Adaptive Mobile Location Estimator with NLOS Mitigation using Fuzzy Inference Scheme

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Abstract — **This paper proposes a fuzzy line of sight (LOS)/non-line of sight (NLOS) smoother based on an adaptive Kalman filter, which can be used for mobile location estimation with the time of arrival (TOA) measurement data in cellular networks to meet the Federal Communications Commission (FCC) requirement for phase Ⅱ. A fuzzy inference scheme is used by the proposed location estimator to detect LOS condition, NLOS condition or LOS/NLOS transition condition and to estimate the noise covariance via fuzzy interpolation. With an accurate estimation of noise covariance, an adaptive Kalman filter is proposed for the range estimation between the base station (BS) and mobile station (MS). Therefore, the proposed mobile location estimator can efficiently mitigate the NLOS effects of the simulated measurement range error even changing condition between LOS and NLOS. Simulation results demonstrate that the performance of the proposed fuzzy LOS/NLOS smoother is improved significantly over the FCC target in both fixed LOS/NLOS and LOS/NLOS transition condition, and outplays other location estimators employing the Kalman filter and NLOS mitigation techniques.**

Ⅰ. INTRODUCTION

Mobile position location has attracted considerable interest in recent research. The mobile location service was driven by FCC, which mandated the wireless networks to provide the location for emergency calls. The Enhanced 911 demands the location accuracy requirement for phase Ⅱ as 100 m for 67% of time and 300 m for 95% of time for network-based location systems [1].

The most accurate and popular position location system is the Global Positioning System (GPS), but it is currently not a viable option for solving the Enhanced 911 location problem due to the expense and technical challenge of replacement of all existing cellular handsets with GPS receivers. Therefore, we limit discussion in this study to those techniques which can be used with existing handsets. Recently, several methods have been employed to estimate the mobile location, signal strength [2], time difference of arrival (TDOA) [3], time of arrival (TOA) [4], and angle of arrival (AOA) in cellular networks. Hearability and NLOS problems are the two biggest challenges for accurate mobile location estimation. When a mobile station is near the serving BS, it must reduce its power to avoid causing interference to other users. However, a too weak transmitted power may not be received by three or more nearby BSs to detect and estimate the mobile location. To solve this problem, the Power Up Function (PUF) was recommended for the current cellular network system IS-95B [4]. Furthermore, in an NLOS condition, the range measurement data was analyzed in [5], and the mean and the standard deviation of range measurement error were in the order of 513 m and 436 m, respectively. NLOS mitigation techniques [6, 7] are necessary for canceling the effects of NLOS measurement error. The Kalman filter was employed in [7] for mobile range measurement smoothing and NLOS effects mitigation. In a realistic condition, the communication channel between the corresponding BS and MS is often changed when the mobile moves randomly with different velocities and accelerations. The LOS/NLOS transition condition will cause a serious measurement error for the range estimation, because the covariance matrices of the measurement noise employed by the corresponding Kalman filter are not adaptively adjusted to match the true covariance variation in the LOS and NLOS cases.

In this paper, we propose a fuzzy LOS/NLOS smoother-based adaptive Kalman filter, which can be used for mobile location estimation with the TOA measurement data in cellular networks to meet the FCC requirement for phaseⅡ. A moving estimation window is employed to calculate the real covariance of the simulated measurement data for real-time identification of LOS/NLOS conditions. A fuzzy logic system is introduced to effectively describe the possible changes among LOS, NLOS and transition condition in cellular networks. Therefore, the fuzzy inference system can be used to mitigate the NLOS effects by a more accurate covariance estimate. With the accurate total noise covariance estimated by the proposed fuzzy inference scheme through fuzzy interpolation, we can employ an adaptive Kalman filter with total noise covariance to smoothly estimate the range distance between the corresponding BS and MS. Simulation results demonstrate that performance of the proposed fuzzy LOS/NLOS smoother is further over the FCC target of both fixed LOS/NLOS and LOS/NLOS transition conditions.

