extract relevant information, to collaborate with other sensors on the application specific task and to provide the resultant information about the monitored events for a number of potential applications, ranging from battlefield monitoring and environmental surveillance to health care [1–3]. To make the data collected from sensor nodes meaningful, it often requires related node positions. Target localization and tracking of mobile nodes are important research directions in WSNs [4–10].

It is often the case with a general assumption that the positions of nodes deployed in the monitoring region are known (called anchor nodes), so that it is possible to track the positions of the mobile target with a sensor node [11]. To track and locate the mobile target node, some measurement approaches are proposed, such as time of arrival (TOA) [12, 13], angle of arrival (AOA) [14], time difference of arrival (TDOA), and received signal strength indication (RSSI) [15]. Some hybrid approaches of TOA, AOA, TDOA, and RSSI have also been proposed for target localization and tracking. The measured results are often transmitted to base station which computes the current position of mobile target node based on the received measurements and the history. Then, the base station reports the tracking results to each sensor node or target node.

Since the range measurements are usually prone to errors, the localization result of target node will be far from the true position [16–18]. Some studies are focused on line-of-sight (LOS) assumption, so the target node can be located precisely with the traditional localization algorithms [19]. However, since the direct path between nodes can be blocked by buildings and other obstacles, the transmitted signal could only reach the receiver through reflected, diffracted, or scattered paths called nonline-of-sight (NLOS) propagation paths. Most of previous researches on NLOS propagation have
focused on the NLOS identification and mitigation [20–22]. In [23], a positioning algorithm in severe NLOS propagation path scenarios is proposed to enhance positional accuracy of network-based positioning systems when the position receiver does not perform well due to the complex propagation environment. In the event that the statistics of the NLOS errors and measurement noise are known, such as those based on field trials, statistical processing can significantly reduce the NLOS effect [24]. When a database is established in advance, signature matching can be employed to greatly improve position accuracy in NLOS scenarios. By exerting constraints or introducing an NLOS error-related parameter into the cost function, optimization algorithms can be developed to mitigate the NLOS effect [25, 26]. Some of researches take advantage of the NLOS propagation paths rather than canceling them [27].

Using its movement velocities, the position of target node can be approximately estimated when the initial position of target node is known. However, the position of iterative estimation with movement equation is prone to error when the movement velocities include noises. In WSNs, the position of target node also can be located by range measurement between the target node and anchor nodes known positions. When the range measurements include noises, the localization result also would be imprecise [28]. Kalman filter (KF) to deal with the linear function and its nonlinear extension, extended Kalman filter (EKF), provide a feasible solution to mitigate the position error of the mobile target node, and therefore improving accuracy of mobile target tracking [29–31].

To track the position of mobile target node precisely, we propose to mitigate the NLOS propagations and make good use of the LOS range measurements by detecting and identifying the NLOS propagation paths. In this paper, we firstly introduce two approaches to detect the NLOS propagation paths when the range measurements conform to Gaussian distribution. The first detection approach utilizes residual of node (RN), which conforms to zero-mean Gaussian distribution when there are no NLOS propagation paths. The second approach to detect NLOS propagation paths utilizes sum of square residual (SSR), which conforms to chi-square distribution when no NLOS propagation paths exist. The anchor nodes with NLOS propagation paths are called NLOS anchor nodes, and the anchor nodes with LOS propagation paths are also called LOS anchor nodes. To identify the NLOS anchor nodes, we propose a residual-error decomposition method to estimate the NLOS range errors. The localization result can be improved when estimated NLOS range errors are used to amend the residuals. Then the corrected position is considered as observation and used to track the mobile target position precisely. The contributions of our work are summarized as follows.

(1) RN and SSR Approaches to Detect the NLOS Anchor Nodes. Using the Jacobian matrix, we derive the residuals coming from range errors between the target node and each anchor node. Applying the analysis method of multiple factor statics, we conclude that RN conforms to Gaussian distribution when the range measurements are Gaussian distributed. Then, we demonstrate that the SSR of all anchor nodes conforms to chi-square distribution when no NLOS anchor nodes exist. So, the probability of RN and SSR can be used to detect the NLOS propagation paths precisely.

(2) An Estimation Method for NLOS Range Errors Is Proposed When Multiple NLOS Anchor Nodes Simultaneously Exist. By analyzing the relationships between the errors and the residuals in the process of nonlinear minimization localization, we propose an estimation method for NLOS range errors. Since the residuals are caused by the range errors, the range errors of NLOS anchor nodes can be estimated approximately by ignoring the assigned residuals from LOS anchor nodes to the NLOS anchor nodes. Using the estimated range errors of anchor nodes, the NLOS anchor nodes can be identified correctly.

