Research Article

Indoor Mobile Localization in Wireless Sensor Network under Unknown NLOS Errors

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Localization is one of the key techniques in wireless sensor network. One of the main problems in indoor mobile localization is non-line-of-sight (NLOS) propagation. And the NLOS effects will lead to a large localization error. So the NLOS problem is the biggest challenge for accurate mobile location estimation in WSN. In this paper, we propose a likelihood matrix correction based mixed Kalman and $H^{-\infty}$ filter (LC-MKHF) method. A likelihood matrix based correction method is firstly proposed to correct the LOS and NLOS measurements. This method does not need the prior information about the statistical properties of the NLOS errors. So it is independent of the physical measurement ways. And then a mixed Kalman and $H^{-\infty}$ filter method is proposed to improve the range measurement. Simulation results show that the LC-MKHF algorithm has higher estimate accuracy in comparison with no-filter, Kalman filter, and $H^{-\infty}$ filter methods. And it is robust to the NLOS errors.

1. Introduction

Localization is one of the most important subjects. Global position system (GPS) is the most common position system in the world. However, research studies show that the GPS performance degrades drastically when the receiver is located in large buildings. In recent years, there has been a growing research interest in wireless sensor network (WSN). Wireless sensor network that consist of thousands of low cost sensor nodes have been used in many promising applications such as health surveillance, robot navigation [1], and environmental monitoring. And localization is one of the important applications of WSN.

The classic methods to estimate the indoor location are time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength (RSS). TOA method measures travel times of signals between nodes. TDOA method is located by measuring the signals’ arrival time difference between anchor nodes and mobile node. It is able to achieve high ranging accuracy but requires extra hardware and consumes more energy. The angles between mobile node and a number of anchor nodes are used in the AOA method to estimate the location. RSS has established the mathematical model on the basis of path loss attenuation with distance, and it requires relatively low configuration and energy. And the data fusion technique has been utilized to improve the accuracy by combining two or more measurements such as TOA/AOA, TDOA/AOA, and TOA/RSS [2]. Accurate position estimation can be obtained by using filtering techniques if there exists direct propagation between the beacon node and the mobile node, also known as the line of sight (LOS). The complicated indoor environment causes non-line-of-sight (NLOS) situation. And the NLOS effects will lead to a large localization error. So the NLOS problem is the biggest challenge for accurate mobile location estimation in WSN.

In indoor environments, the NLOS signal propagation such as reflection and diffraction leads to an overestimation, which in turn results in erroneous measurements containing NLOS errors. There are two ways to deal with the NLOS situation: unknown parameters of NLOS errors and known parameters of NLOS errors.

For the unknown parameters of NLOS errors method, the advantage of this method is that it can be used with any of the ranging technologies and does not require prior information about statistical properties of the NLOS measurements. In
[3], a residual weighting algorithm (Rwgh) which uses the sum of squared residuals of a least squares estimation as the indicator of the accuracy of calculated node coordinates was proposed. This method applies least squares multilaterration on all possible combinations of the distance measurements and then the estimated location is computed as a weighted combination of these intermediate estimates. A Gaussian mixture model (GMM) [4] is used to model the distribution of LOS errors and NLOS errors [5].

For the known parameters of NLOS errors method, the first method attempts to identify the NLOS propagation such as hypothesis test [6], likelihood ratio test [7], and statistical analysis methods [8, 9] and then it mitigates the NLOS errors. If the identification is correct, the localization accuracy can be achieved. However, the probability of wrong identification is inevitable. The second method attempts to combine all of the LOS and NLOS measurements to estimate the location of mobile node. The interacting multiple model (IMM) approach with the Kalman filtering technique is developed [10]. And the data fusion based IMM approach is investigated [11, 12]. An M-estimator [13] is employed to estimate the distribution of NLOS errors. And an IMM based cubature Kalman filter [14] is introduced to deal with the maneuvers of the target. Most of the above mentioned algorithms rely on certain NLOS error distribution which is unknown in practice. However, most of the methods focus on cellular network or ultrawideband communication system. Very few papers investigate the mobile node mobile localization in NLOS environment for WSN.

