Received January 16, 2017, accepted February 21, 2017, date of publication March 2, 2017, date of current version March 28, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2677480

An Improved NLOS Identification and Mitigation Approach for Target Tracking in Wireless Sensor Networks

LEIBING YAN[1,2], YIN LU[1], AND YERONG ZHANG[1]
[1]College of Electronic Science and Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
[2]College of Mechanical and Electrical Engineering, Henan Institute of Science and Technology, Xinxiang 453003, China

Corresponding author: Y. Zhang (zhangyr@njupt.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 61271236 and Grant 61601245, in part by the State Key Laboratory of Millimeter Waves of Southeast University under Grant K201724, and in part by the China Postdoctoral Science Foundation Funded Project under Grant 2016M601693.

ABSTRACT Target tracking has wide-ranging applications in fields using wireless sensor networks. However, localization accuracy is adversely affected by the non-line-of-sight (NLOS) effect. Thus, we propose a three-step localization approach to target tracking to identify and mitigate the NLOS effect. A Bayesian sequential test is designed to identify whether the measurement data are affected by this effect. On the basis of the identified measurement condition, we smooth the measurement range and mitigate the NLOS effect using a modified Kalman filter (MKF). After adjusting the measurement noise covariance and prediction covariance by using an established measurement equation, we apply the MKF, which is a standard Kalman filter with updated parameters. After the distances between the target and the sensor nodes are estimated by the MKF, the final estimated target position can be obtained using a residual weighting algorithm. Experimental and simulation results show that the proposed approach is superior to other methods that do not identify the propagation condition, and it can effectively improve the localization accuracy.

INDEX TERMS Bayesian sequential test, modified Kalman filter, NLOS affect, residual weighting algorithm, target tracking.

I. INTRODUCTION

With the rapid development of the Internet of Things and distributed sensor networks, wireless localization in wireless sensor networks (WSNs) has received considerable attention in recent years [1], [2]. Accurate target position information has become increasingly important since the introduction of regulations on emergency services and commercial application for location-based services by the US Federal Communications Commission (FCC) and other government bodies. Wireless localization systems are extensively used in various fields, such as target tracking, acoustic source localization, navigation, medical location service, and wildlife monitoring [3]–[7]. Target tracking is a fundamental task for WSNs. In any application scenario, target positioning and monitoring should be based on different measuring techniques, such as angle-of-arrival (AOA) [8], time-of-arrival (TOA) [9], time-difference-of-arrival (TDOA) [10], and received-signal-strength (RSS) [11]. Some hybrid approaches of TOA, AOA, TDOA, and RSS have also been proposed for target tracking and localization [12]–[14]. However, the performance of positioning systems is reduced by some noise errors. The major sources of noise errors in the target positioning systems include the measurement noise and the NLOS propagation error [15]. Both of which are random. The measurement noise usually follows a Gaussian random distribution, and the NLOS error commonly obeys a Gaussian random or exponential distribution. As a result, the relationship between the measured and the target states is nonlinear. The nonlinear relationship results in a nonlinear positioning equation. Therefore, the problem of locating the target is a process of solving the nonlinear equation. However, establishing an accurate model for the measurement data under NLOS propagation condition is difficult; thus, NLOS propagation poses a serious challenge to target position estimation. Aiming at the difficulties in localization system, numerous target location methods and techniques have been proposed to solve the nonlinear positioning equation and mitigate the NLOS propagation effect.

For decades, the extended Kalman filter (EKF) is the most widely used deal with nonlinear problem. In the process of nonlinear mode linearization, EKF uses the Taylor series to expand the nonlinear function, which is only to keep the first-order linear term, and then the measurement data is smoothed by the standard KF. Although this method is fast and easy to implement, when the nonlinear function is strong, only the first-order term will bring large error and cause filtering divergence. Meanwhile, calculation of Jacobi matrix requires function derivation, so we must determine the specific expression of the function. Especially when the function is complex, the function expression is not easy to determine. Over the past few decades, many target tracking methods based on EKF were proposed by researchers [16]–[20]. In [16], an adaptive energy-efficient multi-sensor scheduling scheme was proposed for collaborative target tracking based on EKF in WSNs; the proposed scheme can achieve a good trade-off between tracking accuracy and energy consumption. Modalavalasa *et al.* [17] proposed an EKF-based tracking algorithm to solve the difficulties in underwater environments. A generalized EKF based on a multiplicative noise model was proposed in [18] for tracking moving targets in WSNs equipped with distance-estimating sensor. Xu and Liu *et al.* [19] proposed a novel wireless location algorithm based on the extended kalman particle filter (EPF), which combine EKF with the particle filter (PF). Initial estimated position of the target is rectified and smoothed by EPF algorithm to realize fast and high precision passive target's location. However, this method requires multiple simulation experiments and a large number of experimental data. In [20], an EKF-based interacting multiple model (EK-IMM) smoother is proposed for mobile location estimation with the data fusion of the TOA and RSS measurements in a rough wireless environment. Combining EKF with the IMM scheme for accurately smooth range estimation between the corresponding sensor node and moving target in the rough wireless environment, this method can efficiently mitigate the NLOS effects on the measurement range error. However, this method cannot effectively identify NLOS propagation. In a word, EKF methods are limited by the significant deviation of the final state estimate from the actual value in many applications.

NLOS propagation error is considered the major error source in the positioning systems of WSNs. In most cases, the propagation error caused by the NLOS effect cannot be ignored in wireless positioning systems with high accuracy demand. Thus, identifying NLOS propagation and mitigating NLOS effect is important in wireless positioning systems. Borras *et al.* [21] performed a binary hypothesis test to identify NLOS propagation condition. In [22], a prior NLOS measurement correction algorithm was proposed to correct the measurements from NLOS propagation. However, the two methods in [21] and [22] focus on ultra-wideband systems, and they are unsuitable for target tracking in WSNs. In [23], an RSS-based NLOS identification method was investigated using recorded measurements, the NLOS effect was mitigated by subtracting the expected NLOS propagation error, and then the residual weighting algorithm (RWGH) was employed to estimate the location. However, this process is tedious for NLOS identification. Fuzzy modeling was introduced for measurement condition estimation in [24]. Probability-possibility transformation was utilized to calculate the possibility of the measurement data, and the measurement data with high and low possibilities were considered the line-of-sight (LOS) and NLOS measurements, respectively. However, this method fails to mitigate the identified NLOS propagation separately. Moreover, the estimated final position was determined by maximum likelihood estimation and Kalman filter (MLE/KF), such that the positioning accuracy is affected by the position estimation based on the false alarm probability. Evidently, these methods require complex calculation, high sensor density, and extensive prior knowledge.