(3) To Tracking A Mobile Target Node Precisely the Modified KF Is Put Forward by Applying the NLOS Mitigation Method. By mitigating the NLOS propagation paths, the localization accuracy can be improved so the covariance of target node position would be reduced. The covariance of localized position is derived from the range noises between the target node and each anchor node. Considering the localized position as observation, the position of target node is tracked with modified KF based on the movement equation.

This paper presents an effective tracking method of mobile target node with modified KF in NLOS environment. The rest of this paper is structured as follows. Section 2 presents two detection approaches for the NLOS propagation paths. Section 3 describes the estimation method of NLOS range errors. Section 4 introduces the target tracking algorithm with modified KF in NLOS environment. Section 5 analyzes the simulation results. The conclusion is presented in Section 6.

2. Detection of NLOS Propagation Path

For simplicity, we only focus on the case of tracking a single target node in a two-dimensional field covered with multiple anchor nodes. Since most localization systems of wireless communications may suffer from the NLOS propagation paths and dense multipath situation, it is an important issue to obtain higher accuracy in determining range information. In dealing with the NLOS propagation path effects, the range measurement \( \tilde{d}_{ij} \) between target node position \( i \) and the position of anchor node \( j \), corresponding to the TOA measurement metrics, can be modeled as

\[
\tilde{d}_{ij} = d_{ij} + n_{ij} + b_{ij},
\]

where \( i \) means the time instant of tracked mobile node and \( i = 1, \ldots, M \). \( j = 1, \ldots, N \) represents the fact that there are \( N \) measurable anchor nodes corresponding to the target node. As mentioned earlier, usually the measurement noise values \( n_{ij} \) are modeled as zero-mean Gaussian random variables with variance \( \delta_{ij}^2 \). \( b_{ij} \) caused by NLOS propagation path is a positive random variable. There will be no NLOS error component if the LOS propagation path exists; and \( b_{ij} = 0 \). We
define $\Delta d_{ij} = n_{ij} + b_{ij};$ then $\Delta d_{ij} \sim \mathcal{N}(b_{ij}, \delta_{ij}^2).$ Here, $\mathcal{N}(b_{ij}, \delta_{ij}^2)$ denotes the Gaussian distribution with mean $b_{ij}$ and variance $\delta_{ij}^2$. $d_{ij}$ represents the true distance between the target node position $i$ and fixed position of anchor node $j$ and can be written as

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2},$$  \tag{2}

where $z_t = (x_t, y_t)$ is the true position of mobile target node at time instant $t$, whereas $z_j = (x_j, y_j)$ is the position of anchor node $j$. If the positions of anchor nodes are assumed to be accurate, the localization problem can be performed in different ways including the mixed norm [32]. Here, the optimization-based nonlinear minimization is considered. The cost function $f(z_t)$ called as sum of square residual at time instant $t$ is defined as

$$f(z_t) = \sum_{j=1}^{N} \omega_{ij} \Delta d_{ij}^2 = \sum_{j=1}^{N} \omega_{ij} (\tilde{d}_{ij} - d_{ij})^2.$$  \tag{3}

The weights $\omega_{ij}$ are selected to emphasize the contribution of smaller error terms among $\Delta d_{ij}$. Note that, in minimization or optimization, when the weights are properly selected with respect to the quality of each measurement, better estimation results will be expected. When the optimal weights are employed, optimal estimation accuracy would be produced. If the range $\tilde{d}_{ij}$ are supposed to be independent, respectively, $\omega_{ij}$ can be chosen to be inversely proportional to the variances of the distance measurement errors using the classical maximum likelihood (ML) estimator when $\Delta d_{ij} \sim \mathcal{N}(0, \delta_{ij}^2)$. In the event of unknown or very similar statistics of $\omega_{ij}$, equal weights can be simply used. In this paper, we simplify the optimization problem with equal weights and consider $\omega_{ij}$ as one.

