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MOBILE LOCALIZATION AND TRACKING WITH LOS AND NLOS IDENTIFICATION IN WIRELESS SENSOR NETWORKS

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Abstract- This paper addresses the problem of mobile sensor localization and tracking in an obstructed environment. To solve this problem, a combination of three approaches is proposed: a nonlinear Kalman Filter to estimate the mobile position, a sub filter used jointly with the nonlinear filter to estimate the bias due to the Non-Line Of Sight (NLOS) effect and a low complexity method for Line Of Sight (LOS) and NLOS identification. Based on hypothesis testing, this method discriminates between the LOS and NLOS situations using a sequence of estimated biases. Simulation results show that the proposed method provides good positioning accuracy.

Index terms: Localization, Tracking, Wireless Sensor Network, Non Line of Sight, Divided Difference Kalman Filter, Unscented Kalman Filter, Bias estimation, Hypothesis testing.

I. INTRODUCTION

Static and dynamic location of an object or a person in a wireless sensor network (WSN) has become one of the most important tasks, due to its multiple applications (security and surveillance, health care, smart building …). It is true that for localization purposes, some sensor nodes may include a Global Positioning System (GPS), but this solution may not be suitable because it is financially and energetically costly and cannot be adopted for indoor applications. An alternative to this approach would be to exploit some parameters extracted from the radio frequency signals exchanged between the mobile and a number of reference sensors nodes, called "anchors". Among such parameters are the received signal strength (RSS) measurements, the angle of arrival (AOA) measurements, and the propagation time based measurements (time of arrival/ time difference of arrival TOA/TDOA) [1]. Generally, localization methods based on measurements of TOA, TDOA and AOA provide estimated position with good precision, but require accurate synchronization between the transmitter and the receiver and regular calibration, which increases the cost and the energy consumption of the localization system. A solution to this problem would be the use of the measured RSS information, which is always available and requires no additional hardware [2]. The presence of obstacles in the environment where the sensor nodes are deployed provokes NLOS propagation between the anchors nodes and the mobile node. The measurements taken in LOS conditions are affected solely by errors while those taken in NLOS conditions are corrupted by errors and biases, which causes very inaccurate estimated positions [3]. It is therefore indispensable to identify NLOS situations to improve the location accuracy. This problem was the subject of several studies. Modeling the LOS/NLOS situations by a Markov chain process, the authors in [4,5] use the interacting multiple model algorithm, which runs several nonlinear Kalman filters in parallel, to cope with this problem. Other studies propose the use of statistical analysis methods. In [6, 7] the identification of NLOS conditions is achieved by employing the statistical decision theory based on different metrics such as TOA and RSS. The authors in [8] propose a novel NLOS identification technique based on the multipath channel statistics, such as the kurtosis, the mean excess delay spread, and the root mean square delay spread.

Hypothesis testing methods have also been used in this context. The work presented in [9] describes a non-parametric solution for accurate distance-based source localization requiring no prior knowledge of distance estimate statistics. In [10], the authors present a non-line-of-sight mitigation approach, which uses LOS and NLOS identification and a hypothesis testing analysis to achieve accurate identification.

In this paper, we propose a low complexity method which uses a Kalman filter to provide bias estimates that are then used in a hypothesis test, for NLOS identification. This filter is used jointly with a nonlinear Kalman filter to estimate the mobile positions from RSS measurements. As a nonlinear Kalman filter, we propose to use the Unscented Kalman Filter (UKF) or the Divided Difference Kalman Filter (DDKF) because these two filters are robust and provide good positioning accuracy compared to other non-linear filters [11]. The rest of this paper is organized as follows: the measurement model and the proposed methodology are described in section II. In section III, computer simulation results are presented and analyzed. Finally, some conclusions are drawn in section IV.

II. THE PROPOSED LOCALIZATION AND TRACKING ALGORITHM

To determine its position, a mobile sensor node, in a wireless sensor network, detects the radio frequency signals transmitted by the anchors to extract parameters, such as RSS measurements. Then, the localization and tracking algorithm processes these parameters to estimate the position. The following figure illustrates this process.

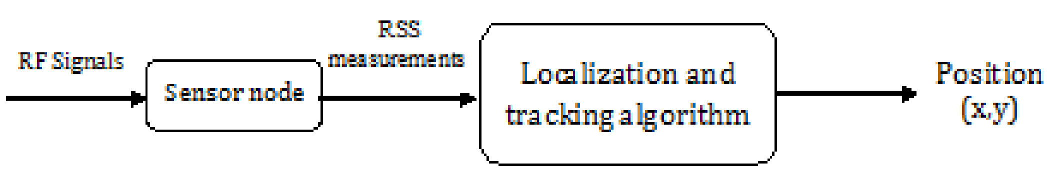

Figure1. Steps for position estimation

Before describing the proposed algorithm, we first define the measurement model under the LOS and the NLOS conditions.