In this study, we propose a simple yet effective approach to target tracking in WSNs for identifying NLOS propagation and mitigating the NLOS effect. First, we establish a range measurement model with measurement noise and NLOS propagation error and analyze the influence of the NLOS effect on target position estimation. Then, a Bayesian sequential test is designed to identify whether the propagation condition is LOS or NLOS propagation on the basis of decision rules. The NLOS measurement data is smoothed, the NLOS positive errors are mitigated using a modified Kalman filter (MKF), and the distances between the target and the different sensor nodes are estimated. Finally, we estimate the target position with the RWGH on the basis of the estimated distances. The simulation and experimental results indicate that the proposed method shows better performance in target positioning than the traditional methods.

The main contributions of this study are as follows:

1. The Bayesian sequential test is usually applied in mathematical and engineering fields, such as statistical decision theory, artificial intelligence, and pattern recognition. In this study, we use the Bayesian sequential test to determine whether LOS or NLOS propagation conditions prevail. New decision constants are determined on the basis of the Bayesian prior probability. Thus, the NLOS measurement data is selected from all the measurements data in accordance with decision rules.
2. After identifying NLOS propagation, the NLOS measurement data is smoothed, and the NLOS positive error is mitigated using the MKF. When the condition is NLOS propagation, the standard deviation of the measurement range and the prediction covariance of the standard KF are adjusted adaptively. We define this updated Kalman filter (KF) as the MKF. Then, we can estimate the measurement distances between the target and different sensor nodes by using the MKF.
3. RWGH is used to estimate the final position of the moving target on the basis of the estimated measurement distances.

The rest of this paper is organized as follows. In Section 2, we briefly introduce the range measurement model and analyze the influence of NLOS propagation errors on target position estimation. In Section 3, the proposed target tracking approach is introduced in detail. The proposed approach is composed mainly of NLOS identification, NLOS mitigation, and the final position estimation using MKF and RWGH. In Section 4, the simulation and experimental results are presented. Finally, in Section 5, the conclusions of the study are elaborated.

II. RANGE MEASUREMENT MODEL

We shall consider the general case of moving target tracking in two-dimensional space, the position of the moving target is estimated in real time with WSNs. The moving target carries a main sensor, which is used to communicate with the other sensor nodes in the WSNs. The main sensor can estimate the distances between the moving target and the sensor nodes by using the measured TOA. Since accurate sensor node position and clock synchronization are identified as two crucial aspects for target tracking in WSNs, we assume that the accurate position sensor nodes are known; the WSNs is a asynchronous networks, the target carries the same synchronization clock as the networks, and besides, there is no clock bias. For simplicity, all the sensor nodes are assumed to be of the same type and have the same noise statistics. The position and velocity of the moving target $\mathbf{u}$ are denoted by (x, y) and (v_x, v_y), respectively. The position of the ith sensor node $\mathbf{s}_i$ is (x_i, y_i). Then, the actual distance between the target and the ith sensor node at time instant t_i is given by

$$r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}, \quad i = 1, 2, \cdots, M, \tag{1}$$

where M is the number of the sensor nodes. The measurement equations for the LOS and NLOS propagation conditions can be written as follows:

$$z_i = r_i + n_i \text{ LOS condition}, \tag{2a}$$

$$z_i = r_i + n_i + e_i \text{ NLOS condition}, \tag{2b}$$

where n_i is the measurement noise, which is commonly assumed a zero-mean Gaussian noise with variance $\sigma^2_{i,LOS}$; e_i is the NLOS propagation error, which is also modeled as a Gaussian distribution with mean μ_i and variance $\sigma^2_{i,NLOS}$. The NLOS environment causes the radio signal to propagate along a longer path than the true distances between the sensor nodes and the target because of the effects of reflection and diffraction. Thus, a larger positive error must be added. We suppose that the measurement noise and the NLOS propagation error are independent of each other and that the sensor node i's total noise, which is denoted by $u_i = n_i + e_i$, is also a Gaussian noise with mean μ_i and variance $\sigma_i^2 = \sigma^2_{i,LOS} + \sigma^2_{i,NLOS}$. Usually, e_i is significantly greater than the absolute value of n_i under NLOS conditions (*i.e.*, $e_i \gg |n_i|$). Although the noise n_i can be reduced by averaging the repeated measurements from each sensor node, the NLOS propagation error e_i will still significantly reduce the accuracy of position estimation, as shown in Fig. 1.

We suppose R1, R2, and R3 are three static sensor nodes. The radii of the circles are the corresponding measurement distances, the black solid lines represent the true distances, and the black dashed lines represent the actual measurement distances. If all the sensor nodes are in an LOS situation, then the estimated position of the target is point M. However, if R3 is in an NLOS situation, then the positive NLOS propagation error e_3 is added to the measurement distance. M', which is considered the estimated position of the target, is highly important in removing the NLOS effect for position estimation. We assume that the main sensor fixed on the target is the fusion computing center, which is connected to the computer, and that all the measurements are gathered at this center.

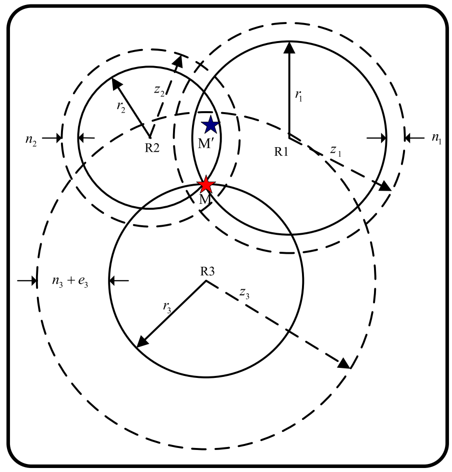

FIGURE 1. Diagram of position estimation.

We aim to estimate the target position reliably and accurately by mitigating the NLOS effect. In the next section, we propose an improved approach to achieve this goal. The proposed approach is divided into NLOS identification, NLOS mitigation, and the target final position estimation.

III. PROPOSED TARGET TRACKING APPROACH

Our proposed three-step approach to target tracking includes the following steps: (1) identify the propagation condition (LOS or NLOS propagation) by using Bayesian sequential test, (2) smooth the measurement data and mitigate the NLOS effect by applying the MKF, and (3) estimate the final target position by RWGH. The flow of the proposed approach is shown in Fig. 2.

A. NLOS IDENTIFICATION

Given the many advantages of Bayesian sequential test, we introduce it to identify propagation condition. Bayesian sequential decision is an optimization decision method for stochastic or uncertain dynamic systems. According to various prior probabilities, it uses the Bayesian theorem to obtain the posterior probability and makes the decision for the propagation condition. Bayesian sequential test is a combination of classical sequential test theory and Bayesian method, it takes a group of experiments one by one and starts from the initial state, the optimal decision is made at each moment, then the state of the next step is observed, and then a new optimal decision is made, repeats decisions until the end.

