Enhanced UWB Indoor Tracking through NLOS TOA Biases Estimation

J. Youssef, B. Denis, C. Godin
CEA-Leti / Minatec
17 rue des Martyrs, 38054 Grenoble Cedex 09, France
E-mails: [joe.youssef, benoit.denis, christelle.godin]@cea.fr

S. Lesecq
INPG / Gipsa Lab, CNRS-INPG-UJF UMR 5216
BP46, 38410 Saint Martin d’Hères Cedex, France
E-mail: suzanne.lesecq@gipsa-lab.inpg.fr

Abstract—Reliable range-based tracking using Ultra-WideBand (UWB) radio signals is traditionally problematic in indoor environments. It is indeed widely admitted that Non Line-Of-Sight (NLOS) channel configurations introduce significant biases on measured temporal metrics such as Times Of Arrival (TOA), and hence, alter position estimates accordingly. In order to enhance the tracking performance, we propose a specific Extended Kalman Filter (EKF) formulation, which enables to estimate as state variables the NLOS biases affecting the measured distances between the Mobile Station (MS) and the fixed Base Stations (BSs). The described solution is mainly based on the modeling of the deterministic angular-dependent bias variation experienced with MS mobility. It is shown that this approach is robust to harmful situations where all the links between the MS and the BSs simultaneously suffer from NLOS. Simulation results are provided for performance assessment in a few canonical scenarios.

Index Terms—Angle Of Arrival, Bias, Extended Kalman Filter, Indoor, Non Line-Of-Sight, Ranging, Time Of Arrival, Tracking, Ultra Wideband.

I. INTRODUCTION

For the last decade, wireless networks employing wideband transmission techniques have been introduced for precise target location in dense multipath indoor environments (e.g. [1]). More recently, Ultra-WideBand (UWB) positioning/tracking systems based on temporal radiolocation metrics, such as the Time Of Arrival (TOA) or the Time Difference of Arrival (TDOA), have proved their relevance, due to their ability to resolve multipath components and provide accurate range-dependent measurements (e.g. [2], [3]).

Beside temporal approaches, the Angle Of Arrival (AOA) may be alternatively considered to localize Mobile Stations (MSs) in wireless networks. However, since AOA represents the angle between the MS and a Base Station (BS), its estimation should be preferentially restricted into Line Of Sight (LOS) configurations. Moreover, in the case of UWB signals, it has been shown in [4] that AOA provides poorer location accuracy in comparison with temporal approaches. Consequently, these metrics are mostly used as additional observations on top of TOA measurements in LOS environments (e.g. [5]). Unfortunately, whatever the retained metrics, the Non Line-Of-Sight (NLOS) phenomenon has been notoriously identified as one challenging problem for indoor radiolocation systems (e.g. [6]). In spite of the fine UWB high-resolution capability, the blockage of the direct path can indeed degrade ranging accuracy by biasing the measured metrics. In order to model these biases or mitigate the effects of NLOS configurations on location performances, many techniques have been proposed in the literature.

Some solutions assume prior knowledge on the statistical characteristics of the measured metrics or on the observed signal signatures, depending on the environment. For instance in [7], experienced channel configurations are divided into four different regions with distinct statistical bias models, and a Markov model accounts for the probabilities of transition between these regions with mobility. Other approaches, which do not necessitate prior site specific signal collection or statistical metrics characterization, consist in taking into account dynamic bias variations in advanced tracking filters (e.g. [8]–[11]). For instance, the Extended Kalman Filter (EKF) designed for the estimation of 2D coordinates and speeds can also estimate the biases on the TOAs measured with respect to BSs, as additional state variables to be estimated. Although this solution may sound practical, the location error still dramatically increases if the number of available LOS links is too low. At this point, it is worth reminding that the UWB multipath components resolved on the receiver side, as well as the probability of channel transitions, are clearly conditioned upon mobility parameters and geometry. Consequently, measured metrics and observed biases are spatially correlated. As a preliminary attempt in [10], EKF and particle filters have been considered with a random walk bias model that depends on the mobility and refreshment rate parameters. In [11], a particle filter enables to track bias variations modeled by a uniform distribution notched about the current bias values.