Equation (3) can be solved by Gauss-Newton method. Based on a linear approximation to the components of $f(z_t)$ (a linear model of $f(z_t)$), Gauss-Newton method may fail when trapped in a local optimum. Levenberg-Marquardt (L-M) method is recommended for the global optimum [33]. Because L-M algorithm uses the approximate second derivative information, the convergence of L-M is much faster than the gradient descent method of Gauss-Newton. It is proved that L-M algorithm can increase the speed of dozens or even hundreds of times of the original gradient descent method of Gauss-Newton. A compact matrix form of range errors can be written as follows:

$$\Delta d_t = [\Delta d_{i1}, \Delta d_{i2}, \ldots, \Delta d_{iN}]^T.$$  \tag{4}

With the linearization of the system using Taylor series approximation, the optimization problem of (3) can be transform to

$$f(z_t) = (\Delta d_t - J_t \Delta z_t)^T (\Delta d_t - J_t \Delta z_t),$$  \tag{5}

where $\Delta z_t$ is the incremental matrix of the true $z_t$, $J_t$ is the Jacobian matrix of $d_t$ at the true position of target node, $\Delta d_t = [\Delta d_{i1}, \Delta d_{i2}, \ldots, \Delta d_{iN}]^T$. Using the principle of least square method,

$$\Delta z_t = (J_t^T J_t)^{-1} J_t^T \Delta d_t,$$  \tag{6}

$r_i = \Delta d_i - J_i \Delta z_i$ is called residual, which can be rewritten as

$$r_i = [I - J_i (J_i^T J_i)^{-1} J_i^T] \Delta d_i = A_i \Delta d_i,$$  \tag{7}

where

$$A_i = I - J_i (J_i^T J_i)^{-1} J_i^T.$$  \tag{8}

Apparently, $A_i$ represents the distribution relationship between range errors and residuals. As observed from (9), the positions of target node and anchor nodes determine $A_i$, which can be represented as

$$A_i = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix}.$$  \tag{9}

$r_i$ can be rewritten as follows:

$$r_i = [r_{i1}, r_{i2}, \ldots, r_{iN}]^T.$$  \tag{10}

Here, two approaches are introduced to detect the NLOS propagation path: residual of node (RN) and sum of square residuals (SSR).

2.1. Residual of Node (RN). Since $\Delta d_{ij} \sim \mathcal{N}(b_{ij}, \delta_{ij}^2)$, the mean $\mu_{ij}$ and variance $\nu_{ij}^2$ of $r_{ij}$ can be written as

$$\mu_{ij} = \sum_{k=1}^{N} a_{ik} b_{kj},$$  \tag{11}

$$\nu_{ij}^2 = \sum_{k=1}^{N} a_{ik}^2 \delta_{kj}^2.$$  \tag{12}

The RN $r_{ij}$ will conform to Gaussian distribution $\mathcal{N}(\mu_{ij}, \nu_{ij}^2)$. When $b_{ij}$ is equal to zero, a test result of RN probability density function (PDF) is plotted in Figure 1, which shows that the residual approximately conforms to Gaussian distribution with zero-mean. Based on probability theory, we obtain that

$$P \left( \frac{r_{ij} - \mu_{ij}}{\nu_{ij}} < \alpha \right) = \beta.$$  \tag{13}
where $\beta$ is the probability of observing a measurement $r_{ij}$. Typically, when $\beta$ is equal to 99.9%, $\alpha$ is approximately 3.3. Then,

$$r_{ij} - \alpha v_{ij} < \mu_{ij} < r_{ij} + \alpha v_{ij}$$

(14)

If there are no NLOS range errors, $b_{ij}$ must be equal to zero and $\mu_{ij} = 0$. According to (14), $r_{ij} - \alpha v_{ij} < \mu_{ij}$. So, we can conclude that if $r_{ij} - \alpha v_{ij} > 0$, that is,

$$r_{ij} > \alpha v_{ij},$$

(15)

$\mu_{ij} > 0$ and there must be at least one NLOS propagation path. In most actual NLOS situations, we can further assume that $b_{ij} \approx \delta_{ij}$. As observed from (8), the residual $r_{ij}$ is proportional to the NLOS error $b_{ij}$ approximately, so we obtain $r_{ij} > \alpha v_{ij}$ when the NLOS propagation path exists.

In the previous localization model, since there are $N$ anchor nodes, each range measurement is likely to be NLOS. To ensure the probability of observation, $\beta$ can be ensured with

$$\beta^N = \gamma,$$

(16)

where $\gamma$ is the probability of an observation when there are no NLOS propagation paths. $\gamma$ can be determined in prior, $\beta = \sqrt[N]{\gamma}$. Typically when $\gamma = 99.5\%$ and $N = 5$, $\beta = 99.9\%$.

