Multipath Components Tracking Adapted to Integrated IR-UWB Receivers for Improved Indoor Navigation

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***Abstract*—In this paper, we propose a solution adapted to Impulse Radio - Ultra Wideband (IR-UWB) integrated receivers devoted to indoor localization, making usage of multipath information under imposed time resolution and low complexity constraints. The Multipath Components (MPCs) can ideally be tracked by capturing their space-time correlation under mobility. The proposed architecture is composed of Multiple Hypothesis Kalman Filters (MHKFs) in parallel, each filter tracking one single MPC while detecting measurement outliers or maneuvering paths. A data association procedure enables to map the MHKFs' outputs onto delays associated with receiver's energy bins. The relative temporal variations of MPCs are used to collectively infer the missing direct path's information in case of Non-Line of Sight (NLoS). The corrected observations finally feed a conventional Extended Kalman Filter (EKF) that estimates mobile's position. We evaluate the performance of the proposed scheme through realistic simulations in terms of both MPC and mobile tracking.**

***Index Terms*—Data Association, Impulse Radio, Indoor Localization, Integrated Devices, Mulipath Components, Pedestrian Navigation, Time of Arrival, Tracking Filter, Ultra Wideband.**

I. Introduction

With the emergence of location-based services (indoor navigation, context awareness, personal items monitoring, user-centric mobility learning or detection...), wireless localization has been identified as a key enabler for the last past years, experiencing a significant growth from both academic and industrial perspectives. In this context, the Impulse Radio - Ultra Wideband (IR-UWB) technology has been regularly promoted as a credible candidate due to its fine multipath resolution capabilities, making possible the accurate estimation of direct path's Time of Arrival (ToA) [1]. Despite these promising properties, harmful propagation phenomena in uncontrolled operating conditions, such as link obstructions or dense multipath, still play a critical role on the performance of ToA-based ranging and localization.

However, recent studies have shown that the space-time correlation of Multipath Components (MPCs) under mobility could be beneficial to indoor tracking [2], [3]. For instance, some approaches aim at modeling and estimating the Non-Line of Sight (NLoS) bias affecting the ToA of the first detected path as a random walk process [4], or as a pseudo-deterministic function depending on the moving direction [5]. Other advanced solutions have been put forward more recently, relying on the concept of virtual scatterers. First, the Multipath-aided Indoor Navigation and Tracking (MINT) technique, which requires the building layout, assumes a geometric model accounting for wall reflections (at arbitrary high orders) [6]. As another example, the Channel - Simultaneous Localization And Mapping (Channel-SLAM) method estimates the scattering points in addition to the mobile position, while considering generalized MPC interactions within the environment (e.g., incorporating also diffracted paths) [7]. However the previous solutions are either unstable over long-term trajectories and under generalized NLoS situations [4], [5] or they may be computationally demanding (e.g., concatenating several particle filters in charge of estimating very large state vectors). Finally, they may require specific hardware or additional processing capabilities to estimate the Angle of Arrival (AoA) out of phase difference measurements, mobile's heading based on inertial units [7], or high-speed sampling and aggressive sensitivity/dynamics for received signal acquisition [6]. The previous requirements are hardly compatible with currently available low-cost and low-power integrated devices.

In this paper, we thus propose a global low-complexity solution suitable to integrated IR-UWB receivers under stringent hardware constraints. Significant MPCs are detected out of raw channel estimates, associated to an a priori evolution model and tracked independently, before being collectively exploited to infer the missing leading edge's ToA in detected NLoS situations. This proposal is made deliberately compatible with a reference mobile tracking filter, which admits one single ToA estimate as observation per radio link. The new solution is expected to be mostly beneficial in case of generalized obstructions with respect to fixed bases.

II. Problem Statement and Modeling

A. Receiver Specificities and Channel Representation

The receiver of interest is part of a complete system on chip designed for low-power IR-UWB localization applications [8]. The received signal is amplified, translated to baseband thanks to an In-phase and Quadrature-phase mixer, integrated in windows of 2ns shifted by 1ns (and thus, sampled at the same period) and finally squared, leading to positive values. Therefore, the intrinsic multipath resolution is on the order of 2ns, whereas adjacent windows are overlapping and thus correlated. At each time step k (i.e., for each channel acquisition), the receiver delivers an estimated version of the Channel Impulse Response (CIR) (see Fig. 1), which is made of the $p_{max}^{(k)}$ most energetic delay-amplitude components $bin_p^{(k)}$, $p \in [\![1, p_{max}^{(k)}]\!]$ (also called "bins" hereafter), where $p_{max}^{(k)}$ depends on the receiver architecture specificity (e.g., ≤ 64 here).