II.1 RECEIVED SIGNAL STRENGTH (RSS)

RSS is a measurement of the power of the received signal. A very common radio propagation model to represent the RSS as a function of the distance is the log-normal shadowing path loss model [12]. According to this model, the received signal strength is formally expressed as:

$$P(d) = \begin{cases} P_0 - 10\eta\log_{10}\left(\frac{d}{d_0}\right) + X_{LOS}, & \text{if LOS} \\ P_0 - 10\eta\log_{10}\left(\frac{d}{d_0}\right) + X_{NLOS}, & \text{if NLOS} \end{cases} \quad (1)$$

Where:

P_0 is the received power at a reference distance d_0 (typically one meter) from the transmitter, η is the path loss exponent, which depends on the surrounding and buildings type, and d is the distance between the transmitter and the receiver, in meters. Random variations in the RSS are modeled by a Gaussian random variable that has zero mean and variance σ_{Los}^2 : $X_{LOS} \sim N(0, \sigma_{Los}^2)$ in the LOS case and non-zero mean and variance σ_{NLOS}^2 : $X_{NLOS} \sim N(b, \sigma_{NLos}^2)$ in NLOS case, with $\sigma_{NLos}^2 > \sigma_{Los}^2$.

II.2 THE NONLINEAR KALMAN FILTERING

Since the relationship between the RSS measurements and the mobile state vector, composed for example of its position and its velocity, is non-linear, linear Kalman filtering cannot be applied directly. It first, requires the use of a static localization algorithm, such as the Least Square algorithm [11], to obtain estimates of the mobile position. These estimates are then fed into the linear Kalman as measurements, to obtain refined position estimates. The drawback of this approach is its limited performance. As an alternative, one can use nonlinear Kalman filtering. In this paper we have opted for the UKF and the DDKF, due to their good performance, as stated earlier. This type of filtering is an iterative estimation based on a recurrence relation, which means that only the position previously estimated and actual measurements (RSS measurements) are needed to calculate the estimate of the current position.

II.2.1 THE UNSCENTED KALMAN FILTER (UKF)

Proposed by Julier and Uhlmann in 1997, the UKF uses the unscented transformation which allows calculating the mean and covariance of a transformed variable from a set of sample points, called sigma points that are propagated using the non-linear transformation [13].

A single cycle of the UKF consists of two steps, a prediction step and a correction step.

Prediction step: Since the state equation is linear, the standard equations of a linear Kalman filter may be used in this step. The estimated state at time k-1 is propagated to obtain the a priori (predicted) state estimate at time k, as follows:

$$X_{k|k-1} = F\, X_{k-1|k-1} \tag{2}$$

The state vector $X_k = [x, y, v_x, v_y]^T$ consists of the positions x and y and the velocities v_x and v_y at time k.

Assuming a constant velocity movement model, the state transition matrix which relates the state at time k to the state at time k-1 is given by:

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{3}$$

where T is the sampling interval.

The covariance matrix of the predicted errors, $P_{k|k-1}$, may be expressed as a function of the estimated covariance matrix, $P_{k-1|k-1}$, and the process noise covariance matrix Q as follows:

$$P_{k|k-1} = F P_{k-1|k-1} F^T + Q \tag{4}$$

If the fluctuations of the acceleration around zero are assumed to be constant during each update time interval and if they are modeled by a white noise with variance σ_Q^2, then Q is given by [14]:

$$Q = \begin{bmatrix} \frac{T^4}{4} & 0 & \frac{T^3}{2} & 0 \\ 0 & \frac{T^4}{4} & 0 & \frac{T^3}{2} \\ \frac{T^3}{2} & 0 & T^2 & 0 \\ 0 & \frac{T^3}{2} & 0 & T^2 \end{bmatrix} \sigma_Q^2 \quad (5)$$

The practical choice of the process noise variance σ_Q^2 is discussed in [14].

Update step: First, given the predicted state vector, the sigma points are calculated using equations (6)-(9) and stored in the columns of a matrix χ_k of size L × (2L +1), where L is the dimension of the state vector.

$$(\chi_k)_0 = X_k^- \quad (6)$$

$$(\chi_k)_i = X_k^- + \left(\sqrt{(L+\lambda)\, P_k^-}\right)_i, \; i = 1.........L \quad (7)$$

$$(\chi_k)_i = X_k^- - \left(\sqrt{(L+\lambda)\, P_k^-}\right)_i, \; i = L+1.........2L \quad (8)$$

where $(\chi_k)_i$ denotes the ith column of matrix χ_k and λ is defined by:

$$\lambda = \alpha^2 (L+\kappa) - L \quad (9)$$

In (9), α and κ control the spread of the sigma points. α is usually set to $0 \leq \alpha \leq 1$ and κ is a secondary scaling parameter which is usually set to zero.