Ⅱ. SYSTEM MODEL AND THE PROPOSED MOBILE LOCATION ESTIMATOR ARCHITECTURE

The architecture of the proposed mobile location estimator is illustrated in Figure 1, the raw TOA measurement data at consecutive time samples obtained from different BSs are first calculated to identify any NLOS condition by a moving estimation window. The proposed adaptive identification of LOS/NLOS condition techniques instead of repeatedly checking in [7] is expected to get a better accuracy of location estimation in the complicated mobile environment. According to [6], when the NLOS condition exists, the measurement error covariance is significantly greater than the case of LOS. In the proposed location estimator, a fuzzy inference scheme is employed to mitigate the NLOS effects by a more accurate covariance estimation through fuzzy interpolation method. From the accurately estimated covariance by fuzzy inference scheme, we can apply an adaptive Kalman filter with the total noise covariance update every iteration to smoothly estimate the range distance between the corresponding BS and MS. Finally, these estimated range distances between the three BSs and MS can be calculated to obtain the MS location estimation.

A. System Model

Assume that there are K BSs to detect the range signal from the MS. The simulated range measurement corresponding to TOA data between BS_k and MS at time t_n can be modeled as [6, 7]

$$r_k(t_n) = d_k(t_n) + n_k(t_n) + NLOS_k(t_n), \quad k = 1, \cdots K \quad (1)$$

where $d_k(t_n)$ is the true range between the corresponding BS_k and MS, $n_k(t_n)$ is the measurement noise modeled as a zero mean white Gaussian noise $N(0,\sigma_m)$, and $NLOS_k(t_n)$ is the NLOS measurement error of the kth BS at time sample t_n, the NLOS measurement error can be modeled as a positive mean white Gaussian noise $N(m_{NLOS},\sigma_{NLOS})$ [5, 6]. In an LOS case, the BS range measurement is only corrupted by the system measurement noise $n_k(t_n)$. In this situation, there is no NLOS measurement error and $NLOS_k(t_n)$ can be set to zero. Otherwise, in an NLOS case, the range measurement is corrupted by two sources of errors, $n_k(t_n)$ and $NLOS_k(t_n)$. Measurements taken by Nokia [5] confirm that the NLOS problem dominates the measurement error in the range estimation for the mobile location. We can further transfer the range measurement model in (1) to a corresponding discrete time sequence as

$$r_k(n) = d_k(n) + m_{k\_NLOS} + b_k(n)w_k(n), \quad k = 1, \cdots K \quad (2)$$

where m_{k_NLOS} is the NLOS range offset between the corresponding BS_k and MS, $w_k(n)$ is the normalized zero mean white Gaussian noise $N(0,1)$, and $b_k(n)$ is the standard deviation of the total range measurement error for both LOS and NLOS effects between the corresponding BS_k and MS. So the m_{k_NLOS} and $b_k(n)$ can be defined respectively as :

$$m_{k\_NLOS} = \begin{cases} 0, & \text{if LOS condition} \\ m_{NLOS}, & \text{if NLOS condition} \end{cases}$$

$$b_k(n) = \begin{cases} \sigma_m, & \text{if LOS condition} \\ \sqrt{\sigma_m^2 + \sigma_{NLOS}^2}, & \text{if NLOS condition} \end{cases} \quad (3)$$

B. Moving Window for LOS/NLOS Identification

For the purpose of LOS/NLOS identification, we employ a moving estimation window with size M to make a real-time calculation for the standard deviation $\hat{\sigma}_{m\_k}$ of the range measurement error for the BS_k. This means that the last M samples of $r_k(n)$ are used to calculate its rough covariance of the range measurement error. The window size is chosen empirically to make a better statistical smoothing performance. The rough standard deviation of the range measurement error can be calculated by

$$\hat{\sigma}_{m\_k}(n) = \sqrt{\frac{1}{M}\sum_{j=n-M+1}^{n}(r_k(j) - \bar{r}_k(n))^2}, \; for\, k = 1, \cdots K \quad (4)$$

where $\bar{r}_k(n)$ is the window average mean of $r_k(j)$ from $j = n - M + 1$ to $j = n$ and can be expressed as

$$\bar{r}_k(n) = \frac{1}{M}\sum_{j=n-M+1}^{n} r_k(j) \qquad for \quad k = 1, \cdots K \quad (5)$$

From the proposed moving estimation window, when NLOS condition exists, the measured standard deviation will be significantly greater than the case of LOS. The if-then conditions and their transition condition in (3) can be effectively modeled by a fuzzy logic system, and a fuzzy inference scheme can be used by the proposed location estimator to detect LOS condition, NLOS condition or LOS/NLOS transition condition. And the rough standard deviation $\hat{\sigma}_{m\_k}$ is the input of the fuzzy inference logic system to obtain a more accurate standard deviation and NLOS range offset estimation.