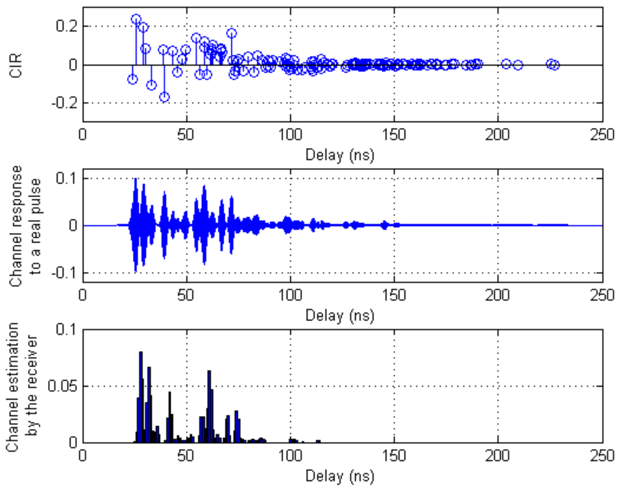

Fig. 1. Theoretical channel impulse response as a Dirac suite (top), received (noise-free) signal after convolution with the transmitted waveform (middle) and corresponding channel estimate available at the receiver (bottom).

B. Multipath Parameters and Evolution Model

Based on the set of observed bins $\{bin_p^{(k)}\}_{p=1...p_{max}^{(k)}}$ over a radio link, the purpose is to track specular[1] MPCs belonging to the theoretical CIR (See Fig. 1) so as to further assist the estimation of mobile position. We first define for each MPC i the vector of parameters:

$$X_i^{(k)} = [\tau_i^{(k)}, \dot{\tau}_i^{(k)}]^T, \quad i = 1...n^{(k)} \tag{1}$$

where $n^{(k)}$ is an arbitrary large number of tracked MPCs at time step k, $\tau_i^{(k)}$ and $\dot{\tau}_i^{(k)} = (\tau_i^{(k)} - \tau_i^{(k-1)})/\Delta T^{(k)}$ are respectively the delay and delay evolution speed of the i-th MPC at the same time step, and $\Delta T^{(k)} = T^{(k)} - T^{(k-1)}$ is the time interval between time steps $k-1$ and k.

Under moderate pedestrian mobility and relatively high refresh rate (i.e., $1/16$ s herein), we indirectly assume a simple constant-velocity evolution model for these MPC parameters:

$$\begin{aligned} X_i^{(k+1)} &= A_i^{(k+1)} \cdot X_i^{(k)} + V_i^{(k+1)} \\ &= \begin{bmatrix} 1 & \Delta T^{(k+1)} \\ 0 & 1 \end{bmatrix} \cdot X_i^{(k)} + \begin{bmatrix} 0 \\ \upsilon^{(k+1)} \end{bmatrix} \end{aligned} \tag{2}$$

where $A_i^{(k+1)}$ represents the state transition matrix between time steps k and $k+1$, and the centered Gaussian random noise term $\upsilon^{(k+1)}$ reflects the constant velocity hypothesis.

If $\tau_1^{(k)}$ is the ToA associated with the direct path in Line of Sight (LoS), which is also abusively called channel Leading Edge (LE) and noted $\tau_1^{(k)} = \tau_{LE}^{(k)}$ in the following, the non-linear function linking $\tau_{LE}^{(k)}$ with the 2D Cartesian coordinates of the mobile $(x^{(k)}, y^{(k)})$ and a particular base (or anchor) with known 2D coordinates (x_j, y_j), $j = 1...Z$, is given by:

$$\tau_{LE,j}^{(k)} = \frac{1}{c}\sqrt{\left(x_j - x^{(k)}\right)^2 + \left(y_j - y^{(k)}\right)^2} \tag{3}$$

where c is the speed of light.

Using straightforward trigonometric relationships illustrated on Fig. 2, one can write the equation binding the mobile speed vector, $\overrightarrow{V_{mobile}}$, and the relative delay variation of a given MPC between two consecutive mobile positions, $\overrightarrow{V_{ToA}}$ (where we omit the indexes i, j and k for notation simplicity) as follows:

$$\|\overrightarrow{V_{ToA}}\| = \|\overrightarrow{V_{mobile}}\| \cdot \cos(\phi) \tag{4}$$

$$\theta = (\overrightarrow{Ox}, \overrightarrow{V_{mobile}}) = \alpha + \phi \tag{5}$$

Under the assumptions of high refresh rate and distant scatterer, the absolute angle α formed between the x axis and the received MPC direction of arrival is supposed time-invariant between consecutive mobile positions in first approximation.