In this paper, we propose a new approach to follow the evolution of the biases that affect the range measurements delivered through TOA estimation in severe NLOS environments. More particularly, the state vector is extended and the related equations are added in the state space model. Ultimately, the AOA information, which may be available at the MS (e.g. with respect to the direction of motion), is also included into our formulation to model the deterministic bias variations.

In Section II, the UWB channel model proposed in the IEEE 802.15.4a standard, as well as its space-time variations, are presented. In Section III, a deterministic model accounts for the bias evolution, in compliance with the channel behavior and MS motion. Then, an EKF associated to this dynamical model, along with the corresponding state and measurement equations, are described in Section IV. Simulation results obtained on a portion of MS trajectory with varying numbers of NLOS links are provided in Section V. Finally, Section VI concludes the paper.

II. UWB CHANNEL MODEL AND VARIATIONS

A. UWB Channel Model

The statistical indoor UWB Channel Impulse Response (CIR) \( C(t) \) proposed by the IEEE 802.15.4a standardization group [12] reproduces the clustering of multipath echoes
initially proposed by Saleh and Valenzuela in [13], as follows:

\[ C(t) = \sum_{l=1}^{L} \sum_{k=1}^{K_l} \beta_{k,l} \exp(i \phi_{k,l}) \delta(t - T_l - \tau_{k,l}) \]  

(1)

where \( L \) represents the number of clusters, \( K_l \) the number of rays in the \( l \)th cluster and \( T_l \) the TOA of the \( l \)th cluster. The parameters \( \beta_{k,l}, \phi_{k,l} \) and \( \tau_{k,l} \) respectively represent the amplitude, phase and TOA associated with the \( k \)th ray within the \( l \)th cluster.

As regards to angular information, Pagani et al. [14] adapted the model proposed by Spencer et al. [15] from UWB indoor measurements. According to this model, the AOA of the \( k \)th ray within the \( l \)th cluster is described by the sum \( \Phi_l + \varphi_{k,l} \), which is uniformly distributed on interval \([0, 2\pi]\), is the mean AOA in the \( l \)th cluster. \( \varphi_{k,l} \) follows a Laplace distribution with zero mean and standard deviation \( \sigma_\varphi \).

B. Spatial Variations

The displacement of at least one antenna over a UWB peer-to-peer communication link introduces a variation of the CIR. This displacement makes the length of each received ray vary in time and hence, leads to a temporal shift and an amplitude variation of this ray, as shown on Figure 1. Pagani et al. [14] proposed to model these fluctuations by considering the relative angle formed between the direction of the moving antenna and the direction of each received ray. The corresponding temporal shift is then modeled as follows:

\[ \Delta \tau_{k,l} = -\frac{\Delta x}{c} \cos(\Phi_l + \varphi_{k,l}) - \frac{\Delta y}{c} \sin(\Phi_l + \varphi_{k,l}) \]  

(2)

where \( \Delta x \) and \( \Delta y \) are the variations of the 2D coordinates of the mobile antenna in a Cartesian system, \( c \) is the lightspeed, and \( \Phi_l + \varphi_{k,l} \) is the angle formed between the motion direction and the ray direction. The amplitude of the ray varies by a factor \( \alpha_{k,l} \), which can be computed as follows:

\[ \alpha_{k,l} = \frac{d_{k,l}}{d_{k,l} + \tau \Delta \tau_{k,l}} \]  

(3)

where \( d_{k,l} \) is the length of the \( k \)th received path within the \( l \)th cluster. For small MS displacements between successive snapshots, it is usually reasonable to assume that AOA are constant over short durations and that \( \alpha_{k,l} \approx 1 \) as \( \Delta \tau \ll d_{k,l} \).

III. SPATIAL BIAS VARIATION

The distance bias observed after TOA estimation can be defined as the difference between the distance associated to the first observable ray and the real MS-BS distance, as follows:

\[ b(x, y) = cT_1(x, y) - d(x, y) \]  

(4)

where \( d(x, y) \) is the real distance between the MS occupying the position \((x, y)\) and the BS, \( T_1(x, y) \) is the TOA of the first ray within the first received cluster (assuming \( \tau_{1,1} = 0 \)).