C. Fuzzy Inference System for estimation of the Standard Deviation of the Range Measurement Error

The fuzzy rule base is the control policy knowledge, characterized by a set of linguistic statement with the form of IF-THEN rules [8]. Here, a set of fuzzy rules is defined to describe the fuzzy logic relationship between the measured standard deviation $\hat{\sigma}_{m\_k}(n)$, the estimated standard deviation $\hat{b}_k(n)$ and the NLOS range offset $\hat{m}_{k\_NLOS}(n)$. With membership functions shown in Figure 1, a fuzzy inference logic-based estimator for the estimation of standard deviation and NLOS range offset is proposed as:

Rule 1: If $\hat{\sigma}_{m\_k}(n)$ is *small*

$$\text{Then } \hat{b}_k(n) = \sigma_m \quad and \quad \hat{m}_{k\_NLOS}(n) = 0 \quad (6)$$

Rule 2: If $\hat{\sigma}_{m\_k}(n)$ is *large*

$$\text{Then } \hat{b}_k(n) = \sqrt{\sigma_m^2 + \sigma_{NLOS}^2} \quad and \quad \hat{m}_{k\_NLOS}(n) = m_{NLOS} \quad (7)$$

The fuzzy inference-based estimator for the standard deviation and the NLOS range offset in (6) and (7) are equivalent to the following interpolatory forms [8]

$$\begin{aligned} &\hat{b}_k(n) = \mu_1(n) \times \sigma_m + \mu_2(n) \times \sqrt{\sigma_m^2 + \sigma_{NLOS}^2} \\ &and \quad \hat{m}_{k\_NLOS}(n) = \mu_2(n) \times m_{NLOS} \end{aligned} \quad (8)$$

respectively, where

$$\mu_1(n) = Z_1(\hat{\sigma}_{m\_k}(n)) / (Z_1(\hat{\sigma}_{m\_k}(n)) + Z_2(\hat{\sigma}_{m\_k}(n)))$$

and

$$\mu_2(n) = Z_2(\hat{\sigma}_{m\_k}(n)) / (Z_1(\hat{\sigma}_{m\_k}(n)) + Z_2(\hat{\sigma}_{m\_k}(n)))$$

in which $Z_j(\hat{\sigma}_{m\_k}(n))$ is the membership function of $\hat{\sigma}_{m\_k}(n)$ for j = 1, 2, and $\mu_1(n) + \mu_2(n) = 1$ in Figure 1. The estimation in (8) is based on the possibilities of noises in LOS, NLOS and LOS/NLOS transition state. Therefore, the fuzzy inference-based estimator in (8) is suitable for estimation under different noise situations, especially in the transition condition between LOS and NLOS through the fuzzy interpolation techniques. After the accurate estimation of standard deviation of the range measurement noise and NLOS range offset by the proposed fuzzy inference scheme, the range distances between the corresponding BSs and MS are estimated by the range measurement model in (2). With the fuzzy inference-based estimator to update the standard deviation $\hat{b}_k(n)$, we can employ an adaptive Kalman filter to smoothly estimate the range distance between the corresponding BS and MS in the next section.

Ⅲ. SMOOTH RANGE ESTIMATION USING ADAPTIVE KALMAN FILTER

A. State Space Signal Model

From the range measurement model in (2), we assume that there are three BSs to detect the range signal from the MS, i.e., K=3, so we can define a state vector

$$\boldsymbol{x}\ (n) = [d_1(n) \quad d_2(n) \quad d_3(n) \quad \dot{d}_1(n) \quad \dot{d}_2(n) \quad \dot{d}_3(n)]^T \tag{9}$$

and dynamics of the state equation can be expressed as

$$\boldsymbol{x}(n+1) = \boldsymbol{F}\,\boldsymbol{x}(n) + \boldsymbol{C}\boldsymbol{v}(n) \tag{10}$$

$$\boldsymbol{r}\ (n) = \boldsymbol{G}\,\boldsymbol{x}(n) + \boldsymbol{m} + \boldsymbol{B}(n)\boldsymbol{w}(n) \tag{11}$$