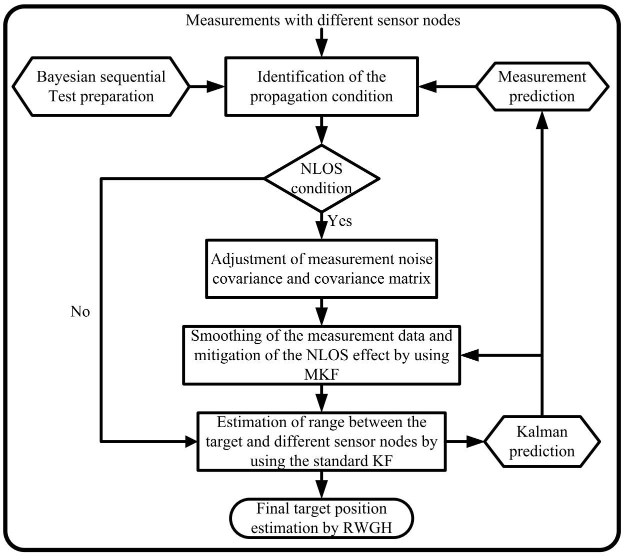

FIGURE 2. The flow chart of the proposed approach.

Since the Bayesian sequential test saves the experiment time and reduces the number of experiments, it has been paid great attention by scientific researchers all over the word. The specific process is as follows: first, according to (2), the probability density function (PDF) of the measurement data z_i is written as follows:

$$p_{LOS}(z_i|x,y) = \frac{1}{\sqrt{2\pi\sigma_{i,LOS}^2}} \times \exp\left\{-\frac{(z_i-r_i)^2}{2\sigma_{i,LOS}^2}\right\} \text{ LOS}, \tag{3a}$$

$$p_{NLOS}(z_i|x,y) = \frac{1}{\sqrt{2\pi(\sigma_{i,LOS}^2+\sigma_{i,NLOS}^2)}} \times \exp\left\{-\frac{(z_i-r_i-\mu_i)^2}{2(\sigma_{i,LOS}^2+\sigma_{i,NLOS}^2)}\right\} \text{ NLOS}. \tag{3b}$$

Before the NLOS propagation condition is identified, the following hypotheses as formulated:

$H_0 : Z_i \sim p_{LOS}(z_{j,i}|x,y)$ with probability P_{HO} (LOS),

$H_1 : Z_i \sim p_{NLOS}(z_{j,i}|x,y)$ with probability P_{H1} (NLOS),

where $Z_i = [z_{1,i}, z_{2,i}, \cdots, z_{n,i}]$ is the measurement data from n tests and $j = 1, 2, 3, \cdots, n$; $z_{j,i}$ is the jth measurement distance of the ith sensor node. We suppose that H_0 is the primary hypothesis whereas H_1 is the alternative hypothesis in the Bayesian sequential test, with P_{H0} representing the pretest probability of H_0 and P_{H1} representing the pretest probability of H_1. Based on (3), the likelihood ratio function of Bayesian sequential test is defined by [25]

$$\eta_n = \frac{P_{H1}}{P_{H0}} \cdot \frac{P(Z_i;\ H_1)}{P(Z_i;\ H_0)}, \tag{4}$$

where $P(Z;\ H_{0/1}) = \prod_{j=i}^{n} p_{LOS/NLOS}\left(z_{j,i}\,|x,y\right)$, and $p_{LOS/NLOS}\left(z_{j,i}\,|x,y\right)$ is the PDF of $z_{j,i}$ under condition $H_{0/1}$. The decision constants in the sequential test are defined by

$$A = \frac{1-\beta_1}{\alpha_0}, \quad B = \frac{\beta_1}{1-\alpha_0}, \tag{5}$$

where α_0 is the probability of abandoning the truth, and β_1 is the probability of adopting the false belief in consideration of the prior information . Thus, we obtain

$$\alpha_0 = \int_{Z\in H_0} \alpha(Z)\mathrm{d}F(Z)$$
$$\because \alpha(Z) \propto \alpha, \text{ suppose, } \alpha(Z) = J\alpha$$
$$\therefore \alpha_0 = K\alpha P_{H0}$$

No prior information is available when $P_{H0} = P_{H1} = 0.5$; consequently, equation $\alpha_0 = \alpha$ is correct. We can then obtain $J = 2\,(i.e.\ \alpha_0 = 2\alpha P_{H0})$, and $\beta_1 = 2\beta P_{H1}$. Subsisting $\alpha_0 = 2\alpha P_{H0}$ and $\beta_1 = 2\beta P_{H1}$ into (5), the equation (5) yields

$$A = \frac{1-\beta_1}{\alpha_0} = \frac{1-2\beta P_{H1}}{2\alpha P_{H0}}, \tag{6a}$$

$$B = \frac{\beta_1}{1-\alpha_0} = \frac{2\beta P_{H1}}{1-2\alpha P_{H0}}, \tag{6b}$$

where α and β are the probabilities of the two types of errors when the prior information is ignored. The error caused by (6) is minimal when α and β are less than 0.5, and the error can meet the requirement of positioning in practical applications. The distribution function of the measurement data $Z$is denoted by $F(Z)$. When the pretest probabilities of H_0 and H_1 are combined, the final expressions of the decision constants are as follows:

$$A' = \frac{1-2\beta P_{H1}}{2\alpha P_{H0}} \cdot \frac{P_{H0}}{P_{H1}} = \frac{1/(2P_{H1})-\beta}{\alpha}, \tag{7a}$$

$$B' = \frac{2\beta P_{H1}}{1-2\alpha P_{H0}} \cdot \frac{P_{H0}}{P_{H1}} = \frac{\beta}{1/(2P_{H0})-\alpha}. \tag{7b}$$

Therefore, the rule of NLOS propagation condition identification based on the Bayesian sequential test can be expressed as follows:

If $\eta_n \le B'$, then accept H_0. The propagation condition is identified as LOS propagation.

If $\eta_n \ge A'$, then accept H_1. The propagation condition is identified as NLOS propagation.

If $B' < \eta_n < A'$, then proceed to the next test.

The process continues until the conditions are identified as either LOS or NLOS propagation.

In the subsequent experiments and simulations, we assume that the accuracy of NLOS identification is higher than 95% and that the probabilities of the two types of errors are $\alpha = 0.1$ and $\beta = 0.2$.

B. NLOS MITIGATION

After the propagation condition is identified as either LOS or NLOS propagation, the measurement data is smoothed, and the NLOS effect is mitigated using MKF.