2.2. Sum of Square Residuals (SSR). The sum of square residuals $f(z_i)$ can be rewritten as

$$f(z_i) = r_i^T r_i = \sum_{j=1}^{N} r_{ij}^2.$$  

(17)

Here, $r_{ij} \sim N(\mu_{ij}, \sigma^2)$. Assuming that there are no NLOS propagation paths and $\mu_{ij} = 0$, $j = 1, \ldots, N$, the PDF of $r_{ij}^2$ can be represented as

$$P(z) = \begin{cases} \frac{1}{\sqrt{2\pi} v_{ij}} z^{-(1/2)} e^{-z/(2v_{ij}^2)} & z \geq 0 \\ 0 & z < 0 \end{cases}.$$  

(18)

where $z = r_{ij}^2$. So, $z/r_{ij}^2$ conforms to the distribution $\chi^2(1)$. Here, $\chi^2(1)$ denotes the chi-square distribution with freedom degree one. When there are no NLOS propagation paths, $r_{ij}$ conforms to the Gaussian distribution $\mathcal{N}(0, \sigma^2)$ and is independent, respectively. We relax the distribution of $\{r_{ij}\}_{j=1,2,\ldots,N}$ to Gaussian distribution $\mathcal{N}(0, \sigma_{\text{max}}^2)$, where $\sigma_{\text{max}}^2$ stands for the maximum variance of all $\{r_{ij}\}_{j=1,2,\ldots,N}$. Then, the PDF of $f(z_i)/\sigma_{\text{max}}^2$ will conform to $\chi^2(N)$ distribution with freedom degree $N$.

A test result of SSR cumulative distribution function (CDF) is plotted in Figure 2, which shows that more anchor nodes will lead to the increasing of SSR. Based on probability theory, we also have

$$P\left\{\chi^2(N) > \chi^2(\theta)\right\} = \theta.$$  

(19)

Typically, when $N = 5$ and $\theta = 0.995$, $f(z_i)$ will be at least 16.75, which is called SSR threshold, denoted as $S_I$. So if

$$f(z_i) > S_I,$$  

(20)

there must be at least one NLOS propagation path.

3. Identification of NLOS Anchor Nodes

The range measurements may be prone to potential NLOS errors. The NLOS range measurements result in a distorted position, whereas LOS measurements can reflect originally the anticipation. In the 2-dimensional plane, node localization requires only three noncollinear anchor nodes. In most situations, the number of anchor nodes is more than three and redundant. Our idea is to identify the NLOS propagation paths and make good use of LOS measurements. When the other anchor nodes happened to be NLOS propagation paths, only using the LOS anchor nodes can locate the target node precisely. Our approach is to correct the localization result and mitigate NLOS with estimated NLOS range errors, so the
mobile target node position can be tracked precisely with modified KF.

If multiple NLOS propagation paths exist, it is necessary to discern which anchor nodes are the NLOS ones. In this section, we introduce a low rank residual-error decomposition method to estimate the NLOS range errors. Expanding (8), the residual between target node position $i$ and anchor node $j$ can be represented as

$$r_{ij} = \sum_{k=1}^{N} a_{jk} \cdot \Delta d_{ik},$$

where $a_{ij} > 0$ and $\Delta d_{ik}$ represents the range error between the target node position $i$ and anchor node $k$. Under most NLOS conditions, the NLOS range error $\Delta d_{ik} \gg 0$. If there is a NLOS propagation path between target node position $i$ and anchor node $k$, the residual $r_{ij}$ must be overenlarged. The larger residuals of all anchor nodes are considered as the more possible to be happening of NLOS propagation paths. To judge whether there are NLOS propagation paths, we consider that there must be at least one NLOS propagation path.

In (8), $A_i = I - J_i (J_i^T J_i)^{-1} J_i$. The localization method represented by (3) locates the target node by L-M algorithm, so $A_i$ and $r_i$ have been calculated out. Since the matrix $A_i$ is not full rank, the range error $\Delta \hat{d}_i$ cannot be directly calculated out. $A_i$ in (8) reveals the relationship between residuals and errors. When the number of NLOS anchor nodes is less, the range errors of NLOS anchor nodes are assigned to the LOS anchor nodes evenly, so a larger residual in $r_i$ will tend to be a larger error in $\Delta \hat{d}_i$. The NLOS anchor nodes can be distinguished from the LOS anchor nodes with the residuals. Resorting $A_i$ according to the residuals, $A_i$ is decomposed as

