Hybrid TDOA/AOA Indoor Positioning and Tracking Using Extended Kalman Filters

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Abstract—**A hybrid time-difference-of-arrival / angle-of-arrival (TDOA/AOA) positioning technique for indoor ultra wideband (UWB) systems is presented in this paper. The non line-of-sight (NLOS) propagation error is considered one of the major error sources in location systems; therefore, NLOS identification and mitigation technique with Kalman filters are utilized to reduce the NLOS time-of-arrival (TOA) errors in indoor UWB environments. To deal with the effects of inaccurate NLOS AOA data, an AOA selection process is included. An adjustable extended Kalman filter (EKF) structure is used to process the formulated TDOA and selected AOA measurements for mobile positioning and tracking. The simulation results show that the proposed hybrid scheme can effectively respond to the NLOS/LOS changes in the UWB environment, and improve the position accuracy.**

Keywords—Extended Kalman filter, TDOA, AOA, indoor positioning, UWB, NLOS error

I. INTRODUCTION

Accurate indoor positioning and tracking play an important role in home safety, public services, and other commercial or military applications [1]. In recent years, indoor geolocation has drawn increasing interests from academia and industry. There is an increasing demand of indoor geolocation systems for tracking persons with special needs, such as the elders and children who may be away from visual supervision. Other applications need the solutions to tracing mobile devices in sensor networks, or localizing accurately in-demand portable equipments in hospitals and laboratories. In public safety and military operations, the systems can be used in navigating and coordinating police officers, firefighters or soldiers to complete their missions inside buildings.

Various positioning techniques have been developed in the past few years. Handset-based positioning methods generally require that a modified handheld device calculate its own position by using a fully or partially equipped global positioning system (GPS) receiver. The method is, however, unfortunately not suitable for indoor geolocation applications. Network-based methods have their advantages for wireless location and indoor positioning. They can be used for location estimation in situations where GPS solutions are not applicable. In the network-based approaches, time of arrival (TOA) and time difference of arrival (TDOA) are two time-related parameters usually used in pinpointing the location of a mobile station. In addition, various wireless location schemes using signal strength or angle of arrival (AOA) have also been extensively investigated in the past. In this paper, we focus on the architecture and performance of methods using time-based and angle-based positioning schemes.

Both time-based and angle-based categories have their own advantages and limitations, it is therefore reasonable to consider hybrid methods to integrate the merits of using the two types of schemes. In [2], a hybrid TDOA/AOA location scheme was proposed for wideband code division multiple access (WCDMA) systems. The scheme uses TDOA information from all base stations (BS's) and the AOA information at the serving base station to perform mobile location estimation.

For the NLOS error problems in mobile position location, several NLOS identification and mitigation techniques have been presented in the past few years [3], [4]. These approaches identify the BS's that have NLOS components in the received range data, and reduce the time-related NLOS errors by using the NLOS mitigation techniques. In [3], a simple binary hypothesis testing was used for NLOS identification. A polynomial fitting was applied to all available measured mobile range data for variance calculation and data smoothing. Since a block of measured data is needed for the process of polynomial fitting, real-time positioning may not be possible. In other methods for mobile location, biased versions of the Kalman filter were used in mitigating the NLOS range error. With a rule-determined coefficient for the measurement noise covariance matrix, good location estimation results could be obtained [4], [5]. In [6], 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.

To meet the demand of high location accuracy in indoor positioning applications, the ultra wideband (UWB) systems are

The work is supported by National Science Council of Taiwan, R. O. C. under Grant NSC 94-2213-E-110-021.

0-7803-9392-9/06/$20.00 (c) 2006 IEEE

considered as candidates for the solutions. The UWB systems are capable of providing high-speed short-range wireless connectivity. Since UWB signals have fine time resolution, the accuracy of position location can be within one inch. The fine resolution of UWB signals provides potentially accurate ranging for indoor location communications, where dense multipath and NLOS errors become the major challenge to the quality of indoor positioning applications. A situation with blocked LOS paths between BS's and the mobile station (MS) usually leads to severe degradation of position accuracy. To improve the accuracy of positioning, methods for eliminating or mitigating the effects of NLOS errors and multipath in the UWB environments need to be applied before the TDOA/AOA location technique is used.