In this paper, we firstly propose a likelihood matrix based correction method. And then a mixed Kalman filter and H-infinity filter method is proposed. A 2-dimensional analysis is provided, as extension to 3 dimensions is rather straightforward. The main contribution of this paper is given as follows.

(1) The proposed likelihood matrix based correction method does not require identification of propagation state, and it is independent of the physical measurement ways.
(2) The proposed method does not require any prior information about the statistical properties of NLOS errors. Therefore, it can be widely used in the cellular network, ad hoc network, and wireless sensor network.
(3) In comparison with other methods, the proposed method is robust to the NLOS errors.

The rest of the paper is organized as follows. Section 2 provides the system model in LOS/NLOS conditions. We will introduce our proposed strategy in Section 3. Some simulation results will present in Section 4. The conclusions are given in Section 5.

2. System Model

In this section, we introduce some technical preliminaries. The assumption of this paper is as follows. Consider a range-based 2D localization problem employing $N$ beacon nodes at known locations $Z_i = [x_i, y_i]^T$, $i = 1, \ldots, N$. The position of the mobile node at time $k$ is $Z^m_k = [x^m_k, y^m_k]^T$, $k = 1, \ldots, t$. The beacon nodes send the signal and the mobile node receives it and converts it to range information. The real distance between $i$th the beacon node and the mobile node at time $k$ is

$$d^i_k = \sqrt{(x^m_k - x_i)^2 + (y^m_k - y_i)^2}. \quad (1)$$

In LOS propagation conditions, the range measurement by $i$th beacon node at time $k$ is modeled as follows:

$$d^i_k = d^i_k + n_i, \quad (2)$$

where $n_i$ is the measurement noise modeled as zero mean white Gaussian with variance $\sigma^2_n$.

In NLOS propagation conditions, the signal does not travel in a straight line when an obstacle exists between the beacon and mobile node due to the reflection or diffusion effect. So the range measurement by $i$th beacon node at time $k$ is modeled as follows:

$$d^i_k = d^i_k + n_i + b_{NLOS}, \quad (3)$$

where $n_i$ is the measurement noise with zero mean and $\sigma^2_n$ variance. $b_{NLOS}$ is the NLOS errors and is assumed to be independent of the measurement noise $n_i$. And the NLOS error $b_{NLOS}$ obeys Gaussian, uniform, exponential, or Delta distribution. The distribution and parameters of $b_{NLOS}$ are different in different indoor environments and measurement methods.

3. Implementation of the Proposed Algorithm

The system flow of the proposed NLOS errors mitigation method is plotted in Figure 1. The input of this method is the measured distance $\hat{d}_k^i$, and the output of the method is filtered distance $\tilde{d}_k$. This method consists of two major stages, that is, likelihood matrix based correction and mixed Kalman and H-infinity filter. The proposed algorithm is described in the following discussion.

3.1. Likelihood Matrix Based Correction. Firstly, a grid-based likelihood matrix is established to provide the initial localization results. And then the corrected range and the factor of the mixed Kalman/H-infinity filter are introduced.

At time $k$, the proposed algorithm consists of the following steps.

