Abstract — In this paper, a range difference estimation technique with NLOS error mitigation by using biased Kalman filter for ultra-wideband (UWB) environments is presented. NLOS error is considered one of the major error sources in wireless location systems. To improve TDOA location accuracy in UWB location systems, NLOS identification and mitigation techniques suitable for UWB systems are derived. Kalman filters (KFs) are used for smoothing range data and mitigating NLOS errors. The simulation results show that the NLOS mitigation method with biased Kalman filter achieves high accuracy in range difference estimation for mobile positioning and tracking.

Key Words — range difference estimation, NLOS mitigation, Kalman filter, TDOA, ultra wideband (UWB).

I. INTRODUCTION

The time-based methods for locating mobile station in wireless systems usually involve the usage of location parameters, such as time of arrival (TOA) or time difference of arrival (TDOA). In general, the true range between a transmitter and a receiver in the wireless environment can be correctly calculated only when the direct path of signal propagation is present, which may not always be possible. Among the error sources which may affect the accuracy of wireless location, non-line of sight (NLOS) error is considered the major one. In wireless and indoor location systems, particularly where higher location accuracy is required, the effects caused by NLOS error usually cannot be ignored.

When line of sight transmission exists between a transmitter and a receiver, the signal arrival time may be correctly obtained if the SNR is high and the multipaths from the propagation channel are resolved properly. In situations where NLOS propagation exists, NLOS mitigation techniques can be used for improving the accuracy of ranging and localization.

Several NLOS mitigation techniques for mobile positioning systems have been presented in the past few years [1]—[4]. In [1], To mitigate the NLOS effects, polynomial fitting was applied to all available measured mobile range data for variance calculation and data smoothing by exploiting the known statistics of the receiver measurement noise. Since a block of measured data is needed for the process of polynomial fitting, accurate and real-time mobile positioning may not be possible due to the time delay for data collecting. [2] describes a technique for range estimation that can also be used to distinguish between LOS and NLOS range measurements. In other methods for mobile location estimation, biased versions of the Kalman filter were used in mitigating the NLOS range error [3]. With an experimentally chosen coefficient in determining the noise covariance matrix, good location estimation results could be obtained. In [4], a modified Kalman algorithm with NLOS bias estimation was proposed for UMTS mobile positioning. The estimation of range bias provided performance improvement of location tracking in NLOS environments.

Since most wireless communications systems used for indoor position location may suffer from NLOS and dense multipath situation, to obtain higher accuracy in determining signal arrival time becomes an important issue for the time-based wireless indoor location systems. As a good candidate for low-power high-speed wireless indoor communications, the ultra wideband (UWB) radio technology has gained many interests in recent years for its applications in wireless communications. In addition to the purpose of communications, the UWB system can provide users with the abilities of high accurate location estimation and tracking. In UWB communication systems, the fine resolution property of UWB signals is used to tackle the multipath effects. With the fine time resolution, the accuracy of UWB location systems can be within one inch. The UWB systems therefore provide potentially accurate ranging for indoor positioning and tracking. The ambiguity in ranging caused by the possible NLOS errors may, however, still yield an error in determining the true signal arrival time. Therefore, suitable NLOS identification and mitigation algorithms designed for wireless UWB location systems are needed for the improvement of location accuracy.

For evaluation and simulation of wireless personal area networks (WPANs) systems, the IEEE 802.15.3a standards task group has established a standard UWB channel model [5]. The UWB channel parameters and related statistical data provided by the task group are used in this paper for formulating the NLOS identification and mitigation techniques.

II. RANGE MEASUREMENT MODEL AND NLOS IDENTIFICATION

The range measurement between a mobile station and a single base station corresponding to TOA data of the m-th base stations can be modeled as

\[ r_m(t_i) = L_m(t_i) + n_m(t_i) + NLOS_m(t_i) \]  \hspace{1cm} (1)

where \( r_m(t_i) \) is the measured range at the sampling time \( t_i \), \( L_m(t_i) \) is the true range, \( n_m(t_i) \) is the measurement noise.
and can be modeled as a zero-mean additive Gaussian random variable with variation \( \sigma_m \), and \( \text{NLOS}(t) \) is the NLOS error component in the received signal. There is no NLOS error if the line-of-sight exists, and \( \text{NLOS}(t) = 0 \). The measurement error \( \eta_m(t) \) becomes the only source of range measured error.