Then, the sigma points $(\chi_k)_i$ are transformed by the measurement function,

$$(Z_k)_i = h((\chi_{k-1})_i), \; i=0........2L \quad (10)$$

The function h(x,y) is defined as:

$$h(x,y) = \begin{bmatrix} P_0 - 10\,\eta \log_{10}\left(\frac{d_1}{d_0}\right) \\ P_0 - 10\,\eta \log_{10}\left(\frac{d_2}{d_0}\right) \\ \vdots \\ P_0 - 10\,\eta \log_{10}\left(\frac{d_n}{d_0}\right) \end{bmatrix} \quad (11)$$

with d_n denoting the Euclidean distance function, defined by:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (12)$$

In the above equation (x_i, y_i), $i = 1, \dots, n$ represent the coordinates of the i-th anchor node. The weighted mean is computed as:

$$\hat{Z}_k = \sum_{i=0}^{2L} w_i^{(m)} (Z_k)_i \,, \tag{13}$$

where $w_i^{(m)}$ is the weight associated with the sigma point i, defined by:

$$w_0^{(m)} = \lambda / (L+\lambda) \tag{14}$$

$$w_i^{(m)} = 1/\{2(L+\lambda)\},\ i=1\ldots..2L \tag{15}$$

The vector $\hat{Z}_k$, plays the role of the predicted measurement vector that may be used to calculate the a posteriori state estimate:

$$X_k = X_k^- + K_k (Z_k - \hat{Z}_k) \,, \tag{16}$$

where Z_k is the vector of measurements and K_k is the Kalman gain, given by:

$$K_k = P_{xz} P_{zz}^{-1}, \tag{17}$$

with:

$$P_{zz} = \sum_{i=0}^{2L} w_i^{(c)} [(Z_k)_i - \hat{Z}_k] [(Z_k)_i - \hat{Z}_k]^T + R \tag{18}$$

$$P_{xz} = \sum_{i=0}^{2L} w_i^{(c)} [(\chi_k)_i - X_k^-] [(Z_k)_i - \hat{Z}_k]^T \tag{19}$$

In (18), R represents the covariance matrix of the measurement noise and can be expressed as follows:

$$R = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_n^2 \end{bmatrix}, \tag{20}$$

where *n* is the number of anchor nodes and

$$\sigma_i^2 = \begin{cases} \sigma_{LOS}^2, & if\ LOS \\ \sigma_{NLOS}^2, & if\ NLOS \end{cases} \tag{21}$$

The weight $w_i^{(c)}$ is defined by:

$$w_0^{(c)} = \frac{\lambda}{(L+\lambda)} + (1 - \alpha^2 + \beta) \tag{22}$$

$$w_i^{(c)} = \frac{1}{2\,(L+\lambda)}\ , i=1\ldots..2L \tag{23}$$

β is a parameter used to incorporate any prior knowledge about the error distribution (for Gaussian distribution, β = 2 is optimal).

Finally the estimated covariance matrix is updated as follows:

$$P_k = P_k^- - K_k P_{zz}\ K_k^T \tag{24}$$

II.2.2 THE DIVIDED DIFFERENCE KALMAN FILTER (DDKF)

Based on Stirling's interpolation, the DDKF was proposed to solve the nonlinearity problem by approximating the mean and the covariance of stochastic variables generated by nonlinear transformation of stochastic variables with known mean and covariance [15].

First, the Kalman Filter state prediction is applied (equations (2) and (4)) due to the assumed linear process dynamics.

Update step*:* The DDKF computes the mean and covariance of a nonlinearly transformed random variable by using the second order polynomial approximation.

Let L_k denote the Cholesky decomposition of the predicted covariance matrix $P_{k|k-1}$:

$$L_k = \mathrm{Chol}\ (P_{k|k-1}) \tag{25}$$

The predicted measurement, $\hat{Z}_k$, is calculated by:

$$\hat{Z}_k = \frac{\xi^2 - L}{\xi^2} h\big(J(X_{k|k-1})\big) + \frac{1}{2\xi^2}\sum_{i=1}^{L} h\ \big(J(X_{k|k-1} + \xi\ (L_k)_{\ i})\big) + h\ \big(J(X_{k|k-1} - \xi(\ L_k)_{\ i})\big), \tag{26}$$

where L is the dimension of the state vector, $(L_k)_i$ denotes the i^{th} column of matrix L_k.