$$A_i = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix},$$

where $A_{11}$ shows that the range errors of LOS anchor nodes are assigned to the residuals of LOS anchor nodes. $A_{12}$ shows that the range errors of LOS anchor nodes are assigned to the residuals of NLOS anchor nodes. $A_{21}$ shows that the range errors of NLOS anchor nodes are assigned to the residuals of LOS anchor nodes. $A_{22}$ shows that the range errors of NLOS anchor nodes are assigned to the residuals of NLOS anchor nodes. When the range errors of LOS anchor nodes are much less than those of NLOS anchor nodes, the range errors of NLOS anchor nodes can be roughly estimated by ignoring the impact of LOS anchor nodes. To identify the NLOS anchor nodes correctly, at least two anchor nodes are firstly chosen to be LOS ones, so the matrix $A_{11}$ would be $2 \times 2$ one. The anchor nodes with less residuals are considered as more possible to be LOS ones, so the two anchor nodes with least residuals are chosen to be LOS ones. Similarly, the residual $r_i$ and the estimated range error $\Delta \hat{d}_i$ can also be decomposed as

$$r_i = \begin{bmatrix} r_{11} \\ r_{21} \end{bmatrix},$$

$$\Delta \hat{d}_i = \begin{bmatrix} \Delta \hat{d}_{11} \\ \Delta \hat{d}_{21} \end{bmatrix}.$$ (23)

Therefore, the NLOS range errors can be approximately estimated with

$$\Delta \hat{d}_2 = A_{22}^{-1} \cdot r_2.$$ (24)

In $\Delta \hat{d}_2$, the anchor nodes with the larger estimated error are considered as the NLOS ones and the NLOS anchor nodes are identified.

Recalculating the Jacobian matrix with all anchor nodes in (7) and letting $F_i = (J_i^T J_i)^{-1} J_i$, the covariance of increment $\Delta z_i$ can be written as

$$\text{Cov}(\Delta z_i) = F_i \Sigma_i F_i^T,$$ (25)

where $\Sigma_i$ is the covariance of range error $\Delta d_i$. If $\Delta d_{ij}$ is independent for $j = 1, 2, \ldots, N$, $\Sigma_i$ can be represented as

$$\Sigma_i = \text{diag} \{ \delta_{i1}^2, \delta_{i2}^2, \ldots, \delta_{iN}^2 \}.$$ (26)

4. Tracking with Modified KF

In target tracking applications, the most popular methods for updating target node position incorporate variations of Kalman filter estimator. Kalman filter assumes that the dynamics of the target can be modeled and that noise affects the target dynamics and sensor measurements. Since the localization of target node is an optimization problem of nonlinear function, the measurement conversion method is proposed to transform the nonlinear measurement model into linear one and estimate the covariances of the converted measurement noises before applying the standard Kalman filter.

4.1. Target Motion Model. A standard target moving in a two-dimensional field for the mobile target node is usually described by its position and velocity in the $X$-$Y$ plane

$$x_i = [x(i) \ v_x(i) \ y(i) \ v_y(i)]^T,$$ (27)

where $x(i)$ and $y(i)$ are the position coordinates of the target node along $X$ and $Y$ axes at time $t_i$, respectively. $v_x(i)$ and $v_y(i)$ are the velocities of the target node along $X$ and $Y$ axes at time $t_i$, respectively. The following nearly constant velocity model is adopted to represent the motion of the target node:

$$x_{i+1} = \Phi_i x_i + \Gamma_i w_i,$$ (28)

where $\Phi_i$ is called state transition matrix, which can be written as

$$\Phi_i = \begin{bmatrix} 1 & \Delta t_i & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$ (29)
and \( \Gamma_i \) is called as noise transition matrix, which can be written as
\[
\Gamma_i = \begin{bmatrix}
\frac{\Delta t_i^2}{2} & 0 \\
0 & \Delta t_i^2 \\
- \frac{\Delta t_i^2}{2} & 0 \\
0 & \Delta t_i^2 \\
\end{bmatrix}. \tag{30}
\]
In the previous equations, \( \Delta t_i = t_{i+1} - t_i \) is the sampling time interval between \( t_i \) and \( t_{i+1} \). \( w_i = [w_{x_i} \ w_{y_i}] \) is a white Gaussian noise sequence with zero mean and covariance matrix \( Q_w \). \( w_x \) and \( w_y \) represent the correspondence to noisy accelerations along the \( X \) and \( Y \) axes, respectively. If we assume that \( w_x \) is uncorrelated with \( w_y \), \( Q_w \) can be given by
\[
Q_w = \begin{bmatrix}
\delta_{w_x}^2 & 0 \\
0 & \delta_{w_y}^2 \\
\end{bmatrix}, \tag{31}
\]
where \( \delta_{w_x}^2 \) and \( \delta_{w_y}^2 \) are the variances of noisy acceleration \( w_x \) and \( w_y \), respectively. It is noted that our moving model of target node does not consider the case where the moving target node follows a given trajectory, which happens when the target node travels on a given road segment. But if such trajectory is available as in the case when a road map is available, the system model for the moving target node can be easily modified and our approach is still applicable.