To derive suitable NLOS identification and mitigation algorithms for UWB systems, parameters of the standard UWB channel models provided by the IEEE 802.15.3a standards task group [7] are used in this paper. In order to achieve improved accuracy in indoor geolocation, a hybrid TDOA/AOA positioning scheme with an AOA selection function is proposed. In contrast to the scheme in [2], all good AOA data along with TDOA information from all BS's will be used in locating the MS position. The AOA and TDOA information are processed centrally by the extended Kalman filter (EKF) for MS positioning and tracking. The architecture of location estimator is illustrated in Fig. 1.

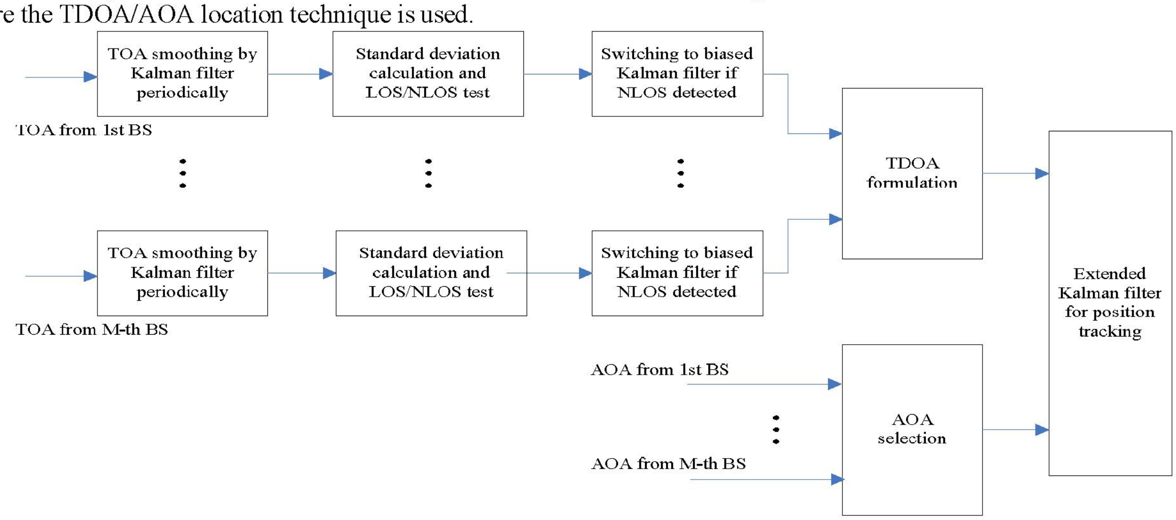

Figure 1. Architecture for NLOS test and hybrid TDOA/AOA positioning and tracking

II. NLOS Test and Error Mitigation

The main idea of the hybrid TDOA/AOA scheme is to use as many good location measurements as possible to achieve higher location accuracy through diversity combining. In an LOS scenario, if there are *m* BS's, the number of available TDOA and AOA data to the location system are *m-1* and *m*, respectively. When LOS propagation between a BS and the MS is blocked, the number of good measurement data would be affected. The system would need to identify the change in the scenario, and respond accordingly by adjusting the parameters in the system. To determine the parameters in the positioning system, NLOS identification and error mitigation are required.

A. NLOS Identification

Let the range $r_m(t_k)$ and bearing $\theta_m(t_k)$ between the *m*-th BS and the MS at time instant t_k be modeled respectively as

$$r_m(t_k) = r_{LOS,m}(t_k) + n_{range,m}(t_k) + r_{NLOS,m}(t_k) \tag{1}$$

$$\theta_m(t_k) = \theta_{LOS,m}(t_k) + n_{bearing,m}(t_k) + \theta_{NLOS,m}(t_k) \tag{2}$$

where $m = 1, \ldots, M$, and $k = 0, \ldots, K-1$. The two terms $r_{LOS,m}(t_k)$ and $\theta_{LOS,m}(t_k)$ are the true range and bearing, respectively. The range measurement noise and bearing measurement noise are represented by $n_{range,m}(t_k)$ and $n_{bearing,m}(t_k)$, respectively; while the NLOS error of range and bearing are written as $r_{NLOS,m}(t_k)$ and $\theta_{NLOS,m}(t_k)$, respectively. The range and bearing measurement noise terms are assumed to be additive white Gaussian noise with variance σ_r^2 and σ_θ^2, respectively. The NLOS range error component in UWB indoor environment is modeled as exponential distributed [8] and the NLOS bearing error is uniformly distributed [9].