where

$$\boldsymbol{F} = \begin{bmatrix} 1 & 0 & 0 & T_s & 0 & 0 \\ 0 & 1 & 0 & 0 & T_s & 0 \\ 0 & 0 & 1 & 0 & 0 & T_s \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad \boldsymbol{C} = \begin{bmatrix} T_s^2/2 & 0 & 0 \\ 0 & T_s^2/2 & 0 \\ 0 & 0 & T_s^2/2 \\ T_s & 0 & 0 \\ 0 & T_s & 0 \\ 0 & 0 & T_s \end{bmatrix} \tag{12}$$

$$\boldsymbol{v}(n) = [v_1(n) \quad v_2(n) \quad v_3(n)]^T, \tag{13}$$

T_s is the sample period, and $\boldsymbol{v}(n)$, dependent on the acceleration of the MS, is the process driving noise. Here, we model $v_k(n)$ as a Gaussian random process with zero mean and variance σ_v^2 for k = 1, 2 and 3. The simulated range measurement signal according to TOA data can be expressed as

$$\boldsymbol{r}(n) = [r_1(n) \quad r_2(n) \quad r_3(n)]^T,$$

and

$$\boldsymbol{G} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}, \quad \boldsymbol{B}(n) = \begin{bmatrix} b_1(n) & 0 & 0 \\ 0 & b_2(n) & 0 \\ 0 & 0 & b_3(n) \end{bmatrix} \tag{14}$$

where $b_k(n)$ is the standard deviation of the total range measurement error between the corresponding BS_k and MS. $\boldsymbol{w}(n) = [w_1(n) \quad w_2(n) \quad w_3(n)]^T$, where $w_k(n)$ is a independent identically distributed (*i.i.d.*) normalized zero mean white Gaussian noise $N(0,1)$,
and

$$\boldsymbol{m} = [m_{1\_NLOS}(n) \quad m_{2\_NLOS}(n) \quad m_{3\_NLOS}(n)]^T \tag{15}$$

are the NLOS range offsets between the three individual BSs and MS. The standard deviation $b_k(n)$ and NLOS range offset $m_{k\_NLOS}(n)$ can be estimated by the proposed fuzzy inference-based estimator in (8). Therefore, the dynamics of the state equation in (10) and (11) can be modified as follows

$$\boldsymbol{x}(n+1) = \boldsymbol{F}\,\boldsymbol{x}(n) + \boldsymbol{C}\boldsymbol{v}(n) \tag{16}$$

$$\boldsymbol{r'}\ (n) = \boldsymbol{G}\,\boldsymbol{x}(n) + \boldsymbol{B}(n)\boldsymbol{w}(n) \tag{17}$$

where $\boldsymbol{r'}(n) = \boldsymbol{r}(n) - \boldsymbol{m}$, is the non-NLOS range offset measurement data. Then this measurement data is employed by an adaptive Kalman filter to estimate the smooth range $\boldsymbol{x}(n)$ between the corresponding BS and MS. However, since the covariance of $\boldsymbol{B}(n)$ is uncertain due to the transition between LOS and NLOS condition, the fuzzy inference scheme (8) is employed to update the total noise covariance of the Kalman filter every iteration to achieve a precise estimation of smooth range.

B. Range Estimation Using Adaptive Kalman Filter

From the dynamics of the state equation in (16) and (17), the adaptive Kalman filter algorithm [9] can be employed for the smooth range estimation.

$$\hat{\boldsymbol{x}}(n) = \boldsymbol{F}\hat{\boldsymbol{x}}(n-1) + \boldsymbol{K_a}(n)\boldsymbol{e}(n) \tag{18}$$

where $\boldsymbol{e}(n) = \boldsymbol{r'}(n) - \boldsymbol{GF}\hat{\boldsymbol{x}}(n-1)$ denotes the innovation process of the range prediction error, and $\boldsymbol{K}_a(n)$ is the Kalman filter gain, which is employed to minimize the covariance $E\{\boldsymbol{e}^T(n)\boldsymbol{e}(n)\}$ of the smooth range prediction error. The Kalman filter gain and the error covariance matrices of the smooth range prediction and estimation are obtained from the following equations [9]

$$\boldsymbol{P_{n|n-1}} = \boldsymbol{F}\boldsymbol{P_{n-1}}\boldsymbol{F}^T + \boldsymbol{C}\boldsymbol{Q_v}\boldsymbol{C}^T \tag{19}$$