4.2. Modified Observation Model. The localization result by (3) is considered as the observation. Here, the localization result is denoted as \( \tilde{z}_i \) by (3). The position of target node can be modified as
\[
z_i = Hx_i + u_i, \tag{32}
\]
where \( H \) is called measurement matrix, which can be written as
\[
H = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 \\
\end{bmatrix}. \tag{33}
\]
\( u_i \) is called as measurement noise, which is equal to \( \Delta z_i \) determined by localization algorithm and range errors. It remains to specify the statistics for noise \( u_i \) before the localization result \( z_i \) can act as observation and be used in Kalman filtering. The covariance matrix of \( u_i \) is denoted as \( R_i \), which will be used to evaluate the observation quality in Kalman filtering. Apparently, the NLOS propagation paths would make the observation \( z_i \) greatly far from the true position. In order to track the target node position precisely \( R_i \) should be increased when there are NLOS propagation paths. Observed from (7), \( \Delta z_i \) also conforms to Gaussian distribution since it is linear with range error \( \Delta d_i \). So we obtain that
\[
R_i = \text{Cov} (\Delta z_i) = F_i \Sigma_i F_i^T, \tag{34}
\]
If there are no NLOS propagation paths, \( z_i = \tilde{z}_i \) in (32). The NLOS propagation paths aggravate the localization result, so the observation of target node position would be far from the true position. The estimated NLOS range errors in (24) can be used to correct the observation. The range errors of LOS anchor nodes are assumed as zero; then
\[
\Delta d = [0; 0; \Delta d_3]. \tag{35}
\]
So, if there are NLOS propagation paths, the observation \( z_i \) will be modified as
\[
z_i = \tilde{z}_i + F_i \Delta d, \tag{36}
\]
where \( F_i \Delta d \) represents the incremental position errors caused by NLOS range errors.

4.3. Kalman Filtering. The iterative operations of the Kalman filter can be summarized as follows:
\[
x_{i+1|j} = \Phi x_{i|j},
\]
\[
P_{i+1|j} = \Phi P_{i|j} \Phi^T + \Gamma_i Q_i \Gamma_i^T,
\]
\[
K_{i+1} = P_{i+1|j} H^T (H P_{i+1|j} H^T + R_{i+1})^{-1}, \tag{37}
\]
\[
x_{i+1|j+1} = x_{i+1|j} + K_{i+1} (z_{i+1} - H x_{i+1|j}),
\]
\[
P_{i+1|j+1} = P_{i+1|j} - K_{i+1} H P_{i+1|j}. \]
The initial estimates are given as \( x_{0|0} = x_0 \) and \( P_{0|0} = P_0 \), which is defined as a large positive definite value in prior. Under the LOS case, unbiased smoothing is used for estimating the true position of target node. When the NLOS status is detected, the uncertainty of target node position observation will be increased. Our scheme of target tracking with KF in NLOS environment can be illustrated in Figure 3 and Algorithm 1.

5. Simulation Results

To track the target node in NLOS environment, we firstly identify the NLOS anchor nodes based on statics model and estimate the NLOS range errors with the method of residual-error decomposition. We derive the covariance of localization result coming from range noises, when the range errors conform to Gaussian distribution. By correcting the observations with the estimated NLOS range errors, the positions of target node would be tracked precisely. Then, the iterative KF algorithm is applied to improve the accuracy of mobile target node position. The simulations firstly demonstrate the two detection approaches for NLOS propagation paths.

5.1. Detection of NLOS Propagation Paths. Residual of node (RN) and sum of square residuals (SSR) are used to judge whether there are NLOS propagation paths or not, when the range errors conform to Gaussian distribution. In (8), \( A_i \) represents the relationship between residual of nodes and range errors. When single anchor node NLOS propagation
Algorithm 1: Target tracking with modified KF in NLOS environment.

If there is only one NLOS propagation path of all anchor nodes, the sum of square residuals (SSR) will be increased monotonously with the increasing of NLOS range error. The principle of SSR is same as that of RN, since the single NLOS anchor node dominates most residual in all anchor nodes. The simulations show that more NLOS propagation paths can be concluded. Apparently, the number of NLOS anchor nodes also affects RN and SSR. The simulations show that more NLOS anchor nodes cannot ensure the increasing of RN and SSR. Observed from the matrix $A_i$, the exact position distribution of NLOS anchor nodes would make the residuals offset each other. When there are multiple NLOS propagation paths, RN and SSR are possible to be reduced. In the situations, the detection approaches of RN and SSR would be invalid. A feasible approach is to reselect the less anchor nodes again and compare with the previous RN and SSR, when multiple anchor nodes are involved in NLOS propagation paths. If the multiple RN and SSR are in accord with each other, no NLOS propagation paths can be concluded. Apparently, the reselecting and detection with different anchor nodes need plenty of computation costs.