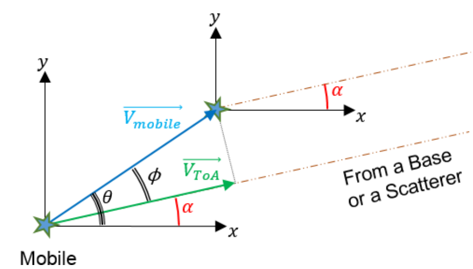

Fig. 2. Geometric relationship between consecutive mobile positions and multipath delay variation.

Using (5) in (4) and re-introducing the 2D Cartesian notations $(V_x^{(k)}, V_y^{(k)})$ for the mobile speed of norm $\|\overrightarrow{V_{mobile}^{(k)}}\|$, the mobile localization problem could be explicitly formulated with the system of equations (6) and (3), involving all MPCs i with respect to all bases j.

$$\dot{\tau}_{i,j}^{(k)} = \sqrt{\left(V_x^{(k)}\right)^2 + \left(V_y^{(k)}\right)^2} \cdot \cos\left(\theta^{(k)} - \alpha_{i,j}\right) \tag{6}$$

As seen hereafter, the previous equations can be simplified for easier and more stable implementation, while still capturing the time-invariance of $\alpha_{i,j}$.

III. Proposed Algorithms

The overall proposed framework is shown on Fig. 3. The mobile tracking is performed like in [9] using a conventional Extended Kalman Filter (EKF) based on LE ToA measurements $\{\hat{\tau}_{LE,j}^{(k)}\}_{j=1...Z}$ with respect to Z bases, using (3) as observation equations. Similarly to [4], an additional innovation monitoring procedure is also implemented for preliminary NLoS detection, determining the Channel Status $C_{S_j}^{(k)} = \{LoS, NLoS\}$ between the mobile and each base j at time step k. Alternatively, one could for instance rely on the channel energy distribution (e.g., delay spread) or on sudden variations in the short-term history of LE ToA measurements (i.e., larger than expected, under reasonably

[1] Contrarily to diffuse components, which may be less correlated in time-space under mobility and thus, less relevant into the mobile tracking problem.

slow mobility). $C_{S_j}^{(k)}$ enables to trigger measurement outliers mitigation or correction. More particularly, in case of detected NLoS, we use the relative drift parameters associated with the tracked secondary MPCs to collectively reinforce (and hopefully correct) the estimated value $\hat{\tau}_{LE}^{(k)}$ feeding the mobile tracking EKF as input observation.

A. MPCs Tracking

The tracking of each MPC i is ensured by an independent EKF based on a preliminarily associated bin delay $\widetilde{Y}_i^{(k)}$, where the observation equation simply accounts for the delay quantization noise $W^{(k)}$ due to the finite bin width:

$$\begin{aligned}\widetilde{Y}_i^{(k)} &= \mathrm{round}(X_i^{(k)}) \\ &= \begin{pmatrix} 1 & 0 \end{pmatrix} \cdot X_i^{(k)} + W_i^{(k)} \\ &= C^{(k)} \cdot X_i^{(k)} + W_i^{(k)}\end{aligned} \tag{7}$$

Note that in (7), $\widetilde{Y}_i^{(k)}$ at time step k is the mapping result between the predicted state $\hat{X}_i^{(k|k-1)}$ (based on $A_i^{(k)}$) and the set $\{Y_i^{(k)}\}_{i=1\dots m^{(k)}}$ of $m^{(k)}$ raw (i.e., unassociated) detected bins' delays (See Fig. 3):

$$\widetilde{Y}_i^{(k)} = \mathcal{H}^{(k)}\left(\hat{X}_i^{(k|k-1)}, \{Y_i^{(k)}\}_{i=1\dots m^{(k)}}\right) \tag{8}$$

where $\mathcal{H}^{(k)}$ represents the mapping function (detailed later).

With the intention to track several paths at once but independently to avoid cross-divergence or error propagation issues, the architecture is then parallelized by considering one filter per tracked MPC like in [10], whose innovation $\sigma_i^{(k)}$ and innovation covariance $\Sigma_i^{(k)}$ are calculated as follows:

$$\begin{aligned}\sigma_i^{(k)} &= \widetilde{Y}_i^{(k)} - C^{(k)} \cdot \hat{X}_i^{(k|k-1)} \\ \Sigma_i^{(k)} &= C^{(k)} \cdot P_i^{(k|k-1)} \cdot (C^{(k)})^T + R^{(k)}\end{aligned} \tag{9}$$

where at time step k, $R^{(k)}$ is the observation noise covariance (i.e., associated with $W_i^{(k)})^2$ and $P_i^{(k|k-1)}$ the predicted state covariance matrix.

