AOA Measurement based Localization Using RLS Algorithm under NLOS Environment

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Abstract. In localization problem, the estimation accuracy of a target location is one of the most significant issues. The global positioning system (GPS) that is the most widely used localization method can be disrupted by some disturbances under non-line-of-sight (NLOS) condition such as indoor environment and downtown. In this paper, we suggest a localization algorithm using the angle of arrival (AOA) measurements. AOA measurement based localization is one of the most efficient geolocation methods that use a wireless active signal. Moreover, AOA method has an advantage that only two base stations are required to estimate the target location. In all kinds of localization methods using wireless signal, the NLOS and measurement noise are the significant problems that decrease an estimation accuracy of a target location. In this paper, we suggest a Kalman filter based hypothesis test and a recursive least square scheme to overcome NLOS and measurement noise problem, respectively. Using Kalman filter based hypothesis test, the measurement data set from each base station can be identified whether it contains the NLOS noise or not. Also, recursive least square (RLS) scheme can obtain the precise location of a target with rapid calculation speed when additional measurement data is received from auxiliary base stations. Simulation result confirms the high estimation accuracy and computational speed of our proposed scheme.

1. Introduction
In accordance with the recent improvement of location based service (LBS), localization methods are widely researched and used in many kinds of industrial fields such as internet of things, augmented reality, target tracking, and the mobile application. The AOA scheme using the measurement angle data of signal incidence on an antenna array is one of the typical localization methods using active wireless signal due to its robustness of the environmental disturbance. Although AOA measurements based localization method estimates the relatively exact location of a target compared with GPS, AOA method is insufficient to satisfy the location estimation accuracy that is demanded in recent LBS. AOA method calculates the incidence direction of radio signal by measuring the difference of arrival time at individual elements of the array [1].

However, some noise factors cause that the arrival time of signal propagation at each antenna is delayed and the incidence angle is changed. Especially the NLOS noise that generally occurs in indoor environment is the significant problem of localization. NLOS noise is a radio transmission across a path that is partially obstructed by a physical object such as walls, buildings, and trees. In order to mitigate the NLOS problem, Wang [2] proposed a RSS based localization algorithm to handle the problem of simultaneously localizing the unknown node in LOS/NLOS environments. The proposed algorithm could identify the propagation conditions of the beacon nodes and the measurements which
contain the NLOS error are corrected. Silva [3] discussed principles and challenges pertaining to impulse radio ultra wideband ranging and NLOS identification in harsh industrial environments. Xiao [4] has proposed two regressors based on machine learning with propagation models to accurately estimate the transmitter-receiver distances in NLOS conditions.

In this paper, we propose the NLOS data discrimination algorithm based on Kalman filter to recognize whether the measurement data group contains NLOS noise or not. Kalman filter is a recursive estimator in which the estimated state from the previous time step and the current measurement are needed to compute the estimation for the current state. The standard deviation of the distance between a target and each base station that can be obtained from the estimated state using Kalman filter is used to discriminate the NLOS data. Moreover, we suggest the RLS algorithm to estimate a target location precisely. RLS is an iterated optimization method of least square (LS) to minimize the estimation error. The remainder of this paper is organized as follows. The NLOS data is discriminated and eliminated using Kalman filter based hypothesis test in Section 2. In Section 3, the localization model is derived using AOA measurements. Moreover, the recursive estimation algorithm for localization of a target is explained through RLS scheme. The performance of our proposed algorithm is demonstrated through the simulation result in Section 4. Conclusions are presented finally in Section 5.

2. NLOS data discrimination using Kalman filter

In localization problem using wireless signal source, NLOS problem that is occurred by some obstacles on the signal pathway causes the deflection of the signal. Especially in downtown or indoor case, NLOS problem is one of the most significant disturbance factors that cause the discrepancy between the real location and the estimated location of a target [5]. In Section 2, the discrimination algorithm of the NLOS noise included in measurement data at a specific base station is proposed before a localization solution is derived. For the discrimination of NLOS data, the measured distance and velocity data that can be obtained with the measured time of arrival data is divided into some data groups depending on sampling time interval. Each data group is discriminated whether NLOS data or not by the Kalman filter based hypothesis test on the basis of the definite LOS data.

We derive the state equation for the \( x \) and \( y \)-coordinate of a target independently as follows

\[
X_{k+1} = \Phi X_k + \Pi \gamma_k, \quad k = 1, \ldots, N
\]  

(1)

Where

\[
\Phi = \begin{bmatrix} 1 & \Delta n \\ 0 & 1 \end{bmatrix}, \quad \Pi = \begin{bmatrix} 0 \\ \Delta n \end{bmatrix}. \]  

(2)

State vector of a target \( X_k \) denotes as \([s_{x,k}, v_{x,k}]^T\) for \( x \)-direction or \([s_{y,k}, v_{y,k}]^T\) for \( y \)-direction at the sampling time \( t_k \). \( s_{x,k} \) and \( v_{x,k} \) are the location and velocity of \( x \)-coordinate, respectively. In the state equation (1), \( \gamma_k \) is the driving noise vector with a covariance of \( Q = \sigma^2_q I \). The measurement location of a target \( m_k \) can be obtained as follows

\[
m_k = A X_k + \rho_k
\]  

(3)

With \( A = [1 \ 0] \), \( \rho_k \) is the measurement noise value with a covariance of \( \rho = \sigma^2_m \).