A Kalman filter is used for range data smoothing. The state vector is written as

$$\mathbf{X}_{k+1} = \mathbf{\Phi X}_k + \mathbf{\Gamma W}_k \tag{3}$$

where $\mathbf{X}_k = \begin{bmatrix} r_k & r_k \end{bmatrix}^T$ is the state vector at time instant *k*, and r_k denotes the first derivative of the range r_k. $\mathbf{W}_k$ is the driving noise vector with covariance matrix $\mathbf{Q} = \sigma_u^2 \mathbf{I}$. $\mathbf{\Phi} = \begin{bmatrix} 1 & \mathrm{T} \\ 0 & 1 \end{bmatrix}$ and $\mathbf{\Gamma} = \begin{bmatrix} 0 \\ \mathrm{T} \end{bmatrix}$ are two transition matrices. The measurement process can be represented as

$$\mathbf{Y}_k = \mathbf{M}\mathbf{X}_k + \mathbf{U}_k \tag{4}$$

where $\mathbf{Y}_k$ is the measured data vector, $\mathbf{M} = [1 \;\; 0]$ and $\mathbf{U}_k$ has covariance matrix $\mathbf{R} = \sigma_x^2 \mathbf{I}$.

The function of a Kalman filter consists of two recursive steps [10]. The first step is for state prediction, written as

$$\mathbf{X}_{k+1,k} = \mathbf{\Phi}\mathbf{X}_{k,k} \tag{5}$$

$$\mathbf{C}_{k+1,k} = \mathbf{\Phi}\mathbf{C}_{k,k}\mathbf{\Phi}^T + \mathbf{\Gamma}\mathbf{Q}\mathbf{\Gamma}^T \tag{6}$$

$$\mathbf{K} = \mathbf{C}_{k+1,k}\mathbf{M}^{\mathrm{T}}(\mathbf{M}\mathbf{C}_{k+1,k}\mathbf{M}^{\mathrm{T}} + \mathbf{R})^{-1} \tag{7}$$

The second step performs measurement correction:

$$\mathbf{X}_{k+1,k+1} = \mathbf{X}_{k+1,k} + \mathbf{K}(\mathbf{Y}_{k+1} - \mathbf{M}\mathbf{X}_{k+1,k}) \tag{8}$$

$$\mathbf{C}_{k+1,k+1} = \mathbf{C}_{k+1,k} - \mathbf{K}\mathbf{M}\mathbf{C}_{k+1,k} \tag{9}$$

where $\mathbf{K}$ is Kalman gain and $\mathbf{C}_{k,k}$ is the covariance matrix of $\mathbf{X}_{k,k}$.

For each BS, an NLOS/LOS hypothesis testing is performed periodically by collecting a block of N_{test} TOA raw data. The period for repeated checking for LOS/NLOS conditions and the number of samples for standard deviation calculation are usually chosen experimentally. Let $X_m(t_k)$ be the smoothed range of the m-th BS at time instant t_k from the Kalman filter, the standard deviation of the measured range data can be calculated by

$$\hat{\sigma}_m = \sqrt{\frac{1}{N_{test}} \sum_{k=1}^{N_{test}} (r_m(t_k) - X_m(t_k))^2} \tag{10}$$

Based on the calculated standard deviation of the block of TOA data, the hypothesis testing decides whether NLOS components exist. The decision rule of the NLOS/LOS hypothesis testing for UWB systems is chosen as follows.

$$\begin{aligned} &H_0 : \hat{\sigma}_m < \gamma\sigma_r \quad \text{LOS condition} \\ &H_1 : \hat{\sigma}_m > \gamma\sigma_r \quad \text{NLOS condition} \end{aligned} \tag{11}$$

where the scaling factor $\gamma > 1$ and is experimentally chosen to increase the probability of detection.

B. NLOS TOA Error Mitigation and AOA Selection

The NLOS error mitigation consists of two parts: the NLOS TOA error mitigation and the AOA information selection. If the LOS TOA propagation scenario is decided, an unbiased Kalman filter is used to smooth the TOA data at each BS. In the contrast, if the NLOS propagation scenario is detected, a biased Kalman filter is used in mitigating the NLOS TOA error. The positive NLOS range bias can be reduced by assigning the diagonal elements of noise covariance matrix as

$$\begin{aligned} \hat{\sigma}_x &= \alpha\sigma_r, \text{ if } \mathbf{Y}_{k+1} - \mathbf{M}\mathbf{X}_{k+1,k} > 0 \text{ and NLOS detected,} \\ &= \sigma_r, \quad \text{otherwise,} \end{aligned} \tag{12}$$

where α is an experimentally chosen scaling factor. The processed TOA data from all base stations are then used in formulating the TDOA data, which are then used for mobile positioning and tracking.