ξ is the interval step-size for the approximation, with $\sqrt{3}$ being the optimal value for a Gaussian distribution [15].

The matrix J in equation (26) allows the retrieval of the position vector from the state vector. It is given by:

$$J = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{27}$$

The Kalman gain can be calculated by:

$$K_k = P_{xz} P_{zz}^{-1} \quad (28)$$

Where P_{zz} is the measurement prediction covariance defined as:

$$P_{zz} = H(X_{k|k-1}, L_k, \xi)H^T(X_{k|k-1}, L_k, \xi) + H^{(2)}(X_{k|k-1}, L_k, \xi)H^{(2)T}(X_{k|k-1}, L_k, \xi) + P\_b_{k|k-1} + R \quad (29)$$

and P_{xz} is the covariance between the variable to be estimated and the observation given by:

$$P_{xz} = L_k H^T(X_{k|k-1}, L_k, \xi) \quad (30)$$

In the two previous equations the (i, j) element of matrices H and $H^{(2)}$ are defined as:

$$H_{i,j}(X_{k|k-1}, L_k, \xi) = \left(h_i\big(J(X_{k|k-1} + \xi(L_k)_j)\big) - h_i\big(J(X_{k|k-1} - \xi(L_k)_j)\big)\right)/2\xi \quad (31)$$

$$H_{i,j}^{(2)}(X_{k|k-1}, L_k, \xi) = \frac{\sqrt{\xi^2-1}}{2\xi^2}\left(h_i\big(J(X_{k|k-1} + \xi(L_k)_j)\big) + h_i\big(J(X_{k|k-1} - \xi(L_k)_j)\big) - 2h_i\big(J(X_{k|k-1})\big)\right) \quad (32)$$

Where $h_i(\bullet)$ denotes the i^{th} element of $h(\bullet)$, defined in equation (11).

$P\_b_{k|k-1}$ in equation (29) is the covariance matrix of the predicted bias (bias estimation will be detailed in the next sub-section).

The a posteriori state vector $X_{k|k}$ and the associated covariance matrix $P_{k|k}$ are updated according to:

$$X_{k|k} = X_{k|k-1} + K_K V_k \quad (33)$$

$$P_{k|k} = P_{k|k-1} - K_K P_{zz} K_k^T \quad (34)$$

V_k in equation (33) is the innovation or measurement residual calculated as follows:

$$V_k = Z_k - \hat{Z}_k - b_{k|k-1}\,, \quad (35)$$

Where Z_k is the n-dimensional vector of RSS measurements at time instant k and $b_{k|k-1}$ is the vector of predicted biases.

II.3 BIAS ESTIMATION

Since the measurements collected under NLOS conditions are biased, it is essential to estimate the bias to reduce the NLOS effect. This is achieved by a linear Kalman filter that is linked to the UKF or the DDKF; its formulation is summarized in the following [16]:

$$b_{k|k-1} = b_{k-1|k-1} \tag{36}$$

$$P\_b_{k|k-1} = P\_b_{k-1|k-1} + Q_b \tag{37}$$

$$K\_b_k = P\_b_{k|k-1} P_{zz}^{-1} \tag{38}$$

$$b_{k|k} = b_{k|k-1} + K\_b_k V_k \tag{39}$$

$$P\_b_{k|k} = [I - K\_b_k]\, P\_b_{k|k-1} \tag{40}$$

Where $b_{k|k}$ represents an estimate of the bias vector, and Q_b is the covariance matrix that models the uncertainty about the bias evolution model. The initial value of the bias vector is set to zero.

II.4 LOS/NLOS DISCRIMINATION

To decide whether the mobile sensor node is in LOS or NLOS situation with respect to each anchor node, a hypothesis test is applied. The null (H_0) and alternative (H_1) hypothesis are defined as:

$$\begin{aligned} H_0&: \text{bias} = 0 \quad \text{LOS} \\ H_1&: \text{bias} \neq 0 \quad \text{NLOS} \end{aligned} \tag{41}$$

Assuming that $b_1, b_2, \ldots, b_M$, is a sequence of M measurements of estimated biases, the test statistic is defined as:

$$S = \frac{\sum_{j=1}^{M} b_j}{\sqrt{M\sigma_0^2}} \, , \tag{42}$$

where σ_0^2 is the variance of the bias estimator.