$$\boldsymbol{K_a}(n) = \boldsymbol{P_{n|n-1}}\boldsymbol{G}^T[\boldsymbol{G}\boldsymbol{P_{n|n-1}}\boldsymbol{G}^T(n) + \boldsymbol{Q_B}]^{-1} \tag{20}$$

$$\boldsymbol{P_n} = [\boldsymbol{I} - \boldsymbol{K_a}(n)\boldsymbol{G}]\boldsymbol{P_{n|n-1}} \tag{21}$$

where

$$\boldsymbol{Q_v} = E\{\boldsymbol{v}(n)\boldsymbol{v}^T(n)\} = \sigma_v^2 \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{22}$$

$$\boldsymbol{Q_B} = E\{\boldsymbol{B}(n)\boldsymbol{B}^T(n)\} = \begin{bmatrix} b_1^2(n) & 0 & 0 \\ 0 & b_2^2(n) & 0 \\ 0 & 0 & b_3^2(n) \end{bmatrix} \tag{23}$$

where $b_k^2(n)$ is the variance of total measurement error between the corresponding BS_k and MS, which is updated every iteration by the proposed fuzzy inference-based estimator in (8). In this situation, the algorithm (18)-(23) and (8) is called an adaptive Kalman filter. Without the fuzzy inference-based estimator in (8), the algorithm (18)-(23) is only a Kalman filter with fixed covariance. The error covariance matrices of the range prediction and estimation are given by

$$\begin{aligned} \boldsymbol{P_{n|n-1}} &= E\{[\boldsymbol{x}(n) - \boldsymbol{F}\hat{\boldsymbol{x}}(n-1)][\boldsymbol{x}(n) - \boldsymbol{F}\hat{\boldsymbol{x}}(n-1)]^T\} \\ \boldsymbol{P_n} &= E\{[\boldsymbol{x}(n) - \hat{\boldsymbol{x}}(n)][\boldsymbol{x}(n) - \hat{\boldsymbol{x}}(n)]^T\} \end{aligned} \tag{24}$$

Therefore, from the estimated state vector $\hat{\boldsymbol{x}}(n)$, the mobile smooth range output can be obtained by

$$\hat{\boldsymbol{d}}(n) = [\hat{d}_1(n) \quad \hat{d}_2(n) \quad \hat{d}_3(n)]^T = \boldsymbol{T}\hat{\boldsymbol{x}}(n) \tag{25}$$

where

$$\boldsymbol{T} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

After the accurate estimation of the range distances between the corresponding BS_k and MS, we can calculate the mobile location from $\hat{\boldsymbol{d}}(n)$ in (25) by the geometric method in [2].

C. Performance Analysis of Smooth Range Estimation

In this subsection, we analyze the performance of the smooth range estimations between the BSs and MS for the proposed fuzzy LOS/NLOS smoother-based adaptive Kalman filter. For a sufficiently large N_0, according to (17), (18) can be approximated by

$$\begin{aligned} \hat{\boldsymbol{x}}(n) &= \sum_{i=0}^{N_0}\left(\prod_{j=n-i+1}^{n}\boldsymbol{\Theta}(j)\right)\boldsymbol{K_a}(n-i)[\boldsymbol{G}\,\boldsymbol{x}(n-i) + \boldsymbol{B}(n-i)\boldsymbol{w}(n-i)] \\ &= \boldsymbol{\Phi}(n)\bar{\boldsymbol{x}}(n) + \boldsymbol{\Psi}(n)\bar{\boldsymbol{w}}(n) \end{aligned} \tag{26}$$

where

$$\prod_{j=n_1}^{n_2}\boldsymbol{\Theta}(j)=\begin{cases}\boldsymbol{\Theta}(n_1)\boldsymbol{\Theta}(n_1+1)\cdots\boldsymbol{\Theta}(n_2), & if\ n_2\ge n_1\\ \boldsymbol{I}, & if\ n_2<n_1\end{cases}$$

$$\boldsymbol{\Theta}(n)=(\boldsymbol{I}-\boldsymbol{K_a}(n)\,\boldsymbol{G})\boldsymbol{F},$$

$$\overline{\boldsymbol{x}}(n)=[\boldsymbol{x}^T(n),\,\boldsymbol{x}^T(n-1),\cdots\boldsymbol{x}^T(n-N_0)]^T,$$