In a dense multipath environment, the estimation of the arrival time of the first path can be directly related to the range data at each base station, as in (1). The IEEE UWB channel modeling subcommittee adopted a modified Saleh-Velazenuela (S-V) model, which seemed to best fit the UWB channel measurements [5]. The S-V model was used to model the multipath of an indoor environment for wideband channel. The channel measurements showed that multipath arrivals in clusters rather than in a continuous form [6]. Assume that \( T_0 \) is the arrival time of the first path in the first cluster. The arrival time \( T_0 \) can be related to the positive NLOS error component \( NLOS(t) \) at the time instant \( t_i \). For the LOS cases, we have \( T_0 = 0 \) and \( NLOS(t_i) = T_0 \times c = 0 \) and \( c \) is the speed of light. The arrival time \( T_0 \) for the NLOS cases can be modeled as an exponential distribution and described by the following formula [5]

\[
p(T_0) = \Lambda \exp[-\Lambda(T_0)]
\]

where \( \Lambda[1/\text{nsec}] \) is the cluster arrival rate.

To mitigate the NLOS errors \( NLOS(t_i) \), the existence of non-zero NLOS component needs to be identified first. The range (or TOA) measurements related to each base station can be smoothed by using least squares technique to solve the coefficients for the modeled \( N \)-th order polynomial fit [1]. To calculate the standard deviation of the measured range data, (3) can be applied over a block of \( K \) range data \( r_m(t_i) \) periodically.

\[
\hat{\sigma}_m = \sqrt{\frac{1}{K} \sum_{i=1}^K (r_m(t_i) - S_m(t_i))^2}
\]

where \( S_m(t_i) \) is the smoothed range data, which are obtained from polynomial fitting. The range data can also be smoothed by using Kalman filters [3]. In this case, the smoothed range data \( S_m(t_i) \) is obtained from Kalman filtering. The standard deviation estimated in (3) can then be used in a simple hypothesis testing:

\[
H_0 : \hat{\sigma}_m < \gamma \sigma_m \quad \text{LOS case}
\]

\[
H_1 : \hat{\sigma}_m \geq \gamma \sigma_m \quad \text{NLOS case}
\]

where \( \gamma \sigma_m \) is the standard deviation of the measurement noise in the LOS environment. The scaling parameter \( \gamma \) is chosen experimentally for the testing to reduce the probability of false alarm [3]. In this paper, a scaling value \( \gamma = 1.6 \) is chosen for the UWB channels.

In applying the hypothesis testing, a periodical interval checking method, considered as an improved method from polynomial fit, was proposed in [3]. The periodical NLOS/LOS checking method, however, includes some drawbacks. First, all the block of data samples for variance calculation needs to be chosen experimentally. Secondly, the period of hypothesis testing may not be easily determined and must be decided experimentally as well. In addition, since the NLOS/LOS hypothesis testing result is assumed to be the channel situation until the next periodical checking result is obtained, it is very likely that the NLOS-to-LOS or LOS-to-NLOS transition time cannot be detected correctly.

To avoid the above-mentioned drawbacks, the method with a sliding window is proposed in this paper for processing the measured range data of UWB location system. The function of the sliding window method spans data smoothing, calculation of standard deviation, and identification of the NLOS/LOS condition in UWB systems.