We let $\hat{\sigma}_i^2(k)$ be the updated standard deviation of the measurement range z_i at time instant t_i in accordance with the method in [26], and $\hat{\sigma}_i^2(k)$ can be obtained with the block of C data samples as follows:

$$\hat{\sigma}_i^2(t_i) = \sqrt{\frac{1}{C}\sum_{i=k-C+1}^{k}(z_i - \hat{r}_i)^2}, \tag{8}$$

where $\hat{r}_i$ is the estimated measurement range using the standard KF. We define the state vector in the $i$thsensor node at time instant $t_i$as $\mathbf{X}_i(t_i) = [\, r_i(t_i)\ \dot{r}_i(t_i)\,]^{\mathrm{T}}$, where $r_i(t_i)$ is the distance, and $\dot{r}_i(t_i)$ is the distance rate. After the standard KF is used to update the state vector related to the moving target, the following is obtained:

$$\mathbf{X}_i(t_{i+1}) = \mathbf{F}\mathbf{X}_i(t_i) + \mathbf{\Gamma} W(t_i), \tag{9}$$

where $W(t_i)$ represents the process noise with an assumed covariance $\mathbf{Q} = \sigma_w^2$; $\mathbf{F} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$ and $\mathbf{\Gamma} = [\Delta t^2/2\ \Delta t]^T$ represent the state and noise transition matrices, respectively; and Δt is the sampling time interval. Therefore, the measurement equation for the ith sensor node can be written as

$$\mathbf{Z}_i(t_i) = \mathbf{\Phi}\mathbf{X}_i(t_i) + U(t_i), \tag{10}$$

where $\mathbf{\Phi} = [1 \quad 0]$ is the measurement matrix, and $U(t_i)$ is the measurement noise with covariance $\mathbf{R} = \sigma_u^2$. The updated process of the standard KF can be summarized as follows:

$$\hat{\mathbf{X}}_i(t_{i+1}\,|t_i) = \mathbf{F}\hat{\mathbf{X}}_i(t_i\,|t_i), \tag{11}$$

$$\mathbf{P}_i(t_{i+1}\,|t_i) = \mathbf{F}\mathbf{P}_i(t_i\,|t_i)\mathbf{F}^{\mathrm{T}} + \mathbf{\Gamma}\mathbf{Q}\mathbf{\Gamma}^{\mathrm{T}}, \tag{12}$$

$$\mathbf{K}_i(t_{i+1}) = \mathbf{P}_i(t_{i+1}|t_i)\mathbf{\Phi}^{\mathrm{T}}\left[\mathbf{\Phi}\mathbf{P}_i(t_{i+1}|t_i)\mathbf{\Phi}^{\mathrm{T}} + \mathbf{R}\right]^{-1}, \tag{13}$$

$$\hat{\mathbf{X}}_i(t_{i+1}\,|t_{i+1}) = \hat{\mathbf{X}}_i(t_{i+1}\,|t_i) + \mathbf{K}_i(t_{i+1}) \times \left[\mathbf{Z}_i(t_{i+1}) - \mathbf{\Phi}\hat{\mathbf{X}}_i(t_{i+1}\,|t_i)\right], \tag{14}$$

$$\mathbf{P}_i(t_{i+1}\,|t_{i+1}) = \mathbf{P}_i(t_{i+1}\,|t_i) - \mathbf{K}_i(t_{i+1}) \times \left[\mathbf{\Phi}\mathbf{P}_i(t_{i+1}\,|t_i)\mathbf{\Phi}^{\mathrm{T}} + \mathbf{R}\right]\mathbf{K}_i^{\mathrm{T}}(t_{i+1}). \tag{15}$$

In (11)-(15), $\hat{\mathbf{X}}_i$ is the estimate of $\mathbf{X}_i$, $\hat{\mathbf{X}}_i(t_i|\,t_i)$ is the state estimate at time t_i, and $\hat{\mathbf{X}}_i(t_{i+1}\,|t_i)$ is the predicted state at time t_{i+1}, $\mathbf{K}(t_{i+1})$ is the Kalman gain, and $\mathbf{P}(t_i|t_i)$ is the covariance matrix of $\hat{\mathbf{X}}(t_i)$. The positive NLOS error component is mitigated by adjusting the measurement noise covariance $\sigma_u^2(t_i)$ and prediction covariance $\mathbf{P}_{1,1}(t_{i+1}|t_i)$. The adjustment rules are as follows:

Case 1: $\mathbf{Z}_i(t_{i+1}) - \mathbf{\Phi}\mathbf{X}(t_{i+1}|t_i) > 0$, and for NLOS propagation condition, let

$$\hat{\sigma}_u^2(t_{i+1}) = \hat{\sigma}_i^2(t_i) + \left[\frac{\mathbf{Z}_i(t_{i+1}) - \mathbf{\Phi}\mathbf{X}(t_{i+1}|t_i)}{\beta}\right]^2. \tag{16}$$

Case 2: $\mathbf{Z}_i(t_{i+1}) - \mathbf{\Phi}\mathbf{X}(t_{i+1}|t_i) < 0$, and for NLOS propagation condition, let $\hat{\sigma}_u^2(t_{i+1}) = \hat{\sigma}_i^2(t_i)$ and

$$\mathbf{P}_{1,1}(t_{i+1}|t_i) = \mathbf{P}_{1,1}(t_{i+1}|t_i) + \left[\frac{\mathbf{Z}_i(t_{i+1}) - \mathbf{\Phi}\mathbf{X}(t_{i+1}|t_i)}{\beta}\right]^2. \tag{17}$$

Case 3: For LOS propagation condition, let $\hat{\sigma}_u^2(t_{i+1}) = \hat{\sigma}_i^2(t_i)$.

In (16) and (17), the standard deviation $\hat{\sigma}_i^2(t_i)$ is obtained from the previous prediction, and $\mathbf{P}_{1,1}(t_{i+1}|t_i)$ is the upper-left entry in the covariance matrix $\mathbf{P}(t_{i+1}|t_i)$. The constant β is selected such that the minimum value is within the scope of βtimes of the $\mathbf{P}(t_{i+1}|t_i)$ related to the maximum value. We set β at 3 after numerous tests. Adjusting of the measurement noise covariance $\hat{\sigma}_u^2(t_{i+1})$ and the prediction covariance $\mathbf{P}_{1,1}(t_{i+1}|t_i)$ in (16) and (17) can reduce the effects of the negative range rate $\dot{r}_i(k)$ and consequently mitigate the positive NLOS range error. When measurement noise covariance and prediction covariance are adjusted, the standard KF becomes the MKF.

The estimation for the measurement distance by the MKF is expressed as

$$\hat{\hat{r}}_i(k) = [\,1\ \ 0\,]\hat{\mathbf{X}}_i(t_{i+1}|t_{i+1}). \tag{18}$$

C. TARGET POSITION ESTIMATION

After the estimated distances between the target and the sensor nodes are determined using MKF, the target can be located using the estimated distance. We use RWGH in estimating the position of the moving target. The steps of target localization using RWGH follow [27].