The iterative process of Kalman filter can be derived using the equations (1) and (3) as follows
\[
\hat{X}_k = \Phi \hat{X}_{k-1} \\
P^-_k = \Phi P^-_{k-1} \Phi^T + \Pi Q \Pi^T \\
K_k = P^-_k A^T (A P^-_k A^T + \rho)^{-1} \\
\hat{X}_k = X^-_k + K_k (m_k - A \hat{X}^-_k) \\
P_k = P^-_k - K_k A P^-_k. 
\]

In equation (4), \( P^-_k \) means the covariance matrix of a state vector \( X_k \). The updated estimate \( \hat{X}_k \) and covariance \( P_k \) in equation (4) are valid for the optimal Kalman gain which is derived by \( K_k \) in equation (4). Kalman gain gives the relative weight to the measurements and current state estimate. The state of a target \( \hat{X}_k \) at the sampling time \( t_k \) can be estimated through this update operation.

We compare the measured distance data with estimated one between a target and each base station for the discrimination of the measurement data group whether under LOS or NLOS condition. The distance between a target and \( i \)-th base station can be acquired with the multiplication of the signal propagation speed and TOA data. The measured distance data \( d_m(t_k) \) at the sampling time \( t_k \) is comprised of real distance \( d_i(t_k) \), a measurement error \( \Delta d_m(t_k) \), and an NLOS error \( \Delta d_{\text{los}}(t_k) \) as a following equation.

\[
d_m(t_k) = d_i(t_k) + \Delta d_m(t_k) + \Delta d_{\text{los}}(t_k)
\]

The estimated location of a target can be derived by using Kalman filter process which is expressed by equation (3). The estimated distance \( d_{\text{kalman}}(t_k) \) can be calculated with the distance difference between a target and each base station. On the basis of this estimated distance, the standard deviation of measured distance \( \hat{\sigma} \) can be formulated as follows

\[
\hat{\sigma} = \sqrt{\frac{1}{P} \sum_{k=1}^{P} (d_m(t_k) - d_{\text{kalman}}(t_k))^2}.
\]

The parameter \( P \) is the number of distance data \( d_m(t_k) \) in each partition.

At least one base station is supposed to be located under LOS environment in this paper. Then, the measurement data group which contains the NLOS noise can be discriminated with the following hypothesis test.

\[
H_1(\text{LOS condition}) : \hat{\sigma} < \tau \sigma_{\text{LOS}} \\
H_2(\text{NLOS condition}) : \hat{\sigma} \geq \tau \sigma_{\text{LOS}}
\]

The parameter \( \tau \) can be determined depending on a localization environment. The data group of distance measurements \( d_m(t_k) \) from each base station can be discriminated whether under LOS or NLOS environment by using hypothesis test of equation (6). Both AOA and TOA data are obtained with the same wireless signal. Therefore, AOA data that is measured at the time interval when the TOA data is determined LOS data is also under LOS environment. Only the discriminated AOA data that is measured under LOS environment is used for localization in Section 3.

3. Recursive estimation of a target location using AOA measurements

In this section, we derive the target localization formula using AOA measurement data under LOS environment. AOA method is one of the most efficient localization approaches. The localization
formula can be acquired using the measured angle data of a signal from at least two base stations. When the known location of \( i \)-th base station is represented as \((x_i, y_i)\), the measured incidence angle of the propagation signal from the target to the \( i \)-th base station, denoted by \( \theta_i \), satisfies the following equation.

\[
x \sin (\theta_i) - y \cos (\theta_i) = x_i \sin (\theta_i) - y_i \cos (\theta_i)
\]  

(8)

With the unknown target location \( \varphi = [x \ y]^T \). Equation (8) can be rewritten by the matrix form of localization formula as follows

\[
Z \varphi = \zeta
\]  

(9)

Where

\[
Z = \begin{bmatrix}
\sin (\theta_1) & -\cos (\theta_1) \\
\vdots & \vdots \\
\sin (\theta_M) & -\cos (\theta_M)
\end{bmatrix}, \quad \zeta = \begin{bmatrix}
x_1 \sin (\theta_1) - y_1 \cos (\theta_1) \\
\vdots \\
x_M \sin (\theta_M) - y_M \cos (\theta_M)
\end{bmatrix}.
\]  

(10)

Since the measurement noise causes the refraction of a propagation signal, however, the intersection of AOA lines is not just exact one point in real environment. In equation (11), the matrices \( Z \) and \( \zeta \) that are subordinated to the measured AOA data \( \theta_i \) contain the measurement noise. In order to minimize the localization error that is caused by measurement noise, we suggest RLS algorithm.