The AOA information from all base stations are processed by the AOA selection to avoid introducing large NLOS bearing error into the position tracking stage. Only AOA data from LOS base stations are selected for further processing. In other words, those NLOS AOA data are discarded.

III. Extended Kalman Filter for TDOA/AOA Positioning

The formulated TDOA data and the selected AOA data are processed by the extended Kalman filter to obtain the MS location. The state vector of a mobile station is defined as

$$\mathbf{S}_{k+1,k} = \mathbf{\Phi}'\mathbf{S}_{k,k} + \mathbf{W}'_k \tag{13}$$

where $\mathbf{S}_k = [x_k \; y_k \; \dot{x}_k \dot{y}_k]^T$ is the state vector at time instant k. The coordinate (x_k, y_k) is the MS position, and $(\dot{x}_k, \dot{y}_k)$ denotes the velocities of the MS in the x-axis and y-axis. The covariance matrix of the driving noise vector $\mathbf{W}'_k$ is

$$\mathbf{Q}' = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_u^2 & 0 \\ 0 & 0 & 0 & \sigma_u^2 \end{bmatrix},$$

and the state transition matrix is

$$\mathbf{\Phi}' = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

In the case where LOS exists between the mobile station and all base stations, the TDOA/AOA measurement process can be represented as

$$\mathbf{Z}_k = f(\mathbf{S}_k) + \mathbf{U}'_k \tag{14}$$

where $\mathbf{Z}_k$ is the measured data vector, $f(\mathbf{S}_k)$ is a nonlinear transformation, and $\mathbf{U}'_k$ is the measurement noise. The covariance matrix of $\mathbf{U}'_k$ is

$$\mathbf{R}' = \begin{bmatrix} \mathbf{H}\boldsymbol{\sigma}^2\mathbf{H}^T & \mathbf{0} \\ \mathbf{0} & \sigma^2_{\mathrm{AOA}}\mathbf{I} \end{bmatrix}_{(2\mathrm{M}-1)\times(2\mathrm{M}-1)},$$

in which

$$\mathbf{H} = \begin{bmatrix} -1 & 1 & 0 & & 0 \\ -1 & 0 & 1 & & 0 \\ & & & & \\ -1 & 0 & & 0 & 1 \end{bmatrix}_{(\mathrm{M}-1)\times\mathrm{M}}, \text{ and}$$

$$\boldsymbol{\sigma}^2 = \begin{bmatrix} \sigma_R^2 & 0 & & 0 \\ 0 & \sigma_R^2 & & 0 \\ & & & \\ 0 & 0 & & \sigma_R^2 \end{bmatrix}_{\mathrm{M}\times\mathrm{M}},$$

where σ^2_{R} is the variance of the range related to the output of the unbiased or biased Kalman filter. The variance σ^2_{AOA} is related to the selected LOS AOA data. The dimension of the matrix $\mathbf{I}$, $m \times m$ is the determined number of LOS base stations from the AOA selection.

When the NLOS situation occurs, the covariance matrices of the processed TDOA and AOA data are different from those in the LOS situation. The dimension of the matrix in measurement process for the NLOS situations will be decreased, and determined by the sum of the number of TDOA and the number of LOS AOA data.

Similar to the function of Kalman filter, the operations of the extended Kalman filter can be represented by two recursive steps [10]. The difference is that a linear approximation of the function $f(\mathbf{S}_k)$ is used in the EKF procedure. The prediction step includes the following operations,

$$\mathbf{S}_{k+1,k} = \mathbf{\Phi}'\mathbf{S}_{k,k} \tag{15}$$

$$\mathbf{C}'_{k+1,k} = \mathbf{\Phi}'\mathbf{C}'_{k,k}\mathbf{\Phi}'^T + \mathbf{Q}'^T \tag{16}$$

$$\mathbf{K}' = \mathbf{C}'_{k+1,k}\,\mathbf{M}'^{\mathrm{T}}(\mathbf{M}'\mathbf{C}'_{k+1,k}\,\mathbf{M}'^{\mathrm{T}} + \mathbf{R}')^{-1} \tag{17}$$

where

$$\mathbf{M}' = \left.\frac{\partial f}{\partial \mathbf{S}}\right|_{\mathbf{S}=\mathbf{S}_{k+1,k}}.$$