This statistic has a unit variance Gaussian distribution with a mean equal to zero under H_0 and $\frac{\sqrt{M}}{\sigma_0} b$ under H_1. If $|S| < \lambda$, the hypothesis H_1 is rejected, where λ is a specified threshold that must be chosen so that the error probability is minimized.

III. SIMULATION RESULTS

A number of Monte Carlo simulations were carried out to assess the performances, in terms of localization accuracy, of the proposed tracking methods, referred to as the HT-UKF and the HT-DDKF. These performances are compared to the performances of each filter under LOS situation and NLOS situation. In these simulations, a mobile node moves at a constant speed of 1 *m/s* in a 20m x 20m rectangular area, containing several obstacles. We have deliberately considered a non maneuvring movement, in order to distinguish between the errors due to the visibility between the mobile and the anchors and those due to the maneuvers of the mobile. Four anchors nodes located at the four corners of this area are used, as shown in figure 2. The evolution of the mobile situation with respect to the anchors nodes is depicted in Figure 3.

The other parameters used in the simulations are as follows: The signal strength P_0 at the reference distance, d_0 = 1m, is set to - 60 dBm. Since we assume that the mobile node moves in an obstructed environment, the value assigned to the path loss exponent η is set to 4. The RSS measurements standard deviations under LOS and NLOS are set, respectively, to 0.5 and 4 dB, and the RSS measurements mean, b, in the NLOS situation is -5 dB.

To initialize the state vector of the nonlinear filters (UKF and DDKF), the initial positions are calculated using a multilateration approach, which provides estimates of the x and y positions, from distances obtained using the propagation model [17]. The velocities v_x and v_y are initialized to zero assuming no prior knowledge about the movement speed of the mobile node.

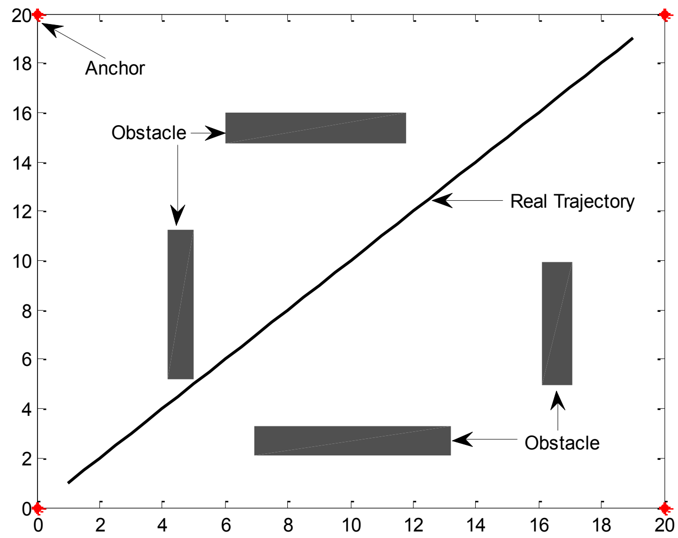

Figure 2. Illustration of the simulation scenario

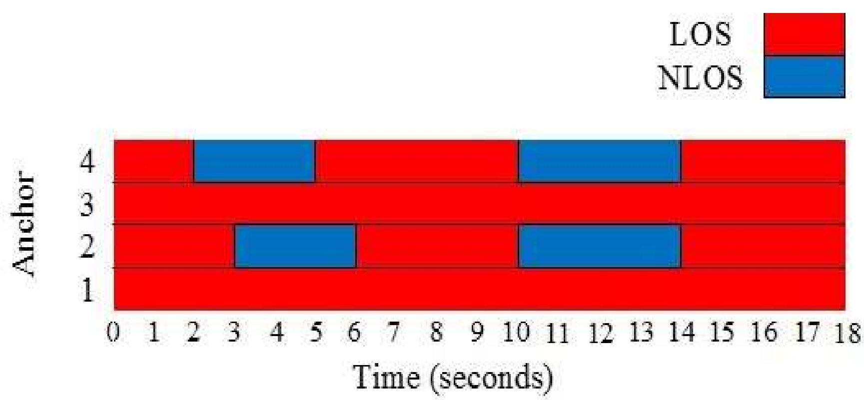

Figure 3. Evolution of the mobile situation with respect to the anchors nodes

The localization accuracy is an important criterion for assessing localization algorithms; it is evaluated using the Root Mean Square Error (RMSE) in position and the cumulative distribution function (CDF) of the estimation errors. The RMSE is calculated as follows:

$$\mathrm{RMSE}(k) = \sqrt{\frac{1}{R}\sum_{i=1}^{M} \left(x_0(k) - \hat{x}_i(k)\right)^2 + \left(y_0(k) - \hat{y}_i(k)\right)^2}\ , \qquad (43)$$

where M is the total number of runs, $(\hat{x}_i(k), \hat{y}_i(k))$ is the estimated position at run i and time k, and $(x_0(k), y_0(k))$ is the true position of the mobile node, at time k.