In the sequel, we assume that \( \Phi \) is the angle between the direction of arrival of this first ray and the motion direction. Figure 1 illustrates the subsequent elongation of the ray length and the variation of the real distance, as the mobile moves between \((x_0, y_0)\) and \((x, y)\):

\[ T_1(x, y) = T_1(x_0, y_0) - \frac{\sqrt{\Delta x^2 + \Delta y^2}}{c} \cos \Phi \]  

\[ d(x, y) = d(x_0, y_0) - \frac{\sqrt{\Delta x^2 + \Delta y^2}}{c} \cos \alpha \]  

(5)

Using the state variables in (5), one can now write that:

\[ d(x, y) = b(x_0, y_0) + \frac{\sqrt{\Delta x^2 + \Delta y^2}}{c} \cos \alpha - \frac{\sqrt{\Delta x^2 + \Delta y^2}}{c} \cos \Phi \]  

Expression (6) accounts for a deterministic bias variation binding the MS displacement. Contrarily to the classical random walk models used to describe the bias evolution in [10] and [9], we propose to include (6) in the state equation of an EKF.

IV. ADAPTED EXTENDED KALMAN FILTER

In this section, we describe an Extended Kalman Filter that can handle the models presented in the previous section. For the proposed illustrating embodiment, this EKF enables to locate a MS through TOA estimation when three BSs are set at known locations. However, note that the related concepts could be easily extended to other configurations including a larger number of BSs and even to other temporal metrics such as TDOAs. We also assume that the filter has a perfect knowledge of the LOS/NLOS situations.

A. State Vector and Equation

First, let \( s_1^{(k)} \) be a vector describing the MS state at time \( k \):

\[ s_1^{(k)} = [x^{(k)} y^{(k)} v_x^{(k)} v_y^{(k)} b_1^{(k)} b_2^{(k)} b_3^{(k)}]^T \]  

(7)

where \( x^{(k)} \) and \( y^{(k)} \) are the coordinates of the MS in a 2D Cartesian system, \( v_x^{(k)} \) and \( v_y^{(k)} \) are the 2D velocities, \( b_i^{(k)} \) \( i = 1...3 \), is the bias between the MS and the \( i \)th BS.

Assume first that the angle associated to the first ray is the same over the MS displacement. Then one can represent the ray direction with a constant vector \( v_c = \cos \theta \sin \theta \), where \( \theta \) is the angle between \( \Phi \) and the first ray with respect to the \( i \)th BS. Hence, it comes:

\[ \cos \Phi_1^{(k)} = \frac{1}{v_1} \begin{bmatrix} v_x^{(k)} \\ v_y^{(k)} \end{bmatrix} \cdot \begin{bmatrix} \cos \theta_1 \\ \sin \theta_1 \end{bmatrix} \]  

(9)

Note that \( \theta_1 \) is unknown and independent from the state variables since it is rigorously constant in time. Furthermore, we consider a MS displacement with no significant velocity variations, we can make the following approximation:

\[ d(t) \cos \Phi_1^{(k)} = dt \begin{bmatrix} v_x^{(k)} \\ v_y^{(k)} \end{bmatrix} \cdot \begin{bmatrix} \cos \theta_1 \\ \sin \theta_1 \end{bmatrix} \approx dt \begin{bmatrix} v_x^{(k-1)} \\ v_y^{(k-1)} \end{bmatrix} \cdot \begin{bmatrix} \cos \theta_1 \\ \sin \theta_1 \end{bmatrix} \]  

(10)

Using the state variables in (5), one can now write that:

\[ d(t) \cos \Phi_1^{(k-1)} = d_{i}^{(k-1)} + b_1^{(k-1)} - b_i^{(k)} \]  