Step 1. The area is divided into a grid $\Phi$ with $W \times W$ cells and grid resolution $\omega$, for example, a $100 \times 100$ field with $W = 5$ and a grid resolution $\omega$ is equal to 20. The number of cells is a tradeoff between estimation accuracy and computational complexity. $C(i, j)$, for $i, j = 1, \ldots, W$, denotes the centers of these cells in a matrix form. And then we construct a $W \times W$ likelihood matrix $V$. The elements of the likelihood matrix are obtained by

$$V(m, n) = \sum_{i=1}^{N} b_{j}(m, n), \quad \text{for} \ m, n = 1, \ldots, W. \quad (4)$$
where

\[ b_i (m, n) = \begin{cases} 
1, & \bar{d} - \varepsilon \leq d_{imn} \leq \bar{d} + \varepsilon \\
0, & \text{otherwise}, 
\end{cases} \tag{5} \]

\( d_{imn} \) is the Euclidean distance between the \( C(m, n) \) and \( i \)th node. \( \bar{d} \) is the measured distance of \( i \)th node. And we set \( \varepsilon = \sigma_i \).

Let \((m^*, n^*)\) be the element of \( V \) with the maximum value, that is, \( V(m^*, n^*) \geq V(m, n) \), for \( m, n = 1, \ldots, W \), then the estimated location of mobile node is \( C^* = [C_1^*, \ldots, C_v^*] \). \( C^* \) is the initial results set of localization. The center of the initial results set can be expressed as \( \bar{C} = \sum_v C_i^* / v \).

In order to illustrate Step 1, we provide a simple example using a square measured distance. The measured distances of sensors are 2, 2, and 3 respectively. The locations of the sensors are illustrated in Figure 2. For the construction of the likelihood matrix \( V \), each sensor node adds a positive one contribution to the element of \( V \) that corresponds to the cells that the measured range meets the condition \( \bar{d} - \varepsilon \leq d_{imn} \leq \bar{d} + \varepsilon \). On the other hand, sensor node adds zero contribution to these elements. The resulting likelihood matrix after computing these contributions of three sensor nodes is shown in Figure 2. The mobile node is correctly localized in the grid cell with the maximum value 3.
Step 2. The corrected range by \( i \)th beacon node at time \( k \) is can be expressed as
\[
d_k^i = \| \mathbf{C}_k^i - Z_i \|. \tag{6}
\]
Step 3. The factor of the mixed Kalman/H\(-\infty\) filter can be obtained as
\[
d_k^i = \frac{d_k^i - \hat{d}_k^i}{\sum_{i=1}^{N} \| \hat{d}_k^i - d_k^i \|} \tag{7}
\]

3.2. Kalman Filter. Kalman filter is the most widely used method for tracking and mobile location estimation. And the Kalman filter is suggested as a promising method to range measurement for smoothing and mitigating Gaussian noise. A modified Kalman filter \([15, 16]\) is employed to reduce the NLOS error in rough wireless environments. A modified extended Kalman filter \([17]\) is proposed to jointly estimate the mobile state and the LOS/NLOS sight state based on the measurements. Then a Bayesian data fusion algorithm is applied to achieve high estimation accuracy. An extended Kalman based interacting multiple model smoother (EKF-IMM) \([11]\) is proposed. The IMM is employed as a switch between the LOS and NLOS condition, which are considered to be a Markov process with two interactive models. And then the Kalman filter is used for nonlinear estimation. In this paper, we employ the Kalman filter to mitigate the measurement noise.

The state vector at time \( k \) is defined as \( X_k = [\hat{d}_k, \hat{d}_k]^T \), where \( [\hat{d}_k, \hat{d}_k]^T \) represents the measured distance and the corresponding velocity. Then the motion model with random acceleration can be modeled as
\[
X_{k+1}^i = \Phi_k X_k^i + \nu_k, \tag{8}
\]
where \( \nu_k \) is the random process noise modeled as zero mean with variance \( Q_k \). The state transition matrix \( \Phi_k \) is defined as \( \Phi_k = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \), and \( \Delta t = t_{k+1} - t_k \) is the sampling period.