The measurement correction step is written as follows.

$$\mathbf{S}_{k+1,k+1} = \mathbf{S}_{k+1,k} + \mathbf{K}'[\mathbf{Z}_{k+1} - \mathbf{M}'\mathbf{S}_{k+1,k}] \tag{18}$$

$$\mathbf{C}'_{k+1,k+1} = \mathbf{C}'_{k+1,k} - \mathbf{K}'\mathbf{M}'\mathbf{C}'_{k+1,k} \tag{19}$$

The BS positioning and tracking can be obtained from the output state vector of the extended Kalman filter.

IV. Simulation Results

The performance of the hybrid TDOA/AOA location scheme for indoor UWB systems is investigated by computer simulations. We assume that three base stations are used in the location system. The coordinates are BS1: (*0*, *0*), BS2: (*5m*, *8.66m*), and BS3: (*10m*, *0*), respectively. The NLOS range error is assumed to be an exponential distribution, which is defined in the standard indoor UWB channel model [7],[8]. A multipath cluster arrival rate 0.0667×10^9 is adopted for situations where the distance between any BS and the MS is within the range of four to *10* meters. The NLOS bearing is assumed to be uniformly distributed from $-\pi$ to π [9].

In the first case, the effect of measurement noise on the location accuracy is investigated. The mobile station is assumed to be staying at (*7m*, *4.5m*). An LOS scenario is assumed. Different pairs of standard deviations of the range and bearing measurement noises are investigated. The interval for periodical LOS/NLOS checking is *50* samples, and the length N_{test} for calculating variance of data samples is *15*. For comparison of performance, the location root mean square errors (RMSEs) of the TDOA/AOA method presented in [2] are shown in Fig. 2. The results of the proposed hybrid TDOA/AOA scheme in Fig. 3 show that the proposed scheme has better position accuracy. The results imply that the position accuracy can be significantly improved by utilizing all available AOA information in the positioning scheme, especially when the standard deviation of bearing measurement noise is small.

In the second case, the performance of the proposed scheme under the varying LOS/NLOS situation is investigated. It is assumed that an MS travels from location (*7m*, *4.5m*) to (*4m*, *0.5m*) with a constant velocity, *0.5m/s*. The length of observation time is *10s*, and the sample spacing is *25ms*. In the scenario, the propagation between the MS and two BS's becomes NLOS at t = *2s*, and remains NLOS until t = *10s*. In the situation, the data available to the extended Kalman filter decrease from two TDOA's and three AOA's to two TDOA's and one selected AOA. The simulation results in Fig. 4 shows that the proposed positioning scheme with the AOA selection has better performance than the method of [2]. Without the function of

AOA selection, the NLOS bearing error may lead to severe degradation of positioning and tracking accuracy.

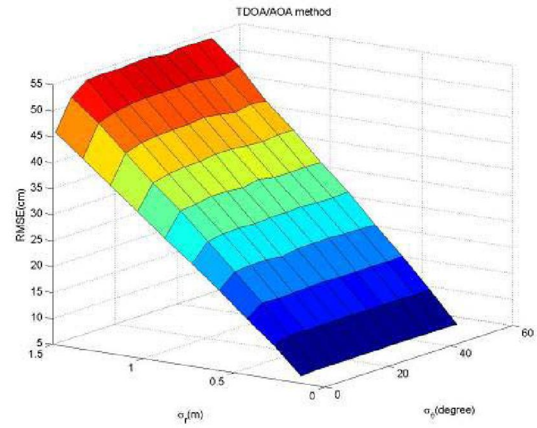

Figure 2. RMSEs for the hybrid TDOA/AOA positioning technique of [2] in LOS situation