Another concerned problem is the successful detection ratio of NLOS propagation path. We assume that the variances of range error $\Delta d_{ij}$ are all equal to $\delta^2$ for $j = 1, 2, \ldots, N$. The variance $\delta^2$ of LOS range error determines the detection threshold. Less $\delta^2$ will ensure to detect NLOS propagation paths successfully when keeping the NLOS range error invariable. Similarly, five anchor nodes are placed on $100 \times 100 \text{ m}$ region, and the target node is set at $(50, 50)$.

The curves in Figure 4(c) compare the successful detection ratio of NLOS propagation path with RN and SSR.
It can be seen that the successful detection ratio of NLOS propagation path increases with larger NLOS range error and smaller variance of LOS range error. When the NLOS range error is equal to 4 m and \( \delta^2 = 0.25 \), the successful detection ratio of NLOS propagation path is almost 100% with the approach of RN and SSR. However, when the NLOS range error is equal to 4 m and \( \delta^2 = 1 \), the successful detection ratio of NLOS propagation path is decreased to 59.9% with SSR approach or 45.6% with RN approach. However, when the NLOS range error is equal to 4 m and \( \delta^2 = 4 \), the successful detection ratio of NLOS propagation path is decreased to 7.7% with SSR approach or 3.8% with RN approach. Comparing the successful detection ratio with two different approaches, the performance of SSR approach is slightly better than that of RN approach.

### 5.2. Estimation of NLOS Range Errors

The RN and SSN approaches can judge whether there are NLOS propagation paths. When the NLOS propagation paths are identified, the residual-error decomposition method is used to estimate the NLOS range errors which correct the observation. Equation (24) illustrates the estimated NLOS range errors with the method of low rank residual-error decomposition. With the estimated NLOS range errors, the NLOS anchor nodes can be identified. The estimation method of residual-error decomposition can estimate multiple NLOS range errors simultaneously. The simulations test the performance of our NLOS range errors estimation method.

Let the geographical region be marked by a 100 m × 100 m region. There are 10 anchor nodes placed randomly in the region, and a target node is placed randomly in the area. Each
The range error of three NLOS anchor nodes, \( \text{RMSE}_i = \sqrt{\frac{1}{T} \sum_{k=1}^{T} (x_{ik} - x_{is})^2 + (y_{ik} - y_{is})^2} \). (39)

The simulation results are plotted in Figure 6. Since the residual of LOS anchor node is also affected by the NLOS range error, the estimated LOS error is close to zero. The estimated NLOS range error is far from the estimated LOS range error and fluctuated with the true slightly.

5.3. Tracking with Modified KF. If the movement equation and observation can be represented with the linear functions, the position of mobile target node can be tracked more precisely with KF. The movement equation is simulated as linear one affected by a white Gaussian noise \( \mathbf{w}_t \). Correcting the observation with the estimated NLOS range errors, the NLOS propagations will be mitigated. The simulations also demonstrate the performance of target tracking with modified KF.

There are six anchor nodes placed in a 200 m \( \times \) 200 m region, on which a target node is moving at the velocities of \( 1 \text{ m/s}, 1 \text{ m/s} \) in the direction of axis \( X \) and \( Y \). The velocities are affected by the noise acceleration with the covariance of \( \mathbf{Q}_w = \begin{bmatrix} 0.04 & 0; 0 & 0.04 \end{bmatrix} \). The sampling time is \( \Delta t_i = 1 \text{ s} \). All of range errors between the target node and each anchor nodes conform to Gaussian distribution \( \mathcal{N}(0, 1) \), but one of anchor nodes includes NLOS range error of 10 m. Let \( \mathbf{x}_0 = \begin{bmatrix} 0 & 1 & 0 & 1 \end{bmatrix} \), and \( \mathbf{P}_0 = \begin{bmatrix} 0.04 & 0; 0 & 0.04 \end{bmatrix} \).