The measurement model is defined as (2) and (3) in LOS and NLOS environments, respectively. So the measurement model can be rewritten as
\[
z_k^i = H_k X_k^i + \nu_k, \tag{9}
\]
where \( H_k = [1, 0] \). Most of the papers assume that \( b_{\text{NLOS}} \) is Gaussian distribution, that is, \( b_{\text{NLOS}} \sim N(\mu_{\text{NLOS}}, \sigma_{\text{NLOS}}^2) \). So, \( \nu_k \sim N(0, \sigma_k^2) \) can be rewritten as
\[
v_k \sim N(0, \sigma_k^2), \quad \text{LOS}
\]
\[
v_k \sim N(\mu_{\text{NLOS}}, \sigma_k^2 + \sigma_{\text{NLOS}}^2), \quad \text{NLOS}. \tag{10}
\]

Therefore, the Kalman filter cannot perform better performance when the NLOS noise is non-Gaussian distribution.

The operation of the Kalman filter can be represented by two recursive steps. The prediction step includes the following operations:
\[
\hat{X}_{k+1|k}^i = \Phi_k X_{k|k}^i, \tag{11}
\]
\[
P_{k+1|k}^i = \Phi_k P_{k|k}^i \Phi_k^T + Q_k + R_{k+1}.
\]

The update step includes the following operations:
\[
\hat{X}_{k+1|k+1}^i = \hat{X}_{k+1|k}^i - H_k^T S_k^{-1} z_{k+1|k}^i, \tag{12}
\]
\[
S_{k+1} = H_k^T P_{k+1|k}^i H_k + R_{k+1}, \tag{13}
\]
\[
\hat{X}_{k+1|k+1}^i = \hat{X}_{k+1|k}^i + K_{k+1} z_{k+1|k}^i, \tag{14}
\]
\[
P_{k+1|k+1}^i = P_{k+1|k}^i - K_{k+1} S_{k+1}^{-1} K_{k+1}^T, \tag{15}
\]

3.3. \( H\)\(-\infty\) Filter. Although some filtering techniques such as unscented filter \([18]\) and particle filter \([19]\) are superior to the Kalman filter for nonlinear and non-Gaussian noise system, the computational cost is too high that they do not suit for resource limited sensor nodes. The Kalman filter is established on the \( H\)-2 estimate criterion, and it needs to know the statistical properties of the noise. However, it is not practical especially in the complex indoor environment. \( H\)-infinity filter differs from the Kalman filter in that it does not require the knowledge of the noise properties except that the noises are assumed to have bounded power. Therefore, \( H\)-infinity filter is one of the promising methods due to its simplicity, optimality, tractability, and robustness \([20, 21]\). However, very few papers employ the \( H\)-infinity filter into the mobile location estimation field for WSN. The motion model and measurement model are given by
\[
X_{k+1}^i = \Phi_k X_k^i + \nu_k, \tag{14}
\]
\[
z_k^i = H_k X_k^i + \nu_k,
\]
where \( \nu_k \) and \( \nu_k \) are process noise and measurement noise, respectively. And the distribution and the statistical properties of the noises are unknown. The definition of \( \Phi_k \) and \( H_k \) is the same with Kalman filter.

The linear combination of measurement and state vectors \([22, 23]\) is
\[
s_k^i = L_k X_k^i. \tag{15}
\]

We assume that the initial covariance of estimation error is \( P_0^j = E[(X_0^i - \hat{X}_0^i)(X_0^i - \hat{X}_0^i)^T] \). \( s_k^j = F_j(z_0^j, z_1^j, \ldots, z_k^j) \) represents the estimation of \( s_k^j \) using the measurements \( z_k^i \) from 0 to time \( k \). The filtering error is \( \Delta s_k^j = s_k^j - \hat{s}_k^j \). \( T_k(F_j) \) denotes the transfer operators that map the unknown
Table 1: The default parameter values.

| Parameters                      | Symbol | Default values |
|---------------------------------|--------|----------------|
| Number of beacon nodes          | $N$    | 7              |
| The standard deviation of measure| $\sigma_i$ | 4              |
| The NLOS errors                 | $b_{\text{NLOS}} \sim N(\mu_{\text{NLOS}}, \sigma_{\text{NLOS}}^2)$ | $\mu_{\text{NLOS}} = 4, \sigma_{\text{NLOS}} = 5$ |