$$\overline{\boldsymbol{w}}(n)=[\boldsymbol{w}^T(n),\,\boldsymbol{w}^T(n-1),\cdots\boldsymbol{w}^T(n-N_0)]^T,$$

$$\boldsymbol{\Phi}(n)=[\boldsymbol{K_a}(n),\ \boldsymbol{\Theta}(n)\boldsymbol{K_a}(n-1),\ \cdots\ \left(\prod_{j=n-N_0+1}^{n}\boldsymbol{\Theta}(j)\right)\boldsymbol{K_a}(n-N_0)]\boldsymbol{G},$$

$$\boldsymbol{\Psi}(n)=[\boldsymbol{K_a}(n)\boldsymbol{B}(n),\ \boldsymbol{\Theta}(n)\boldsymbol{K_a}(n-1)\boldsymbol{B}(n-1),\ \cdots\ \left(\prod_{j=n-N_0+1}^{n}\boldsymbol{\Theta}(j)\right)\boldsymbol{K_a}(n-N_0)\boldsymbol{B}(n-N_0)]$$

in which the Kalman filter gain $\boldsymbol{K_a}(n)$ is defined in (20), and $\boldsymbol{B}(n)$ is defined in (14) as the standard deviation matrix, whose components b_k(n) are adaptively adjusted by the proposed fuzzy scheme in (8) to match the transmission channel transitions between LOS and NLOS conditions. The smooth range estimation of the kth BS for the proposed location estimator is given by

$$\hat{d}_k(n)=\boldsymbol{\varphi}_k^T(n)\overline{\boldsymbol{x}}(n)+\boldsymbol{\psi}_k^T(n)\overline{\boldsymbol{w}}(n),\quad for\ k=1,\cdots K \qquad (27)$$

where $\boldsymbol{\varphi}_k(n)$ and $\boldsymbol{\psi}_k(n)$ are the kth column vectors of the matrices $\boldsymbol{\Phi}^T(n)$ and $\boldsymbol{\Psi}^T(n)$, respectively. The mean square error of the smooth range estimation between the BS$_k$ and MS can be expressed by

$$\begin{aligned}Q_{d_k}&=E[(d_k(n)-\hat{d}_k(n))(d_k(n)-\hat{d}_k(n))^T]\\&=d_k^2(n)-2d_k(n)E[\hat{d}_k(n)]+E[\hat{d}_k^2(n)]\end{aligned} \qquad (28)$$

where

$$E[\hat{d}_k(n)]=\boldsymbol{\varphi}_k^T(n)\,\overline{\boldsymbol{x}}(n)$$

$$\begin{aligned}E[\hat{d}_k^2(n)]&=E[(\boldsymbol{\varphi}_k^T(n)\overline{\boldsymbol{x}}(n)+\boldsymbol{\psi}_k^T(n)\overline{\boldsymbol{w}}(n))\,(\boldsymbol{\varphi}_k^T(n)\overline{\boldsymbol{x}}(n)+\boldsymbol{\psi}_k^T(n)\overline{\boldsymbol{w}}(n))^T]\\&=\boldsymbol{\varphi}_k^T(n)\overline{\boldsymbol{x}}(n)\overline{\boldsymbol{x}}^T(n)\boldsymbol{\varphi}_k+\boldsymbol{\psi}_k^T(n)\boldsymbol{\psi}_k(n)\end{aligned}$$

in which $\boldsymbol{\varphi}_k(n)$ is the column vector of $\boldsymbol{\Phi}^T(n)$ associated with the desired range distance $d_k(n)$, and $\boldsymbol{\psi}_k(n)$ is the column vector of $\boldsymbol{\Psi}^T(n)$ associated with the total noise effect. The mean square error in (28) can be rewritten as

$$Q_{d_k}=d_k^2(n)-2d_k(n)\boldsymbol{\varphi}_k^T(n)\overline{\boldsymbol{x}}(n)+\boldsymbol{\varphi}_k^T(n)\overline{\boldsymbol{x}}(n)\overline{\boldsymbol{x}}^T(n)\boldsymbol{\varphi}_k+\boldsymbol{\psi}_k^T(n)\boldsymbol{\psi}_k(n) \qquad (29)$$

The fuzzy inference scheme can efficiently mitigate the NLOS effects of range measurement error by adaptively adjusting the standard deviation $b_k(n)$ and $\boldsymbol{Q_B}(n)$, which is defined in (23), to make the item $\boldsymbol{\psi}_k^T(n)\boldsymbol{\psi}_k(n)$ in (29) is as small as possible to improve the performance of smooth range estimation.