The results obtained by averageing over 500 runs are presented in figures 4 to 11.

Figures 4 and 7 show a comparison between the performance of the proposed method based on two variants of the nonlinear Kalman filter, which are the UKF and the DDKF, and the performances of these two filters matched to LOS and NLOS conditions, respectively. It can be observed that the combination of a hypothesis test and the UKF or the DDKF performs better than the single filter approach and provides a good position accuracy in mixed LOS/NLOS conditions.

In Figures 5 and 8 the cumulative distribution function is plotted. As can be seen, the LOS/NLOS identification associated with the UKF or the DDKF, for state estimation, is the most effective approach with a localization error less than 2.5 meters in 100% of cases.

Figures 6 and 9 show the time evolution of the estimated RSS bias. It can be observed that this evolution is consistent with the LOS/NLOS situations, which means that the estimated RSS bias can be used to detect these situations.

In Figures 10 and 11 a comparison between the method based on the UKF and the one based on the DDKF is presented. It can be observed that the HT-DDKF performs better than the HT-UKF.

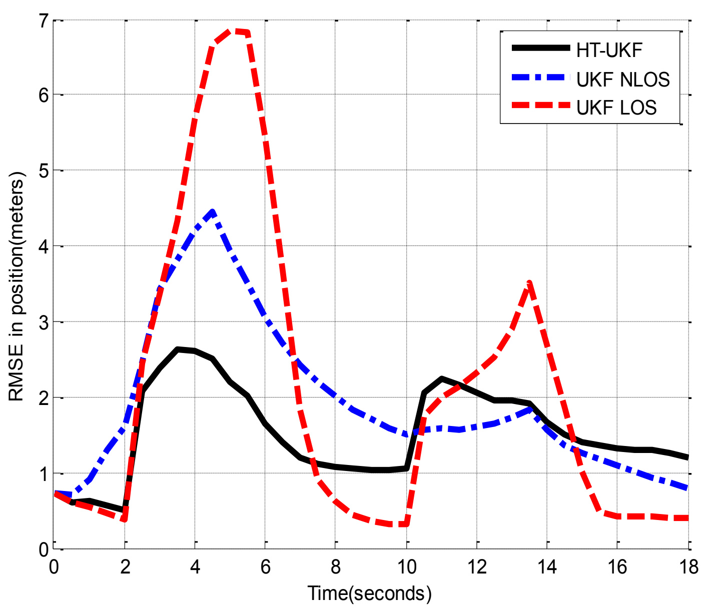

Figure 4. RMSE in position obtained with the HT-UKF and the UKF under LOS and NLOS conditions

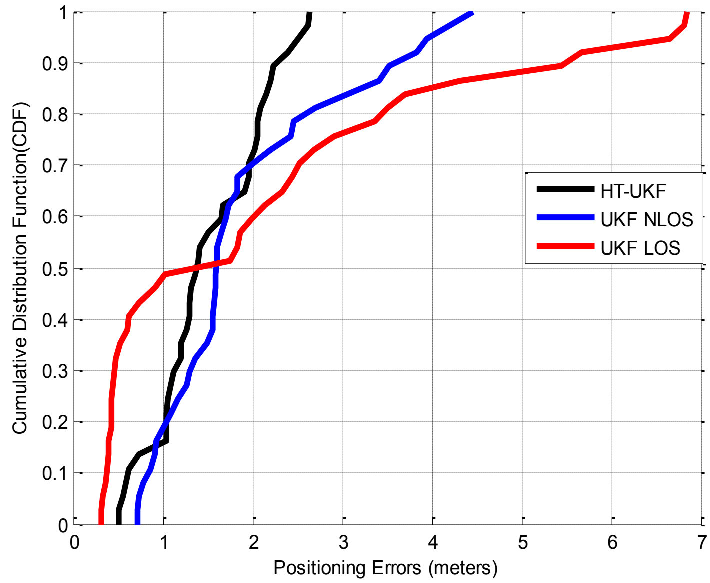

Figure 5. Cumulative distribution function of the location errors of the HT-UKF and the UKF under LOS and NLOS conditions.