Table 1: The default parameter values.

disturbances $\{(P_i^0)^{-0.5}(X_i^0 - \bar{X}_i^0), w_i, v_k\}$ to the filtering error $\Delta s^i_k$. The $H$-infinity norm of the transfer operator $T$ is defined as

$$
\|T_k(F_f)\|_{\infty} = \sum_{i=0}^k (\Delta s^i_k)^T \Delta s^i_k = (X_i^0 - \bar{X}_i^0)^T (P_i^0)^{-1} (X_i^0 - \bar{X}_i^0) + \sum_{k=0}^k w_k^T w_k + \sum_{k=0}^k v_k^T v_k. \quad (16)
$$

So the $H$-infinity filter can be described as follows. Given a scale $\gamma > 0$, find $H$-infinity estimation strategies that achieve $\|T_k(F_f)\|_{\infty} < \gamma$. In this paper, we set $L_k = I$. The recursive steps are as follows:

$$
K_{k+1} = \left( \frac{1}{\gamma} I + \Phi_{k+1}(P_{k+1}^i)^{-1} H_k^T \right)^{-1} \Phi_{k+1}(P_{k+1}^i)^{-1} H_k^T, \quad (17)
$$

$$
\tilde{X}_{k+1|k+1} = \Phi_{k+1} \tilde{X}_{k|k} + K_{k+1}(z_{k+1} - H_{k+1} \tilde{X}_{k|k+1}), \quad (18)
$$

$$
P_{k+1|k+1} = \Phi_{k+1} P_{k|k} \Phi_{k+1}^T + K_{k+1} H_k P_{k+1}^i, \quad (19)
$$

The output of $H$-Infinity filter can be expressed as

$$
\tilde{a}_k^{(H)} = D \tilde{X}_{k+1|k+1}, \quad (20)
$$

$$
D = [1, 0].
$$

4. Performance Evaluation

In this section, we present simulation results for the proposed LC-MKHF algorithm for mobile location estimation in non-line-of-sight environments. As shown in Figure 3(a), we randomly deploy seven beacon nodes in the 100 m x 100 m square area and one mobile node (MN) moving in the area. We assume that the mobile node has the velocity of 1 m/s. The communication range of sensor node is 150 m. We compare the proposed method with no-filter (NF) method, Kalman filter (KF) method, and $H$-infinity Filter (HF) algorithm. The default parameter values in the simulation are shown in Table 1. In each simulation case, 1000 Monte Carlo runs are performed with the same parameters. The performance of the proposed algorithm is measured by average localization error (ALE):

$$
\text{error} = \frac{1}{N} \sum_{r_n=1}^K \sum_{k=1}^{t_n} \sqrt{ (\hat{x}_k - x_k^i)^2 + (\hat{y}_k - y_k^i)^2 }, \quad (21)
$$

where $N = 1000, t_n = 100, (\hat{x}_k, \hat{y}_k)$ is the true location of the mobile node, and $(\bar{x}_k, \bar{y}_k)$ is the estimated location.

Figure 3(a) shows the deployment of the beacon nodes and obstacles. In this paper, the beacon nodes and obstacles are randomly deployed. And Figure 3(b) shows sight state with respect to all the beacon nodes in sample points. We can see that the sight states vary with time. In Figure 3(c), we can obtain the detailed localization errors in each sample point. It can be observed that the proposed method has better performance in comparison with other methods in most of the sample points.
In the following section, we evaluate the performance of our proposed method under different environment, that is, the NLOS errors obey different distribution. We also investigate the effect of various parameters on the proposed method.