1. M sensor nodes form $T = \sum_{i=3}^{M} C_M^i$ range measurement combinations. Each combination is represented by the index set of sensor nodes $\{S_k\,|k = 1, 2, \cdots, T\}$.
2. For each index set of sensor nodes, the MKF is applied to estimation of the target position, which can be represented by $\hat{X}_k = [\,\hat{x}\ \hat{y}\,]^{\mathrm{T}}$. The mean value of the residual (Res) can be described as follows:

$$\overline{\mathrm{Res}}(\hat{X}_k, S_k) = \frac{\mathrm{Res}(\hat{X}_k, S_k)}{\text{size of } S_k}. \tag{19}$$

where

$$\mathrm{Res}(\hat{X}_k, S_k) = \sum\nolimits_{i\in S_k}(\hat{\hat{r}}_i - \sqrt{(x_i - \hat{x}_k)^2 + (y_i - \hat{y}_k)^2})$$

and (x_i, y_i) are the coordinates of ith sensor.
3. The final estimated position of the target can be obtain using the weighted linear combination of the intermediate estimates in step 2. The final estimated position can be expressed mathematically as

$$\hat{X} = \frac{\sum_{k=1}^{T}\hat{X}_k\left(\overline{\mathrm{Res}}\left(\hat{X}, S_k\right)\right)^{-1}}{\sum_{k=1}^{T}\left(\overline{\mathrm{Res}}\left(\hat{X}, S_k\right)\right)^{-1}}. \tag{20}$$

IV. EXPERIMENTAL AND SIMULATION RESULTS

The performances of three algorithms for target tracking are compared on the basis of the experimental and simulation results. The compared algorithms are the RWGH algorithm described in [27], the combined MLE with KF algorithm described in [24], and the proposed approach described in Section 3. The experimental results in small monitoring areas and the theoretical simulation results in large monitoring areas are presented and discussed in the following subsections.

FIGURE 3. Experimental setup.

A. EXPERIMENTAL RESULTS IN SMALL MONITORING AREAS

In the experiment, six sensor nodes and a moving target carrying a main sensor node are employed, and the WSN is established using a wireless communication module cc2530 (Fig. 3). The target can communicate with other sensor nodes, and the distances between the target and the different sensor nodes can be calculated. The target can also transmit the measurement data to a PC. The monitoring area covered by the experiment is 5 m $\times$ 6 m with the coordinates from (0, 0) to (6, 5), and the position coordinates (in meters) of the six sensor nodes are $SN_1(0.25, 0)$, $SN_2(0.25, 5)$, $SN_3(3, 0)$, $SN_4(3, 5)$, $SN_5(5.75, 0)$, and $SN_6(5.75, 5)$. Only one obstacle is present in the monitoring area, and two sensor nodes, namely, SN_3 and SN_5, are considered to be under NLOS propagation condition at a certain period. The others sensor nodes are considered to be under LOS propagation condition at any moment. The measurements noise n_i and the NLOS propagation error e_i are assumed as Gaussian noise sources with $\sigma_{i,LOS} = 0.075$m, $\sigma_{i,NLOS} = 0.2$m, and $\mu_i = 0.55$m (for $i = 1, 2, \cdots, 6$). The target moves along in a line from point (0.5, 1)m with a velocity of (0.5, 0.4)m/s, and the sampling time interval is $\Delta t = 0.05$s. The initial state estimate and the corresponding covariance matrix are selected as

$$\hat{\mathbf{X}}(0|0) = [\,0.5\ 0\ 1.6\ 0\,]^{\mathrm{T}}, \quad \mathbf{P}(0|0) = 0.01 \cdot \mathbf{I}_4, \tag{21}$$

where $\mathbf{I}_4$ represents the 4×4 identity matrix.

Fig. 4 shows the target tracking results obtained using the three algorithms. These results combined with the experimental results show that the accuracy of the three target tracking methods in an LOS environment is higher than that in an NLOS environment. Compared with the two existing methods, the proposed approach can perform steady-state estimation faster from the initial position. The experimental results demonstrate that the proposed target tracking approach is more accurate than the two other methods.

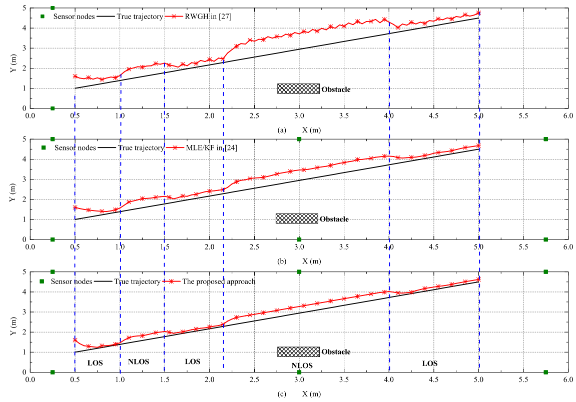

FIGURE 4. Comparison of experimental results of different algorithms for target tracking.

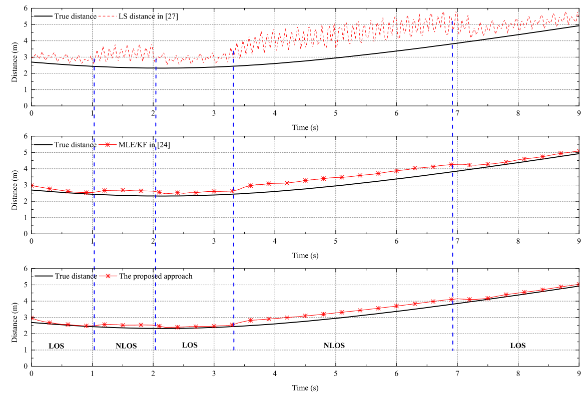

FIGURE 5. Measurement data processing of the compared algorithms.

Fig. 5 shows a comparison of performance of the compared methods in terms of the data processing of measurement distance. The least square (LS) in [27], MLE/KF in [24], and the proposed approach in Section 3 are compared. For simplicity, the measurement distance from the sensor node $SN_3(3, 0)$ to the target is taken as an example. The standard deviation of the measurement distance obtained by LS is greater than those of the two other methods mainly because the LS algorithm does not deal with the measurement data by KF processing. By contrast, the proposed approach not only smoothes the measurement data but also adjusts the measurement noise covariance and prediction covariance adaptively with the standard KF, and the proposed approach can effectively reduce the NLOS propagation error. Thus, the proposed approach shows better performance than the two other algorithms for smoothing measurement data and mitigating NLOS propagation error.