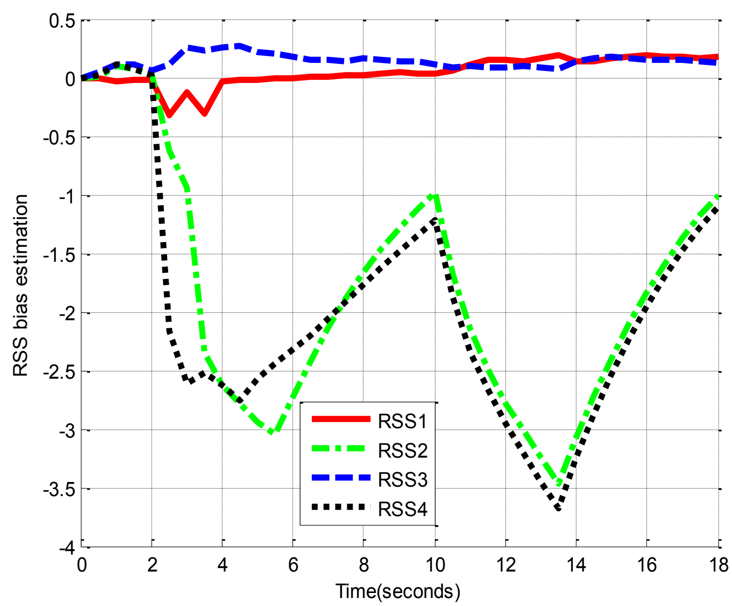

Figure 6. RSS bias estimation in the HT-UKF.

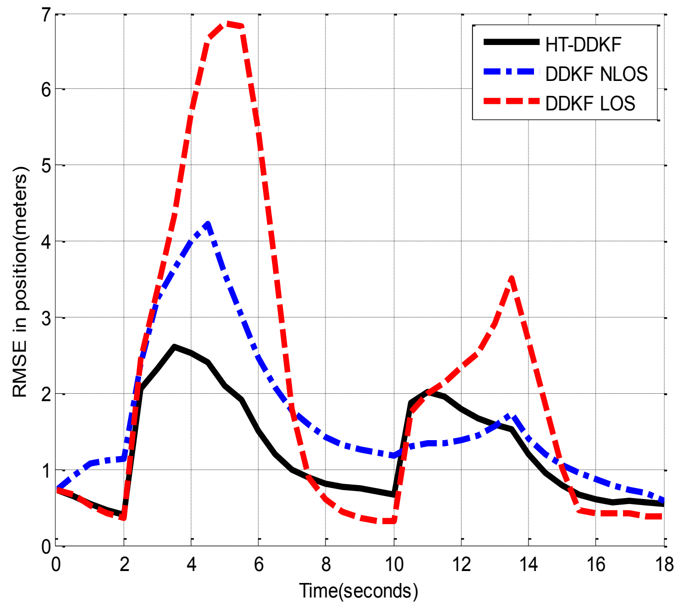

Figure 7. RMSE in position obtained with the HT-DDKF and the DDKF under LOS and NLOS conditions

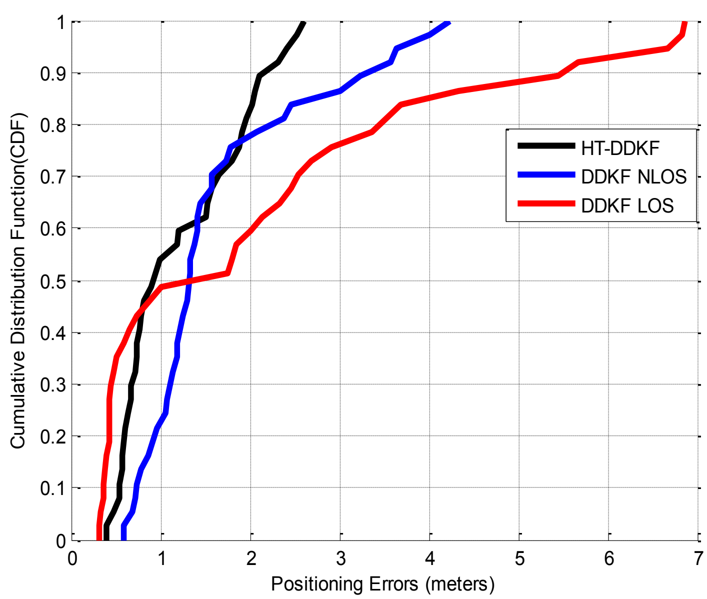

Figure 8. Cumulative distribution function of the location errors of the HT-DDKF and the DDKF under LOS and NLOS conditions.