4.1. The NLOS Errors Obey Gaussian Distribution, That Is, $b_{\text{NLOS}} \sim N(\mu_{\text{NLOS}}, \sigma_{\text{NLOS}}^2)$. In this subsection, we compare the proposed method with other methods when the NLOS errors obey Gaussian distribution. Figure 4(a) shows the relation between the average localization errors and the number of sensor nodes. The average localization errors of all methods decrease with the number of sensor nodes increase. And Figures 4(b) and 4(c) show the impact of mean and standard deviation of NLOS errors on the average localization errors. It can be observed that the mean and standard deviation of NLOS errors have a significant impact on KF and NF methods. The HF and LC-MKHF are robust to the parameters. In Figure 4(b), the proposed method has higher localization accuracy than HK, EK, and NF, about 39.59%, 48.94%, and 54.81%, respectively. In Figure 4(c), the proposed method has higher localization accuracy than HK, EK, and NF, about 28.32%, 47.91%, and 58.26%, respectively.

4.2. The NLOS Errors Obey Uniform Distribution, That Is, $b_{\text{NLOS}} \sim U(2, U_{\max})$. In this subsection, we assume that the
NLOS errors obey uniform distribution. The minimum and maximum values of parameters of uniform distribution are 2 and $U_{\max}$, namely, $U(2, U_{\max})$. We firstly investigate the impact of $U_{\max}$ on average localization errors. As shown in Figure 5(a), the KF has the similar performance with HF when the $U_{\max}$ is low. The NF method owns the worst performance, and our proposed method has the best localization accuracy. In Figure 5(b), we also investigate the influence of standard deviation of measurement noise when $U_{\max} = 7$. It can be observed that the proposed method has the highest localization accuracy in each case.

4.3. The NLOS Errors Obey Exponential Distribution, That Is, $b_{\text{NLOS}} \sim \mathbb{E}(u)$. In this subsection, we study the performance of the methods when the NLOS errors obey exponential distribution. As shown in Figure 6(a), LC-MKHF performs stably when the mean parameter increases. However, the KF and NF methods increase with the mean parameter increase. The localization accuracy improved 58.75%, 52.56%, and 41.18% when comparing with NF, KF, and HF methods. And Figure 6(b) indicates that the proposed method owns the best performance under various standard deviation of measurement noise.
5. Conclusion

This paper presents a novel LC-MKHF method which is robust to the NLOS errors without prior information on error model. A likelihood matrix based correction method is firstly proposed. And then a mixed Kalman and $H\infty$ filter is proposed to further mitigate the NLOS errors. This method does not need much parameters of the measurement model. The simulation results show that the proposed algorithm has the higher localization accuracy, and it is robust to the NLOS errors.

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References

[1] S. Thrun, W. Burgard, and D. Fox, Probabilistic Robotics, MIT Press, Cambridge, Mass, USA, 2005.

[2] W. Li and Y. Jia, “Location of mobile station with maneuvers using an IMM-based cubature Kalman filter,” IEEE Transactions on Industrial Electronics, vol. 59, no. 11, pp. 4338–4348, 2012.

[3] P.-C. Chen, “A non-line-of-sight error mitigation algorithm in location estimation,” in Proceedings of the Wireless Communication and Networking Conference, vol. 1, pp. 316–320, 1999.

[4] Q. H. Wang, I. Balasingham, M. M. Zhang, and X. Huang, “Improving RSS-based ranging in LOS-NLOS scenario using GMMs,” IEEE Communications Letters, vol. 15, no. 10, pp. 1065–1067, 2011.

[5] C. D. Wann and H. Y. Lin, “Hybrid TOA/AOA estimation error test and non-line of sight identification In wireless location,” Wireless Communications & Mobile Computing, vol. 9, no. 6, pp. 859–873, 2009.

[6] L. Cong and W. Zhuang, “Nonline-of-sight error mitigation in mobile location,” IEEE Transactions on Wireless Communications, vol. 4, no. 2, pp. 560–573, 2005.