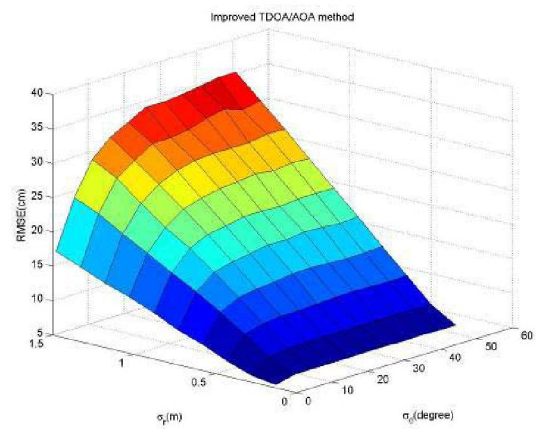

Figure 3. RMSEs for the proposed hybrid TDOA/AOA positioning technique in LOS situation

V. CONCLUSIONS

In this paper, a hybrid TDOA/AOA positioning technique with the function of AOA selection for indoor UWB systems is presented. The positioning architecture consists of NLOS identification and NLOS mitigation by using unbiased or biased Kalman filters for estimation of the LOS TOA (or LOS range). An AOA selection process is presented for reducing the error caused by inaccurate AOA information. An adjustable extended Kalman filter structure is used for location estimation by processing the formulated TDOA and the selected AOA. It is seen that the proposed hybrid technique can effectively respond to the NLOS/LOS changes in the UWB environment, and can efficiently improve the position accuracy. The simulation results show the performance of the proposed technique outperforms other comparative schemes.

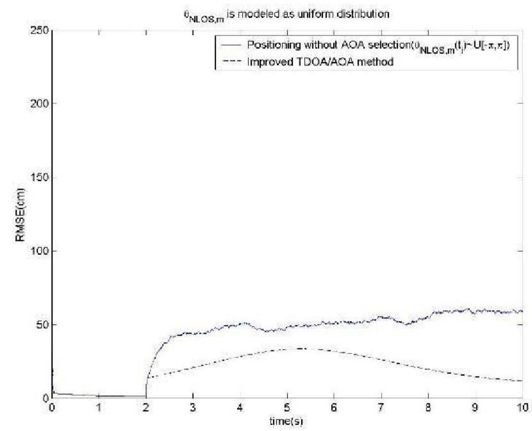

Figure 4. Performance comparison of positioning with and without AOA selection (two NLOS BS's assumed)

REFERENCES

[1] K. Pahlavan, P. Krishnamurthy, and J. Beneat, "Wideband Radio Channel Modeling for Indoor Geolocation Applications," IEEE Communications Magazine, vol. 36, no. 4, pp. 60–65, Apr. 1998.

[2] L. Cong and W. Zhuang, "Hybrid TDOA/AOA mobile user location for wideband CDMA cellular systems, IEEE Transactions on Wireless Communications, vol.1, pp. 439-447, July 2002.

[3] M. P. Wylie and J. Holtzman, "The non-line of sight problem in mobile location estimation," IEEE International Conference on Universal Personal Communications, vol. 2, pp. 827-831, Sept. 1996.

[4] N. J. Thomas, D. G. M. Cruickshank and D. I. Laurenson, "A robust location estimator architecture with biased Kalman filtering of TOA data for wireless systems," IEEE 6th International Symposium on Spread-Spectrum Tech. & Applications, pp.296—300, September, 2000.

[5] B. L. Le, K. Ahmed and H. Tsuji, "Mobile location estimator with NLOS mitigation using Kalman filtering," IEEE Wireless Communications and Networking Conference 2003 (WCNC 2003), Vol. 3, pp. 16—20, March 2003.

[6] M. Najar and J. Vidal, "Kalman tracking for mobile location in NLOS situations," The 14th IEEE International Symposium on Personal, Indoor and Mobile Radio Communication (PIMRC), Vol. 3, pp. 2203—2207, Sept. 2003.

[7] A. F. Molisch, et al., "Channel models for ultrawideband personal area networks," IEEE Wireless Communications, Vol. 10, No. 6, pp. 14—21, Dec. 2003.

[8] J. Foerster, et al., "Channel modeling sub-committee report final," IEEE 802.15-02/490r1, Feb. 2003.

[9] Q. Spencer et al., "A statistical model for angle of arrival in indoor multipath propagation," IEEE Vehicular Technology Conference, vol. 3, pp. 1415—1419, May. 1997.

[10] S. M. Kay, Fundamentals of Statistical Signal Processing: Estimation Theory—Volume 1, Prentice Hall, 1993.