For applying RLS algorithm to localization problem, the LS solution needs to be obtained with initial measurement data. When the additional AOA data set is measured at each base station, the solution can be computed recursively with rapid speed using initial solution and RLS technique. The localization formula using \( n \)'s AOA data and \((c+1)\)-th AOA data can be written based on equation (9) as follows

\[
\begin{bmatrix}
\tilde{Z}_n \\
\tilde{Z}_{n+1}
\end{bmatrix} \varphi = \begin{bmatrix}
\tilde{\zeta}_n \\
\tilde{\zeta}_{n+1}
\end{bmatrix}
\]  

(11)

Where \( \tilde{Z}_n = [Z_1 Z_2 \ldots Z_n]^T \) and \( \tilde{\zeta}_n = [\zeta_1 \zeta_2 \ldots \zeta_n]^T \). \( Z_{n+1} \) and \( \zeta_{n+1} \) are \((n+1)\)-th AOA parameters. The LS solution of equation (11) is obtained as a following equation.

\[
\hat{\varphi}_{n+1} = (\tilde{Z}_{n+1}^T \tilde{Z}_{n+1})^{-1} \tilde{Z}_{n+1}^T \tilde{\varphi}_{n+1}
\]  

(12)

With the definition of \( \mathbf{H}_{n+1} = (\tilde{Z}_{n+1}^T \tilde{Z}_{n+1})^{-1} \) for a notational simplicity, the equation (12) is rewritten as below

\[
\hat{\varphi}_{n+1} = \mathbf{H}_{n+1}^{-1} \mathbf{H}_{n+1} \tilde{\varphi}_{n} + \mathbf{Z}_{n+1}^T \zeta_{n+1}.
\]  

(13)

Since the term \( \mathbf{H}_{n+1} \tilde{Z}_{n+1}^T \zeta_{n+1} \) in equation (13) can be represented as \( \hat{\varphi}_{n} \), the equation (13) can be rewritten as follows

\[
\hat{\varphi}_{n+1} = \hat{\varphi}_{n} + \mathbf{H}_{n+1} \tilde{Z}_{n+1}^T (\mathbf{h}_{n+1} - \mathbf{Z}_{n+1} \hat{\varphi}_{n}).
\]  

(14)

With \( \mathbf{H}_{n+1} = (\tilde{Z}_{n+1}^T \tilde{Z}_{n+1} + \mathbf{Z}_{n+1}^T \mathbf{Z}_{n+1})^{-1} \). Therefore, the recursive solution \( \hat{\varphi}_{n+1} \) can be computed as a following equation.

\[
\hat{\varphi}_{n+1} = \hat{\varphi}_{n} + (\tilde{Z}_{n+1} \tilde{Z}_{n+1} + \mathbf{Z}_{n+1}^T \mathbf{Z}_{n+1})^{-1} \mathbf{Z}_{n+1}^T (\zeta_{n+1} - \mathbf{Z}_{n+1} \hat{\varphi}_{n})
\]  

(15)
The location of a target can be computed more rapidly through equation (15) when we receive additional AOA data sets. $\hat{\phi}_n$ and $\tilde{Z}_n$ are the calculated parameters based on information of $n$'s AOA data in previous $n$-th iteration. $Z_{n+1}$ and $\zeta_{n+1}$ are the additional measured data. We can estimate the location of a target recursively using previous AOA solution and additionally received information with minimizing the estimation error.

4. Simulation results

The effectiveness of our proposed Kalman filter based NLOS discrimination algorithm and RLS scheme based localization using AOA measurements is confirmed with some simulations in Section 4.

![Figure 1. Estimated trajectory of a target.](image)

In our simulation, the wireless propagation signal from a target is supposed to be measured at five base stations of which the locations are (0, 0), (0, 50), (0, 100), (100, 0), and (100, 50) km, respectively. Also, the hypothesis parameter $\tau$ is set as 5. The simulated trajectory has 200 time samples with one second interval. In figure 1, the estimated trajectory compares the performance driven by the general LS algorithm and our proposed scheme. The solid line is the estimated trajectory of a target using our proposed scheme. The dotted line is the estimated trajectory through the general LS algorithm. The recursive solution using Kalman filter based NLOS data discrimination algorithm follows the true trajectory more closely than the estimated trajectory using LS algorithm.

5. Conclusions

In this paper, the AOA measurement based localization method under NLOS environment was explained. The NLOS and measurement noises are the typical factors that cause the estimation inaccuracy of a target location. We estimated the state of a target through Kalman filter and applied the hypothesis test to discriminate the NLOS noise contained AOA measurements. Moreover, the recursive solution was obtained using RLS scheme for the estimation error minimization and the fast computational speed. Therefore, the rapidity of calculation through RLS algorithm facilitated to handle more additional measurement data for precise estimation of a target location. We confirmed the effectiveness of the proposed Kalman filter based NLOS data discrimination algorithm and RLS scheme through our simulation result.
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