(11)
Finally, from the approximation in (10), one gets the equation that bounds the bias variation:

$$h_{ij}^{(k+1)} = h_0(s_1^{(k)}, s_1^{(k-1)}) = 2h_{ij}^{(k)} - h_{ij}^{(k-1)} - \frac{d_i^{(k-1)}}{d_i^{(k)}} + \frac{(x_{BS_i} - x^{(k)})v_i^{(k)}dt}{d_i^{(k)}} + \frac{(y_{BS_i} - y^{(k)})v_i^{(k)}dt}{d_i^{(k)}}$$

(12)

Expression (12) shows that the derivation of $h_{ij}^{(k+1)}$ involves the MS states at time $(k)$ and $(k-1)$. Thus the extended state vector that must be estimated can be built as follows:

$$s^{(k)} = \begin{bmatrix} s_1^{(k)T} & s_2^{(k)T} \end{bmatrix}^T \in \mathbb{R}^{(1+7)}$$

(13)

The state model function $h(.)$ is written as:

$$s^{(k+1)} = h(s^{(k)}) + w^{(k)}$$

where $w^{(k)}$ is the state noise vector defined as:

$$w^{(k)} = \begin{bmatrix} w_{v_x}^{(k)} & w_{v_y}^{(k)} & w_{b_x}^{(k)} & w_{b_y}^{(k)} & 0_{(1+7)} \end{bmatrix}^T$$

with $w_{v_x}^{(k)}$, $w_{v_y}^{(k)} \sim N(0, \sigma_v)$, and $w_{b_x}^{(k)}$, $w_{b_y}^{(k)} \sim N(0, \sigma_b)$. The approximation introduces in (10) implies the following bias noise model:

$$w_{b_x}^{(k+1)} = w_{b_x}^{(k)}dT \cos \theta + w_{b_y}^{(k)}dT \sin \theta$$

(15)

where $w_{v_x}^{(k)} = v_x^{(k)} - v_x^{(k-1)}$, $w_{v_y}^{(k)} = v_y^{(k)} - v_y^{(k-1)}$.

Now, consider that the velocity errors $w_{v_x}$ and $w_{v_y}$ are independent identically distributed (iid) random variables. Then the covariance matrix of biases is written as follows:

$$P_b = \sigma^2_w \begin{bmatrix} 1 & \cos(\theta_1 - \theta_2) & \cos(\theta_1 - \theta_3) \\ \cos(\theta_1 - \theta_2) & 1 & \cos(\theta_2 - \theta_3) \\ \cos(\theta_1 - \theta_3) & \cos(\theta_2 - \theta_3) & 1 \end{bmatrix}$$

(16)

with $\cos(\theta_1 - \theta_2) = \cos(\Phi_i - \Phi_j)$, $\cos(\theta_2 - \theta_3) = \cos(\Phi_i - \Phi_k)$ and $\cos(\theta_1 - \theta_3) = \cos(\Phi_j - \Phi_k)$.

The non-linear state prediction equation can hence be obtained as follows:

$$x^{(k+1/k)} = x^{(k)} + dtv_x^{(k)}$$

$$y^{(k+1/k)} = y^{(k)} + dtv_y^{(k)}$$

$$v_x^{(k+1/k)} = v_x^{(k)} + dt\frac{v_x^{(k)}}{v_y^{(k)}}$$

$$v_y^{(k+1/k)} = v_y^{(k)}$$

$$b_i^{(k+1/k)} = h_b(s_1^{(k)}, s_2^{(k)}) = h_b(s_1^{(k)}, s_1^{(k-1)})$$

and

$$H_j^{(k+1)} = \begin{bmatrix} h_i^{(k+1)} & h_j^{(k+1)} \\ b_i^{(k+1)} & b_j^{(k+1)} \end{bmatrix}$$

with $h_i^{(k+1)} = h_0(s_1^{(k)}, s_1^{(k-1)})$ and $h_j^{(k+1)} = h_0(s_1^{(k)}, s_1^{(k-1)})$.

where $\beta_i^{(k)} = \{0, 1\}$ denotes the activation/inhibition of a NLOS bias with respect to the $i^\text{th}$ BS, and $H_j^{(k)}$ is the derivative of (12) over the different state variables $s_1^{(k-j)}$.