Assuming that the true location of target node is \( (x_{t0}, y_{t0}) \), the root mean square error (RMSE) at the time instant \( i \) is defined as

\[
\text{RMSE}_i = \sqrt{\frac{1}{T} \sum_{k=1}^{T} [(x_{ik} - x_{t0})^2 + (y_{ik} - y_{t0})^2]}.
\]

The curves in Figure 5 plot the relationships between estimated NLOS range errors and true NLOS range errors. When the NLOS range errors of the three NLOS anchor nodes are small, the residuals caused by LOS anchors take most parts in the total residuals, and the estimated NLOS range errors of three NLOS anchor nodes are imprecise enough due to the Gaussian errors of LOS anchor nodes. With the increasing of non-Gaussian NLOS range errors of three NLOS anchor nodes, the residuals caused by non-Gaussian NLOS range errors of three NLOS anchor nodes dominate in the total residuals. Ignoring the impact of LOS anchor nodes, the NLOS range errors of NLOS anchor nodes can be estimated approximately with (24). When the NLOS range errors of three NLOS anchor nodes are set to 10 m, the estimated NLOS range errors of NLOS anchor nodes are close to the true. However, the estimated LOS range error of LOS anchor node is still slightly fluctuated around zero, when the NLOS range errors of three NLOS anchor nodes vary from 1 m to 10 m.

In order to evaluate the accuracy of estimated NLOS range errors to a mobile target node, the NLOS range errors are estimated along the tracking path. In the simulation, six anchor nodes are randomly deployed in a 200 m \( \times \) 200 m region. Range errors of five LOS anchor nodes conform to Gaussian distribution \( \mathcal{N}(0, 1) \), but one of anchor nodes has NLOS propagation path. The target node walks forward at the velocity of 1 m/s, 1 m/s in the direction of axis \( X \) and \( Y \), respectively, from the origin. That is to say, \( \mathbf{x}_0 = \begin{bmatrix} 0 & 1 & 0 & 1 \end{bmatrix} \). The NLOS range error varies from 5 m to 15 m along the simulated trajectory. We keep the sample interval \( \Delta t = 1 \text{ s} \) and

![Figure 5: Estimated range errors and true NLOS range errors.](image)

![Figure 6: Estimated NLOS and LOS range error with time instant.](image)
In order to evaluate the precision obtained by the corrected localization result, we have computed the RMSE of three different conditions. The number \( T \) of Monte Carlo (MC) testing is set to 200. Figure 7(a) plots the RMSE of three different conditions. If the localization result is not corrected with the estimated NLOS range error, the RMSE of target node position is fluctuated around 3.3 m. Due to the NLOS propagation path, the localized position of target node is far away from the true. If there are no NLOS propagation paths, the RMSE of target node position is about 0.7 m. By correcting the localization result with the estimated NLOS range error, the RMSE of target node position is fluctuated around 1.2 m.

The localization result is considered as the observation. Since the modified KF algorithm utilizes the corrected target node position, its position estimation error is much smaller than that of the original KF method. Computer simulations have been conducted to evaluate the tracking performance of the proposed methods by comparing with Cramer-Rao lower bound (CRLB) when the range errors are Gaussian distributed. The curves in Figure 7(b) compare the RMSE of KF algorithm, modified KF algorithm, and CRLB of target node position. Due to the imprecise observation, the RMSE of KF algorithm is much larger than that of modified KF algorithm. The RMSE of modified KF algorithm is almost close to that of CRLB.

6. Conclusion

We have studied the mobile target tracking for wireless sensor networks in NLOS environment and proposed a novel NLOS identification and mitigation method, which are applied to track the mobile target node. Firstly, we provide RN and SSR detection approaches for NLOS propagation path when the range errors conform to Gaussian distribution. The RN and SSR approach are effective to detect the NLOS propagation path when there is only one NLOS anchor node. More than one NLOS propagation paths would make the residuals offset and cannot ensure to detect the NLOS propagation paths successfully. When there are multiple propagation paths simultaneously, selecting the anchor nodes over again and rejudging with RN and SSR can identify the NLOS propagation paths effectively. Apparently, the reselection would improve the performance of the NLOS propagation detection, but it adds the computation costs.

If there are multiple NLOS propagation paths, we propose an estimation method for NLOS range errors with the low rank residual-error decomposition. The method of residual-error decomposition can estimate NLOS range errors quickly even if there are multiple NLOS propagation paths. Since the NLOS range errors are much larger than LOS range errors, the NLOS anchor nodes can be identified with the estimated range errors. Using the estimated NLOS range errors, we correct the localization result and improve the observation. Considering the corrected result as the observation, the position of mobile target node can be tracked precisely. Our approaches to detect and identify the NLOS propagation paths provide a novel idea for tracking the mobile target node for wireless sensor networks.

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