B. SIMULATION RESULTS IN LARGE MONITORING AREAS

Target tracking errors are random in nature, and repeating the experiments numerous times to decrease tracking errors is impractical. Thus, we attempt to evaluate the performance of the proposed approach by using a Monte Carlo test for moving target tracking. In the simulation, we assume a

1500 m × 1000 m monitoring area with eight sensor nodes and three obstacles of different shapes. The target starts moving from point (60, 800)m with a velocity of (5, 4)m/s. The initial state estimate and the corresponding covariance matrix are selected to be

$$\hat{\mathbf{X}}(0|0) = [60 \ \ 0 \ \ 850 \ \ 0]^{\mathrm{T}}, \quad \mathbf{P}(0|0) = 0.01 \cdot \mathbf{I}_4. \qquad (22)$$

We use the average of root mean square error (RMSE) to evaluate the performance of the proposed approach. The average RMSE of the position estimates is defined by

$$\mathrm{RMSE}=\frac{1}{N}\sum_{j=1}^{N}\sqrt{\left[\hat{x}_j(t_i|t_i)-x(t_i)\right]^2+\left[\hat{y}_j(t_i|t_i)-y(t_i)\right]^2}, \qquad (23)$$

TABLE 1. Default parameter values.

Parameters	Default values
Total number of sensor nodes M	8 sensor nodes
Total number obstacles L	3 m
Mean of the LOS measurements noise μ_{LOS}	0 m
Mean of the NLOS propagation error μ_{NLOS}	65 m
Standard variance of measurements noise σ_{LOS}	15 m
Standard variance of NLOS propagation error σ_{NLOS}	60 m

where $N = 2000$ is the total number of Monte Carlo tests with the same parameters, $[x(t_i), y(t_i)]$ is the true position of the moving target, and $[\hat{x}_j(t_i|t_i), \hat{y}_j(t_i|t_i)]$ is the jth position estimate in the Monte Carlo test at time t_i. The default parameter values in the simulation experiment are shown in Table 1.

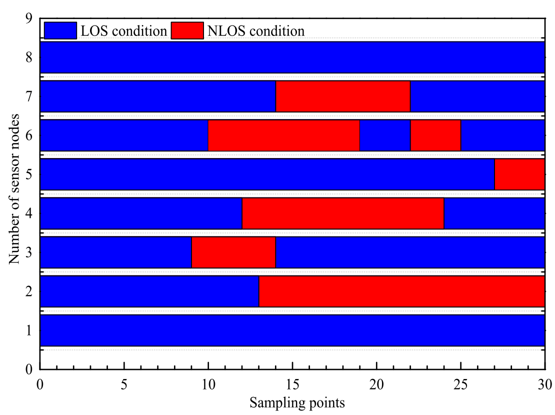

FIGURE 6. LOS/NLOS propagation condition in the sample points.

Fig. 6 shows the sight state between the target and all the sensor nodes in the sampling points. The figure indicates that the sensor nodes 1 and 8 exhibit LOS propagation in all the sampling points, and the sight states of the other sensor nodes vary between LOS and NLOS propagation with time. The first nine sample points are obtained under the condition of LOS propagation between the target and all the sensor nodes. Thus, the estimation errors of the three algorithms under the first nine sampling points may be smaller than those under the other sampling points.

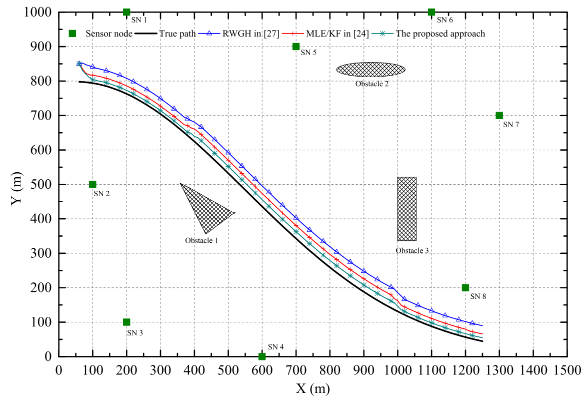

FIGURE 7. Target tracking results of the compared algorithms.

Fig. 7 compares the performances of the target tracking algorithms. The black solid line represents the true trajectory of the moving target. The figure shows interesting results. First, the localization accuracy of the three target tracking algorithms in the first nine sampling points is higher than that in other sampling points. This result confirms the conjecture based on Fig. 6. Second, from the initial position at which a stable tracking error is obtained, the convergence rate of the proposed algorithm is the fastest, followed by MLE/KF in [24] and then RWGH in [27]. Finally, the proposed approach exhibits better performance than MLE/KF and RWGH in all the sampling points.

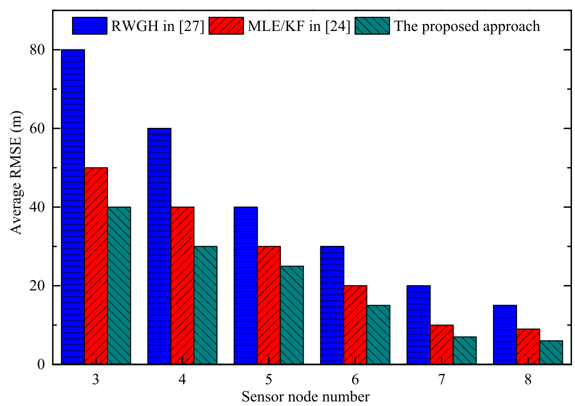

FIGURE 8. Average RMSE versus the number of sensor nodes.

Fig. 8 displays the relationship between the average RMSE and the number of sensor nodes from 3 to 8. The localization errors of the three different target tracking algorithms decrease as the number of sensor nodes increases. The localization errors of the three algorithms decrease rapidly as the number of sensor nodes increases from 3 to 5; however, the decline decelerates from 6 to 8 sensor nodes. In the case of 7 and 8 sensor nodes, the localization errors of MLE/KF and the proposed approach are insignificant. Thus, under the conditions of this simulation experiment, a WSN composed of 7 to 8 sensor nodes presents a reasonable allocation of resources. In addition, the localization accuracy of the proposed approach improves by 25.2% and 9.56% on average compared with MLE/KF and RWGH, respectively.

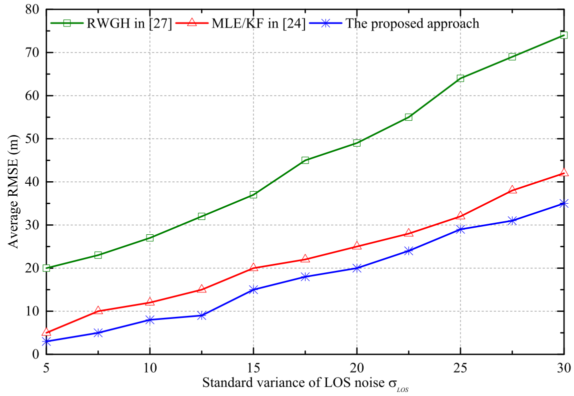

FIGURE 9. Average RMSE versus the standard variance of measurement noise propagation error.