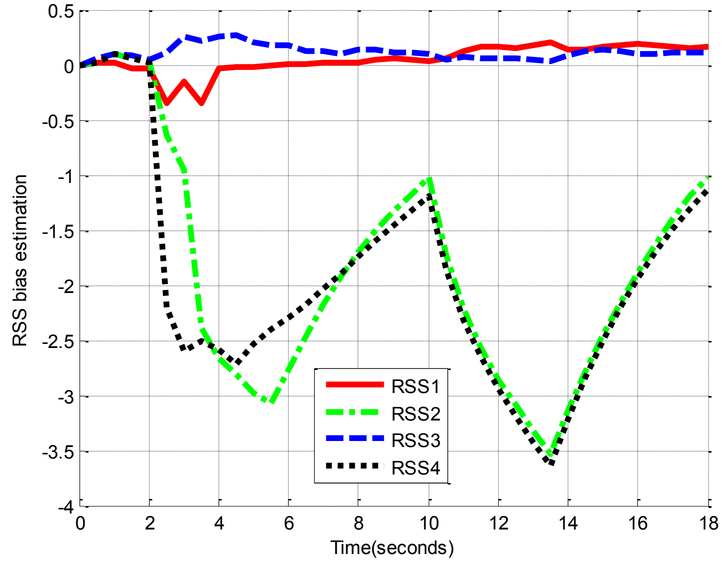

Figure 9. RSS bias estimation in the HT-DDKF.

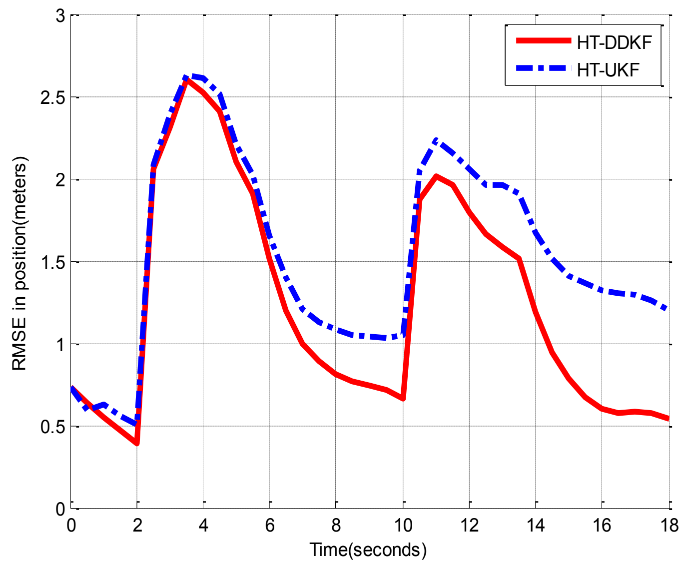

Figure 10. RMSE in position obtained with the HT-DDKF and the HT-UKF.

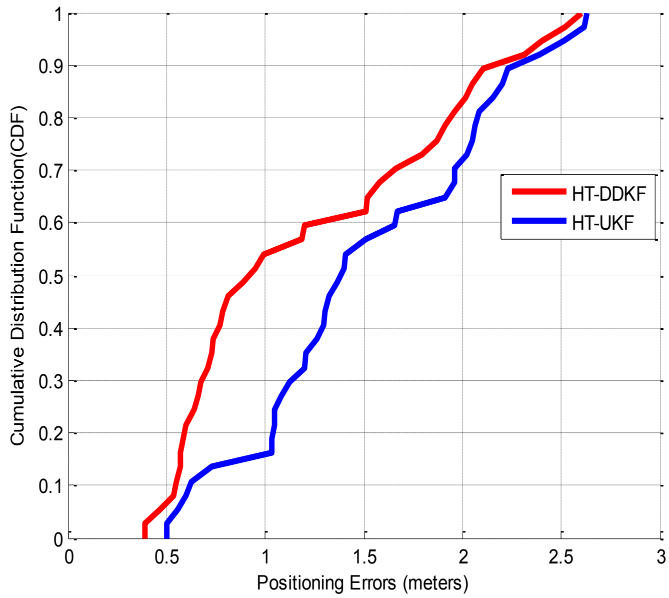

Figure 11. Cumulative distribution function of the location errors of the HT-DDKF and the HT-UKF.

IV. CONCLUSIONS

The problem addressed in this paper concerns mobile localization in mixed LOS/NLOS environments. To solve this problem, we propose as a solution the joint use of a nonlinear Kalman filter and a sub linear Kalman filter; the former is dedicated to the estimation of the state vector (position and velocity) of the mobile, whereas the latter is used to estimate the bias, due to NLOS propagation. To mitigate the effect of this bias a hypothesis test is performed, based on the estimated biases. Two nonlinear variants of the Kalman filter were tested, the Unscented Kalman Filter and the Divided Difference Kalman Filter. The presented results show the efficiency of both filters, with an advantage in terms of precision in favor of the latter one.

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