### B. Observation Vector and Equation

In the minimal configuration, observations are composed of three TOAs, which are measured with respect to the three BSs. These measurements are potentially complemented by further AOA measurements, which can (but not necessarily) be performed at the MS for the identified NLOS links only. Finally, the AOA measurements could also be used as additional observations with LOS links to increase location accuracy in more favorable conditions.

According to the previous model and considering that all the MS-BS links are simultaneously affected by NLOS channel configurations, and that all the corresponding AOAs measurements are available, the observations vector is the following:

$$z^{(k)} = \begin{bmatrix} z_T^{OA_1} & z_T^{OA_2} & z_T^{OA_3} & z_{AO_1} & z_{AO_2} & z_{AO_3} \end{bmatrix}^T$$

where

$$z_T^{OA_i} = \left\{ \begin{array}{cc} 0 & i = 1, 2, 3 \\ z_T^{AO_i} = a cos \left( \frac{d_i^{(k-1)} + b_i^{(k-1)} - b_i^{(k)}}{d_T \sqrt{v_x^{(k-1)} + v_y^{(k-1)}}} \right) + n_T^{AO_i} \end{array} \right. , \ i = 1, 2, 3$$

with $n_T^{AO_i}$ a centered white Gaussian measurement noise term affecting the $i^\text{th}$ TOA and

$$z_{AO_i} = a cos \left( \frac{d_i^{(k-1)} + b_i^{(k-1)} - b_i^{(k)}}{d_T \sqrt{v_x^{(k-1)} + v_y^{(k-1)}}} \right) + n_{AO_i}$$

with $n_{AO_i}$ a centered white Gaussian measurement noise term affecting the $i^\text{th}$ AOA.

### V. Simulation Results and Discussions

In this section, we present simulation results as regards to location accuracy and bias estimation, under the same scenario as in the previous section. More particularly, we compare the performances achieved with a traditional random walk bias model and the new space-time bias formulation. For this purpose, the EKF is applied in the three following cases:

Case a- AOA measurements are available in the observation vector and NLOS biases are tracked according to (17) where the bias noise is defined in (15) and the related covariance matrix is given by (16).

Case b- There is no available AOA measurements in the observation vector and NLOS biases are tracked according to the same bias equation as in Case a.

Case c- There is no available AOA measurements in the observation vector and NLOS biases are tracked according to a state equation that accounts for an underlying random walk process:

$$b_i^{(k+1)} = b_i^{(k)} + w_{b_i}^{(k)}$$

(20)

with $w_{b_i}^{(k)} \sim N(0, \sigma_{w_{b_i}})$. By averaging in (6) over $\alpha \in U[0, 2\pi]$ and $\Phi \in U[0, 2\pi]$, we straightforwardly find:

$$\sigma_{w_{b_i}}^2 = dt^2 v_x^{(k)} + dt^2 v_y^{(k)}$$

978-1-4244-2324-8/08/$25.00 © 2008 IEEE.
This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2008 proceedings.
The standard deviations of TOA and AOA measurements are respectively set to 1 ns and 10° (when applying, i.e. in Case a only). At $k = 0$, we assume $v_x(0) = 30 \text{ cm}$, $v_y(0) = 0$ and the initial coordinates and bias to be known with uncertainty. The corresponding errors are centered Gaussian iid variables with a standard deviation equal to 10 cm.

Figure 2 shows a straight uniform motion of a real MS trajectory where the standard deviation of the velocities are $\sigma_{v_x} = \sigma_{v_y} = 0$, along with the trajectories estimated in Cases a and c, for one LOS link and two NLOS links. Considering the directions of arrival with respect to BS2 and BS3 in the example, it is clear that in NLOS situations the first observed ray and the missing direct path can have opposite directions. Hence, the TOA variation is not always proportional to the real distance variation, but depends on the actual AOA. Consequently, it may happen sometimes that the measured TOA increases while the real distance decreases. As shown on Figure 2, the estimated solution obtained in Case a can still handle such a penalizing situation.