Assume that there are \( M \) base stations available for measuring the TOA for locating a mobile station. For a location system with \( M \) base stations, the range difference of the \( m \)-th and the 1-st base stations between mobile station can be modeled as [7]

\[
d_m(t_i) = r_m(t_i) - r_1(t_i)
\]

where \( n_{d,m}(t_i) \) is the measurement noise of the range difference, then \( n_{d,m}(t_i) = n_{m,1}(t_i) - n_1(t_i) \) and \( \text{NLOS}_{d,m} \) is the NLOS error of the range difference, then \( \text{NLOS}_{d,m} = \text{NLOS}(t_i) - \text{LOS}(t_i) \). Hence \( n_{d,m}(t_i) \) can be modeled as a random variable with the joint pdf of a zero-mean independent and identically Gaussian distribution with variation \( \sigma_m \), then \( n_{d,m}(t_i) \sim N(0, 2 \sigma_m^2) \).

III. KALMAN FILTER FOR SMOOTHING DATA AND NLOS MITIGATION

A Kalman filter can be used in estimating the state vector of a mobile target from the observed range data, and therefore smoothing the range data. Assume that the state vector of a mobile can be represented as in [8]

\[
S(k+1) = AS(k) + GW(k),
\]

where \( S(k) = [r(k) \ i(k)]^T \) is the state vector of the mobile related to a base station at the time \( t_k \), \( W(k) \) is the driving noise vector with covariance matrix \( Q = \sigma_n^2 \), and

\[
A = \begin{bmatrix} 1 & \Delta t & \Delta t^2 / 2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}, \quad \Gamma = \begin{bmatrix} 0 \\ 0 \\ \Delta t \end{bmatrix}.
\]

The measurement process can be written as

\[
Z(k) = HS(k) + U(k)
\]

where \( Z_k \) is the measured data, \( H = [1 \ 0 \ 0] \), and \( U(k) \) is the measurement noise with covariance \( R = \sigma_n^2 \). The iterative operation of the Kalman filter can be summarized as follows:

\[
S(k+1|k) = AS(k|k)
\]

\[
C(k+1|k) = AC(k|k)A^T + \Gamma Q \Gamma^T
\]

\[
K = C(k+1|k)H^T (HC(k+1|k)H^T + R)^{-1}
\]

\[
C(k+1|k+1) = C(k+1|k) - KHHC(k+1|k)
\]
\[ S(k+1|k) = S(k+1|k) + K(Z(k+1) - HS(k+1|k)) \]  

where \( K \) is the Kalman gain vector and \( C(k|k) \) is the covariance matrix of \( S(k|k) \) .

From the process of Kalman filtering, the standard deviation of the observed range data can be calculated and then used in NLOS/LOS hypothesis testing. To avoid the drawbacks of using polynomial fitting or periodical interval checking method, as mentioned in the previous subsection, a sliding window is proposed for processing the measured range data of UWB location system. The standard deviation of data over a sliding block of \( K \) range measurements \( r_{mk}(t_i) \) at the \( m \)-th base station can be obtained by

\[
\hat{\sigma}_{r,m,k} = \sqrt{\frac{1}{K} \sum_{i=1}^{K} \left( r_{mk}(t_i) - S_{m}(t_i) \right)^2} 
\]

The standard deviation of the measured range data at base station \( m \) is obtained and used for hypothesis testing during each process cycle, as in (4).

In this paper, the model parameters of UWB channel models [5] under LOS and NLOS cases are used in simulations of the testing rule. With the results from range data smoothing and NLOS/LOS checking, NLOS mitigation are achieved through the iterative Kalman filtering process.

Range difference estimation with NLOS mitigation for TDOA data processing, a Kalman filter is applied. It is assumed that BS \( n \) is used as the reference station in the TDOA formulation. Similar to the Kalman filter in smoothing stage, biased versions of Kalman filters are applied here. The state vector is

\[ S(k) = \begin{bmatrix} L_{m,1}(k) \\ L_{m,2}(k) \\ L_{m,3}(k) \end{bmatrix} \]

where \( L_{m,i}(k) \) is the true range difference. The biased Kalman filter structure is formulated and shown in Figure 1.

\[ S(k|k) = S(k|k) + K(Z(k|k) - HS(k|k)) \]

The function of location estimation is conducted by using TDOA location method. Range difference estimations are constructed by an unbiased Kalman filter if an all-LOS scenario exists; otherwise, a biased Kalman filter is used for NLOS mitigation.