Fig. 9 depicts the relationship between the average RMSE and the standard variance of measurement noise. The performance of the proposed approach is similar to that of MLE/KF. This finding is verified by the localization error values of the two methods at a probability of 67% in Fig. 12. RWGH exhibits the worst performance. Nevertheless, the average RMSEs of the three methods increase with an increase in measurement noise.

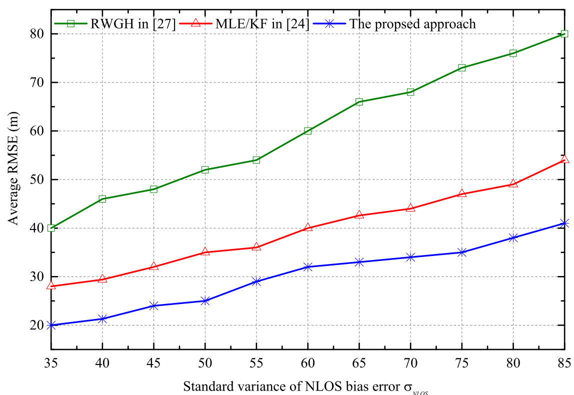

FIGURE 10. Average RMSE versus the standard variance of the NLOS propagation error.

Fig. 10 shows the average RMSE versus the standard variance of the NLOS propagation error. To investigate the performance of the proposed approach comprehensively, we calculate the

average RMSEs of the three methods under different standard variances of the NLOS propagation error. The average RMSE increases with an increase in the standard variance of the NLOS propagation error. However, the proposed approach and MLE/KF are relatively robust compared with RWHG. The proposed approach achieves the highest localization accuracy among the compared methods.

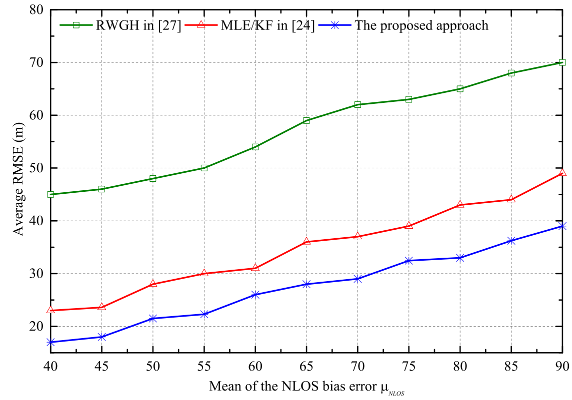

FIGURE 11. Average RMSE versus the mean of the NLOS propagation error.

Fig. 11 plots the average RMSE versus the mean of the NLOS propagation error. The localization accuracy levels of the three methods decrease with an increase in the mean of the NLOS propagation error. However, the proposed approach presents significantly improved the localization accuracy compared with the two other methods. The superiority of the proposed approach is mainly due to the smoothing of the measurement data and the mitigation of the NLOS propagation error by the MKF in the proposed approach. By contrast, MLE/KF only uses the standard KF to predict the state and estimate the position of the target. The average RMSE of RWGH, which uses LS to estimate the measurement range, is the highest.

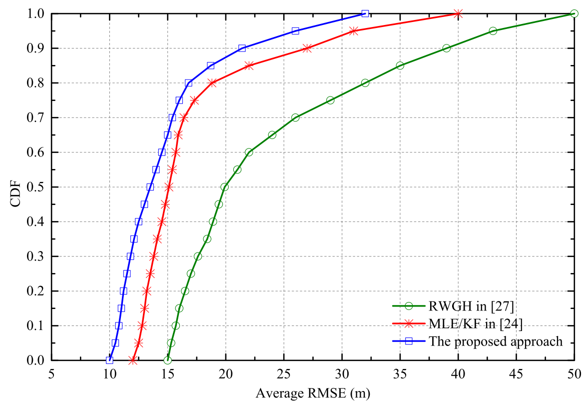

FIGURE 12. Average RMSE versus CDF.

We investigate the cumulative distribution function of the three methods and show the results in Fig. 12. At a probability of 67%, the localization error of the proposed approach is 15.2 m, which is lower than the localization errors of RWGH (24.3 m) and MLE/KF (16.1 m). Therefore, all the three methods meet the E-911 regulations of the FCC. However, the localization accuracy of the proposed algorithm is better than those of the two other methods.

V. CONCLUSION

In this study, we present a three-step target tracking approach that identifies the prevailing NLOS propagation condition and mitigates the NLOS effect in random NLOS propagation environments of WSNs. First, a Bayesian sequential test is developed to identify whether the measurement range is under NLOS condition. Second, the measurement data is smoothed according to the identified measurement condition, and the NLOS effect is mitigated using MKF with the adjustment of the measurement noise covariance and prediction covariance. Finally, the final target position is obtained using RWGH. The experimental and simulation results show that the proposed approach effectively reduces the NLOS effect and improves the localization accuracy, thereby outperforming both RWGH and MLE/KF.

In the experiment and simulation, we assume that the positions of all sensor nodes are known. In addition, the experiment and simulation are performed in a simple outdoor NLOS propagation setup. In practice, however, the positions of the sensor nodes are usually unknown, and the NLOS propagation scenario is highly complex indoors. Furthermore, we fixed the parameters in the Bayesian sequential tests, such as the probability of abandoning the truth and the probability of adopting the false belief. However, these parameters are variable. Thus, in our future work, we will use the target tracking algorithm in an indoor scenario in which the positions of the sensor nodes are unknown. We will also examine the influences of the parameter variations on the target localization accuracy with the Bayesian sequential test.

REFERENCES

[1] W. Li and Y. Jia, "Location of mobile station with maneuvers using an IMM-based cubature Kalman filter," *IEEE Trans. Ind. Electron.*, vol. 59, no. 11, pp. 4338–4348, Nov. 2012.

[2] N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, and R. J. O'Dea, "Relative location estimation in wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 51, no. 8, pp. 2137–2148, Aug. 2003.

[3] W.-P. Chen, J. C. Hou, and L. Sha, "Dynamic clustering for acoustic target tracking in wireless sensor networks," *IEEE Trans. Mobile Comput.*, vol. 3, no. 3, pp. 258–271, Jul. 2004.

[4] S. Nannuru, Y. Li, Y. Zeng, M. Coates, and B. Yang, "Radio-frequency tomography for passive indoor multitarget tracking," *IEEE Trans. Mobile Comput.*, vol. 12, no. 12, pp. 2322–2333, Dec. 2013.

[5] Z. M. Saric, D. D. Kukolj, and N. D. Teslic, "Acoustic source localization in wireless sensor network," *Circuits, Syst. Signal Process.*, vol. 29, no. 5, pp. 837–856, Apr. 2010.