Figure 3 shows the evolution of the average location error in Cases a and c for different numbers of NLOS links. The average is drawn over 10000 trials of iid gaussian process noise as specified previously, for the same trajectory as in Figure 2 and similar BSs positions. For each trial, the initial biases are random Poisson variables as described in [12] and $\theta \sim U[0, 2\pi]$. It is clear here that Case a exhibits approximately the same tracking performances whatever the number of NLOS links, whereas Case c suffers from important performance degradations as the number of NLOS links increases. This result can be explained by the higher tracking capability of Case a, as regards to the bias evolution. One can almost hold a constant error on the estimated bias values, when using AOA measurements as observations in severe NLOS configurations.

On Figure 4, we also compare Cases a and b. For this portion of the MS trajectory affected by smooth state variations (especially as regards to velocities $\sigma_{v_x} = 0.01v_x(0)$), it is evident that no significant performance improvement can be noticed in Case a when including AOA measurements in the observation vector, in comparison with Case b. Thus, performances are very close in both Cases. Practically, these results tend to demonstrate that further angular measurements are not specifically required with our bias modeling in severe NLOS environments, when the refreshment rate of the TOA measurements is sufficiently high, or equivalently, when the variations of 2D velocities are relatively slow.

Mitigating these results, Figure 5 shows estimated trajectories in Case a and b where much higher variations can be observed on instantaneous velocities. Figure 6 represents the location and bias estimation errors (without loss of generality, we consider the same scenario as the one shown in Figure 5, where actual acceleration effects $a_x dt^2 = 10 \text{ cm}$ and $a_y dt^2 = 0$ are modeled by velocity errors with $\sigma_{v_x} = 10 \text{ cm}$ and $\sigma_{v_y} dt = 0.3 \text{ cm}$). Since no AOA estimates are available in Case b, the bias evolution is not adjusted as in Case a where the location performance is much better. In this new example, the bias evolution is no more properly estimated in Case b.

VI. CONCLUSION

In this paper, we have proposed a new model that describes the dynamic behavior of the biases affecting TOA measurements in a UWB indoor tracking context. This model considers angular-dependent variations, accounting for the spatial correlation of observed biases as the MS moves. Subsequently, extended state/observation vectors and appropriate models have been put forward and included into an original EKF formulation. One of the proposed filtering embodiments can also take into account further AOA measurements on top of classical TOAs.

In comparison with standard approaches that assume dynamic biases as simple random walk processes, the described solutions are likely to be satisfactorily robust in severe indoor environments, when numerous radio links with respect to fixed BSs are simultaneously affected by NLOS channel configurations. Finally, under slowly varying velocities, it has been shown that the approximations made for the angular-dependent bias state transitions could be viable in the lack of additional AOA measurements, by relying only on TOA measurements. For less stationary trajectories, the inclusion of relatively coarse AOA measurements into the observation vector seems to be sufficient.

Future studies should address the more theoretical problem of observability with the retained state and observation models.

ACKNOWLEDGMENT

This work has been performed in the framework of the ICT project ICT-217033 WHERE, which is partly funded by the European Union.

REFERENCES

Fig. 1. Blocked direct paths (dashed arrows) associated to real MS-BS distances and first received rays (plain arrows), as a function of the MS displacement.

Fig. 2. Example of estimated trajectories with 1 LOS link MS-BS1 (over 3), for the EKF with angular-dependent bias tracking and measured AOAs (a) and the EKF with random walk bias tracking without measured AOAs (c).

Fig. 3. Average errors on estimated positions (under different numbers of NLOS links) and estimated biases (3 NLOS links case), for the EKF with angular-dependent bias tracking and measured AOAs (a) or without measured AOAs (b).

Fig. 4. Average errors on estimated positions (under different numbers of NLOS links) and on estimated biases (3 NLOS links case), for the EKF with angular-dependent bias tracking and measured AOAs (a) or without measured AOAs (b).

Fig. 5. Example of estimated trajectories for the EKF with angular-dependent bias tracking and measured AOAs (a) or without measured AOAs (b), under rapidly varying velocities ($\Delta x = \Delta t = 0$).

Fig. 6. Average errors on estimated positions and biases for the EKF with angular-dependent bias tracking and measured AOAs (a) or without measured AOAs (b), under rapidly varying velocities ($\Delta x, \Delta t = 0$).