Ⅳ. SIMULATION RESULTS

Simulation results are provided to demonstrate the validity of the proposed mobile location estimator and to compare the relative accuracy of mobile location estimation for different approaches. We assume that the vehicle has a steady velocity of 70 km/hr and move in a straight line [6]. The sample length is 1000, and the sample interval is equal to 0.2s. The measurement noise and NLOS noise are added to the true range distance to generate the simulated range measurement data. The measurement noise is assumed to be a white random variable with zero mean and standard deviation σ_m =150 m, whereas the NLOS measurement noise is also assumed to be a white random variable with positive mean m_{NLOS} = 513 m and standard deviation σ_{NLOS} = 409 m [6].

Two conditions [7] are considered to simulate the mobile communication environment. The first case is the fixed LOS/NLOS condition, and the second case is the LOS/NLOS transition condition with the LOS or NLOS condition of each BS being changed for each 200 samples in a random way. In both the cases, we assume that there are three BSs to detect the range signal from MS. For the proposed mobile location estimator, we employ a moving estimation window to adaptively identify LOS/NLOS condition of the corresponding BS, and the window size M = 20 is chosen empirically to make the statistical smoothing achieve a better performance. In each simulation case, 10 simulations are performed with the same parameters and the mobile location error is calculated from the average with the elimination of the first 100 samples. The variance of the total range measurement noise between the corresponding BS$_k$ and MS, $b_k^2(n)$ in (23), can be determined in (8) by the proposed fuzzy inference system, and σ_v^2 in (22) is the driving noise variance, which depends on the acceleration of the vehicle (MS). In this simulation, a small value σ_v^2 =1 m/s^2 can be chosen.

In the fixed LOS/NLOS condition, the simulation result demonstrates that the proposed Kalman smoother can closely track the true distance between the corresponding BS and MS. These simulation results of location estimation error for four different cases in the fixed LOS/NLOS condition are summarized in Table 1. The location estimation errors of the four cases in the fixed LOS/NLOS condition are further below the FCC target (for 67% location error at 100 m and 95% location error at 300 m). In the LOS/NLOS transition condition, the conventional Kalman filter-based location estimator would be difficult to estimate the accurate range distance between the corresponding BS and MS. Figure 2 shows the range estimation by the proposed Kalman LOS smoother (18)-(23), which uses the LOS noise covariance parameters in the LOS/NLOS transition condition, and simulation results illustrate that the proposed Kalman LOS smoother cannot exactly track the true range distance. Figure 3 shows the range estimation by the Rough LOS/NLOS smoother proposed in [7]. Since this location estimator includes the LOS/NLOS identification and NLOS mitigation techniques, it can accurately estimate the MS location in the LOS/NLOS transition condition than the previous LOS smoother. From the simulation results shown in Figure 4, the proposed fuzzy LOS/NLOS smoother can more correctly track the true distances between the corresponding BSs and MS than the Rough LOS/NLOS smoother in [7], especially in the transitional intervals. These results also demonstrate that the proposed fuzzy LOS/NLOS smoother can efficiently mitigate the NLOS measurement error even when the corresponding BS changes condition between LOS and NLOS.

The simulation results of location estimation error for the three different smoothers in the LOS/NLOS transition condition are summarized in Table 1. As described above, the LOS smoother cannot meet the FCC target in both

67% and 95% location error cases, and the Rough LOS/NLOS smoother cannot meet the FCC target with 67% location error at 126.47 m. The proposed fuzzy LOS/NLOS smoother has an excellent performance in 67% location error at 78.24 m and 95% location error at 161.73 m, and further over the FCC requirement.

V. CONCLUSIONS

This paper proposes a fuzzy LOS/NLOS smoother-based adaptive Kalman filter, which can be used for mobile location estimation in cellular networks to meet the FCC requirement for phase II. With the fuzzy interpolation to update the total noise covariance, an adaptive Kalman filter is used for the range estimation more accurately. Therefore, the proposed mobile location estimator can efficiently mitigate the NLOS effects of the simulated range measurement error. Simulation results demonstrate that the performance of the proposed fuzzy LOS/NLOS smoother-based adaptive Kalman filter can further meet the FCC target in both 67% and 95% location error cases in the fixed LOS/NLOS and LOS/NLOS transition conditions, and outplays other location estimators, which employ the Kalman filter and NLOS mitigation techniques.