[6] M. Z. Win *et al.*, "Network localization and navigation via cooperation," *IEEE Commun. Mag.*, vol. 49, no. 5, pp. 56–62, May 2011.

[7] J. Wang, X. Chen, D. Fang, C. Q. Wu, Z. Yang, and T. Xing, "Transferring compressive-sensing-based device-free localization across target diversity," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2397–2409, Apr. 2015.

[8] Y. S. Lee, J. W. Park, and L. Barolli, "A localization algorithm based on AOA for ad-hoc sensor networks," *Mobile Inf. Syst.*, vol. 8, no. 1, pp. 61–72, Jan. 2012.

[9] J. He, Y. Geng, F. Liu, and C. Xu, "CC-KF: Enhanced TOA performance in multipath and NLOS indoor extreme environment," *IEEE Sensors J.*, vol. 14, no. 11, pp. 3766–3774, Nov. 2014.

[10] K. C. Ho, X. Lu, and L. Kovavisaruch, "Source localization using TDOA and FDOA measurements in the presence of receiver location errors: Analysis and solution," *IEEE Trans. Signal Process.*, vol. 55, no. 2, pp. 684–696, Feb. 2007.

[11] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *IEEE Trans. Mobile Comput.*, vol. 11, no. 12, pp. 1983–1993, Dec. 2012.

[12] B. Y. Shikur, M. Farmani, and T. Weber, "TOA/AOA/AOD-based 3-D mobile terminal tracking in NLOS multipath environments," in *Proc. Positioning Navigat. Commun.*, Mar. 2012, pp. 201–205.

[13] A. Catovic and Z. Sahinoglu, "The Cramer–Rao bounds of hybrid TOA/RSS and TDOA/RSS location estimation schemes," *IEEE Commun. Lett.*, vol. 8, no. 10, pp. 626–628, Oct. 2004.

[14] M. Hedley and Q. Zhai, "Wireless sensor network using hybrid TDOA/RSS tracking of uncooperative targets," in *Proc. Int. Symp. Wireless Pers. Multimedia Commun.*, Jan. 2015, pp. 320–324.

[15] K. Fukuda and E. Okamoto, "Performance improvement of TOA localization using IMR-based NLOS detection in sensor networks," in *Proc. Int. Conf. Inf. Netw.*, Feb. 2012, pp. 13–18.

[16] J. Lin, W. Xiao, F. L. Lewis, and L. Xie, "Energy-efficient distributed adaptive multisensor scheduling for target tracking in wireless sensor networks," *IEEE Trans. Instrum. Meas.*, vol. 58, no. 6, pp. 1886–1896, Jun. 2009.

[17] N. Modalavalasa, G. S. B. Rao, K. S. Prasad, L. Ganesh, and M. N. V. S. S. Kumar, "A new method of target tracking by EKF using bearing and elevation measurements for underwater environment," *Robot. Auto. Syst.*, vol. 74, pp. 221–228, Dec. 2015.

[18] X. Hu, B. Xu, and Y. H. Hu, "Target tracking with distance-dependent measurement noise in wireless sensor networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, May 2013, pp. 5200–5203.

[19] T. Xu and S.-I. Liu, "Algorithm of 3-D single observer passive location with the extended Kalman particle filter," in *Proc. 1st IEEE Int. Conf. Inf. Sci. Eng., IEEE Comput. Soc.*, Dec. 2009, pp. 4704–4707.

[20] B. S. Chen, C. Y. Yang, F. K. Liao, and J. F. Liao, "Mobile location estimator in a rough wireless environment using extended Kalman-based IMM and data fusion," *IEEE Trans. Veh. Technol.*, vol. 58, no. 3, pp. 1157–1169, Mar. 2009.

[21] J. Borras, P. Hatrack, and N. B. Mandayam, "Decision theoretic framework for NLOS identification," in *Proc. IEEE Veh. Technol. Conf.*, vol. 2. May 1998, pp. 1583–1587.

[22] S. Mazuelas *et al.*, "Prior NLOS measurement correction for positioning in cellular wireless networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 5, pp. 2585–2591, Jun. 2009.

[23] Y. Wang, Y. Jing, and Z. Jia, "An indoor mobile localization strategy for robot in NLOS environment," *Int. J. Distrib. Sensor Netw.*, vol. 2013, pp. 1–8, Jan. 2013.

[24] J. Yan, K. Yu, and L. Wu, "Fuzzy modeling, maximum likelihood estimation, and Kalman filtering for target tracking in NLOS scenarios," *EURASIP J. Adv. Signal Process.*, vol. 2014, no. 1, pp. 1–16, Jul. 2014.

[25] Q. Liu, W. Z. Feng, and N. Wang, "Selection and calculation of risks in Bayes sequential test method," *Syst. Eng. Electron.*, vol. 35, no. 1, pp. 223–229, Jan. 2013.

[26] B. L. Le, K. Ahmed, and H. Tsuji, "Mobile location estimator with NLOS mitigation using Kalman filtering," in *Proc. IEEE Wireless Commun. Netw. Conf.*, vol. 3. Mar. 2003, pp. 1969–1973.

[27] P.-C. Chen, "A non-line-of-sight error mitigation algorithm in location estimation," in *Proc. IEEE Wireless Commun. Netw. Conf.*, vol. 1. Sep. 1999, pp. 316–320.

LEIBING YAN was born in Henan, China, in 1980. He received the B.S. degree in electronic information engineering and the M.S. degree in physical electronics from Henan Normal University in 2004 and 2007, respectively. He is currently pursuing the Ph.D. degree in electromagnetic field and microwave technology with the Nanjing University of Posts and Telecommunications.

He is also a Lecturer with the Henan Institute of Science and Technology, Xinxiang, China. His research interests are in signal processing, nonlinear problems, and wireless sensor networks.

YIN LU was born in Jiangsu, China, in 1970. He received the B.S. degree in wireless communication, the M.E. degree in communication and information system, and the Ph.D. degree in electromagnetic field and microwave technology from the Nanjing University of Posts and Telecommunications, Nanjing, China, in 1992, 1999, and 2010, respectively.

He is currently an Associate Research Fellow and a Master Adviser of the College of Communication and Information Engineering, Nanjing University of Posts and Telecommunications. His main research areas are cognitive radio technology, Spectrum management of Internet of Things, dynamic spectrum management based on 5G, research on mobile communication engineering design, and network planning and optimization.

YERONG ZHANG was born in Anhui, China, in 1963. He received the Ph.D. degree in electromagnetic field and microwave technology from the University of Electronic Science and Technology in 1996.

He is currently a Professor and a Ph.D. Supervisor of the College of Electronic Science and Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include the planning and optimization of mobile communication network, wireless communication and electromagnetic compatibility, the numerical simulation of electromagnetic wave propagation, and electromagnetic scattering and imaging in the mobile wireless environment.