The measured data, formulated as the range difference of arrival. To determine the biased measurement noise covariance \( R \), \( R = \hat{\sigma}_r^2 \), three different cases need to be considered.

Case 1: BS \( m \) is an NLOS BS, and BS \( l \) is an LOS BS. We have \( Z_m(k+1) - HS_m(k+1|k) > 0 \)

Case 2: BS \( l \) is an NLOS BS, and BS \( m \) is an LOS BS. We have \( Z_m(k+1) - HS_m(k+1|k) < 0 \)

Case 3: Both BS \( m, n \) and BS \( l \) are NLOS BSs.

The value of \( \hat{\sigma}_r \) is then assigned according to the following rules:

\[ \hat{\sigma}_r = \begin{cases} \alpha \sigma_n, & \text{Case 1 or Case 2}, \\ \sqrt{2} \frac{c}{\Lambda} \sigma_n, & \text{Case 3}, \\ \sqrt{2} \hat{\sigma}_n, & \text{otherwise}, \end{cases} \]

where \( \alpha \) is experimentally chosen scaling factors, \( c \) is the speed of light, \( \Lambda \) is the cluster arrival rate and \( \sigma_n \) is the standard deviation of additive white Gaussian (AWGN) measurement noise. When the three different cases are not met, both BS \( m \) and BS \( l \) are LOS BSs.

IV. SIMULATIONS

Simulations are performed for the range difference estimation with NLOS mitigation by using the proposed architecture in UWB environments. CM2 (based on NLOS channel measurements) UWB channel models [5] are considered. In the case, the model parameter, cluster arrival rate \( \Lambda \) is 0.4/nsec for CM2, respectively. It is also assumed that 1000 data samples are measured with a sampling period 2.5ms. The measurement noise \( U(k) \) is considered as i.i.d. and is assumed to be AWGN with distribution \( U(k) \sim N(0,0.15^2 m^2) \).

Figure 2 shows the trajectory of a rover, which moves in a straight line with a constant velocity. It is assumed that the distances between the rover and beacons (or base stations) are smaller than four meters. The coordinates of Beacons 1, 2 and 3 are (0,0.2), (0, \( \sqrt{3} \),1), (0, -\( \sqrt{3} \),1), respectively and units are meter. The velocity of Rover is \( v = 1.2 m/s \) and moves in a straight line. The state covariance matrix is

\[ C_0 = \begin{bmatrix} \sigma_m^2 & 0 & 0 \\ 0 & v^2 & 0 \\ 0 & 0 & 0.01 \end{bmatrix} \]

In this paper, the scaling value \( \alpha^2 = 60 \), as in (15), is chosen. The simulations are conducted in the three case defined in Section III.

Case 1: In this example, an obstacle is located in the observed area at Beacon 2 with a NLOS condition, while the range data observed at Beacons 1 remains LOS. The results shown in Fig. 3 indicate how the NLOS Error of the range difference measurements are mitigated by using the biased Kalman filter.

Case 2: An obstacle is located in the observed area at Beacon 1, while the range data observed at Beacons 2 is LOS. The results shown in Fig. 4 indicate how the NLOS
Error of the range difference measurements are mitigated by using the biased Kalman filter.

Case 3: In the case, obstacles are located in the observed area at both Beacon 1 and 2. The results shown in Fig. 5 indicate how the NLOS Error of the range difference measurements are mitigated by using the biased Kalman filter.

V. CONCLUSION

In this paper, we have presented a range difference estimation algorithm with NLOS error mitigation using biased Kalman filter for ultra-wideband environments. To improving the TDOA location accuracy in UWB location systems, NLOS identification and mitigation techniques suitable for UWB systems are derived. Simulation results of range difference estimation in UWB environments show that the algorithm of NLOS mitigation method with biased Kalman filter appears to achieve high accuracy for use in mobile positioning and tracking systems.

REFERENCES