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Table 1. Comparison of mobile location estimation errors among the proposed fuzzy Kalman-based smoother and conventional Kalman-based smoothers under the fixed LOS/NLOS and LOS/NLOS transition conditions.

Condition	Configuration/Algorithm	67% error (m)	95% error (m)
Fixed LOS/NLOS (by proposed Smoother)	3 LOS BSs, 0 NLOS BS	38.62	53.55
	2 LOS BSs, 1 NLOS BS	62.93	161.79
	1 LOS BS, 2 NLOS BSs	64.83	153.73
	0 LOS BS, 3 NLOS BSs	84.94	167.94
LOS/NLOS Transition	LOS Smoother	425.40	690.27
	Rough LOS/NLOS Smoother [7]	126.47	246.79
	Fuzzy Smoother (proposed)	78.24	161.73

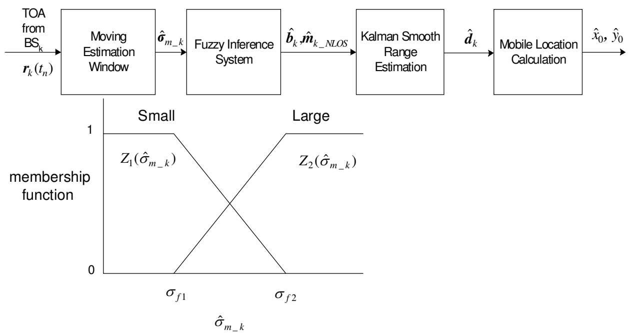

Fig. 1 Fuzzy-based mobile location estimator architecture and the corresponding fuzzy inference logic.

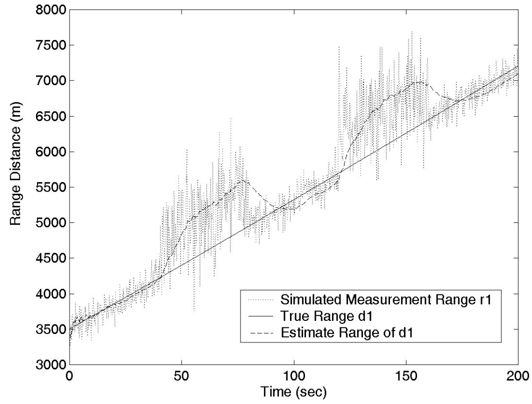

Fig. 2 Range estimation by the LOS Kalman smoother under LOS/NLOS transition condition without update of total noise covariance.

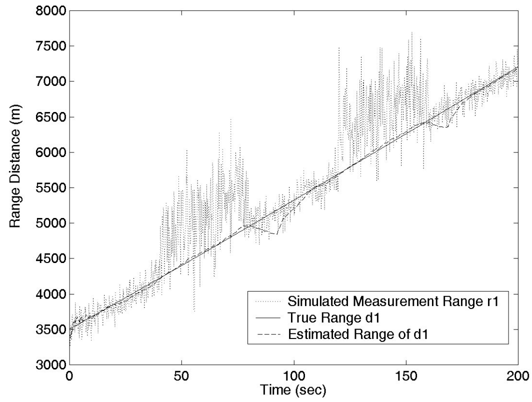

Fig. 3 Range estimation by Rough LOS/NLOS smoother in [7] under LOS/NLOS transition condition.

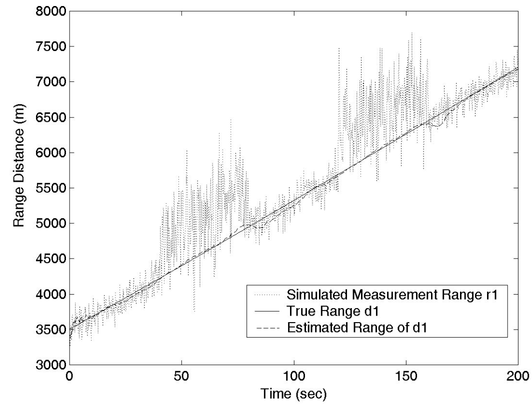

Fig. 4 Range estimation by the proposed fuzzy LOS/NLOS smoother under LOS/NLOS transition condition.