[7] I. G¨uvenc¸, C.-C. Chong, F. Watanabe, and H. Inamura, “NLOS identification and weighted least-squares localization for ubw systems using multipath channel statistics,” EURASIP Journal on Advances in Signal Processing, vol. 2008, Article ID 271984, 14 pages, 2008.

[8] S. Venkatraman, J. Caffery, and H. R. You, “A novel ToA location algorithm using LoS range estimation for NLoS environments,” IEEE Transactions on Vehicular Technology, vol. 53, no. 5, pp. 1515–1524, 2004.

[9] S. Venkataramy and R. M. Buehrer, “Non-line-of-sight identification in ultra-wideband systems based on received signal statistics,” IET Microwaves, Antennas & Propagation, vol. 1, no. 6, pp. 1120–1130, 2007.

[10] J. F. Liao and B. S. Chen, “Robust mobile location estimator with NLOS mitigation using interacting multiple model algorithm,” IEEE Transactions on Wireless Communications, vol. 5, no. 11, pp. 3002–3006, 2006.

[11] 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 Transactions on Vehicular Technology, vol. 58, no. 3, pp. 1157–1169, 2009.

[12] C. Y. Yang, B. S. Chen, and F. K. Liao, “Mobile location estimation using fuzzy-based IMM and data fusion,” IEEE Transactions on Mobile Computing, vol. 9, no. 10, pp. 1424–1436, 2010.

[13] U. Hammes and A. M. Zoubir, “Robust MT tracking based on M-estimation and interacting multiple model algorithm,” IEEE Transactions on Signal Processing, vol. 59, no. 7, pp. 3398–3409, 2011.

[14] W. Li and Y. Jia, “Location of mobile station with maneuvers using an IMM-based cubature Kalman filter,” IEEE Transactions on Industrial Electronics, vol. 59, no. 11, pp. 4338–4348, 2012.

[15] W. Ke and L. Wu, “Mobile location with NLOS identification and mitigation based on modified Kalman filtering,” Sensors, vol. 11, no. 2, pp. 1641–1656, 2011.

[16] M. N´ajar and J. Vidal, “Kalman tracking for mobile location in NLOS situations,” in Proceedings of the 14th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC ’03), pp. 2203–2207, Beijing, China, September 2003.

[17] L. Chen and L. Wu, “Mobile positioning in mixed LOS/NLOS conditions using modified EKF banks and data fusion method,” IEICE Transactions on Communications, vol. E92-B, no. 4, pp. 1318–1325, 2009.

[18] J. M. Huerta, J. Vidal, A. Giremus, and J.-Y. Tourneret, “Joint particle filter and UKF position tracking in severe non-line-of-sight situations,” IEEE Journal of Selected Topics in Signal Processing, vol. 3, no. 5, pp. 874–888, 2009.

[19] M. Boccadore, G. De Angelis, and P. Valigi, “TDOA positioning in NLOS scenarios by particle filtering,” Wireless Networks, vol. 18, no. 5, pp. 579–589, 2012.

[20] W. Wu and F. Zhang, “Robust cooperative exploration with a switching strategy,” IEEE Transactions on Robotics, vol. 28, no. 4, pp. 828–839, 2012.

[21] F. Yang, Z. Wang, S. Lauria, and X. Liu, “Mobile robot localization using robust extended $H_\infty$ filtering,” Proceedings of the Institution of Mechanical Engineers. Part I, vol. 223, no. 8, pp. 1067–1080, 2009.

[22] B. Hassibi, A. H. Sayed, and T. Kailath, “Linear estimation in Krein spaces—part I: theory,” IEEE Transactions on Automatic Control, vol. 41, no. 1, pp. 18–33, 1996.

[23] B. Hassibi, A. H. Sayed, and T. Kailath, “Linear estimation in Krein spaces—part II: applications,” IEEE Transactions on Automatic Control, vol. 41, no. 1, pp. 34–49, 1996.