Since sudden changes in the MPC trajectories (so-called "maneuvering" paths) and frequent MPC collisions in dense multipath environments can seriously alter the tracking performance, as illustrated in [10], we thus propose to use a Multiple Hypothesis Kalman Filter (MHKF) instead of the EKF. This filter aims at discriminating several hypotheses (herein, a MPC "trajectory" change vs. a MPC delay measurement outlier) based on a detection threshold. The latter is based on the normalized innovation (10) and set according to an a priori false alarm rate criterion.

$$\Phi_i^{(k)} = (\sigma_i^{(k)})^T \cdot (\Sigma_i^{(k)})^{-1} \cdot \sigma_i^{(k)} \tag{10}$$

At each iteration, if the normalized innovation $\Phi_i^{(k)}$ exceeds the threshold, then the filter generates in parallel two candidates for the estimated state $\hat{X}_i^{(k|k)}$ of the i-th MPC, $\hat{X}_i^{(k|k)}(H_1)$ and $\hat{X}_i^{(k|k)}(H_2)$, considering:

- (H_1) A measurement outlier: One increases the corresponding term in the observation noise covariance $R^{(k)}$, before calculating $\hat{X}_i^{(k|k)}(H_1)$ and $P_i^{(k|k)}(H_1)$ in the EKF correction step.
- (H_2) A reliable measurement but an uncertain state transition model: One increases the corresponding term in the state noise covariance $Q^{(k)}$ in the EKF prediction step, before calculating $\hat{X}_i^{(k|k)}(H_2)$ and $P_i^{(k|k)}(H_2)$ in the EKF correction step.

[2]Noise covariance matrices are assumed independent of i and set according to the maximum expected MPC delay excursion within the refresh period.

At the next time step $k+1$, one computes the new predictions corresponding to both of the previous candidate estimates. During the new correction step, the final decision is made between the initial estimates by comparing their respective innovation terms, thus determining $\hat{X}_i^{(k+1|k+1)}$ accordingly and $\hat{X}_i^{(k|k)}$ retrospectively. Note that this procedure introduces additional latency (equivalent to one time step).

B. MPCs Detection, Association and Windowing

Contrarily to the MPCs detection solution presented in [11], we aim at reducing complexity by avoiding back and forth moves between time and frequency domains. Moreover, considering the temporal resolution available at the receiver, we cannot apply exactly the same amplitude-based association criterion due to small-scale fading. We thus propose herein an alternative solution. The detected bins' delays $\{Y_i^{(k)}\}_{i=1\dots m^{(k)}}$ described in (8) are determined from the bins $\{bin_p^{(k)}\}_{p=1\dots p_{max}^{(k)}}$. A received pulse typically spreads over several bins due to its temporal width (on the order of a few nanoseconds). But as one single bin per tracked MPC has to be selected for each MHKF, only $m^{(k)}$ local energy maxima will be chosen among all the bins, similarly to [9].

Before feeding the MHKF, we map each tracked MPC with the closest measurement in $\{Y_i^{(k)}\}$. So as to avoid aberrant associations, we proceed to a preliminary windowing of the candidate measurements around the latest estimated ToA value $\hat{\tau}_i^{(k-1|k-1)}$ (i.e., based on the MHKF output at time step $k-1$).

The final MHKF observation input $\widetilde{Y}_i^{(k)}$, from the mapping function $\mathcal{H}^{(k)}$ (see (8)), then corresponds to the closest allowed bin delay $Y_{l_i}^{(k)}$ (providing a local energy maximum) associated with $\hat{\tau}_i^{(k|k-1)}$, where l_i is defined by:

$$l_i = \underset{p\in[\![1,\, m^{(k)}]\!]\cap Win_i^{(k)}}{\mathrm{argmin}} \left(|\hat{\tau}_i^{(k|k-1)} - Y_p^{(k)}|\right) \tag{11}$$

where $Win_i^{(k)}$ denotes the window for the i-th MPC, set to encompass maximal shifts of $\tau_i^{(k)}$ within the refresh period.

For benchmark purposes, we also consider a receiver that selects only the five most energetic bins (depicted as *Fingers* hereafter) in the estimated channel profile at each time step.

C. MPC-Assisted Mobile Tracking

Equation (6) are highly non-linear and their direct introduction as observations in the mobile tracking EKF would imply high computational complexity due to the number of state variables to be estimated (i.e., considering numerous MPCs per radio link, and multiple links with respect to bases), as well as instability or even observability issues due to the noisy angular arguments in the cosine function.

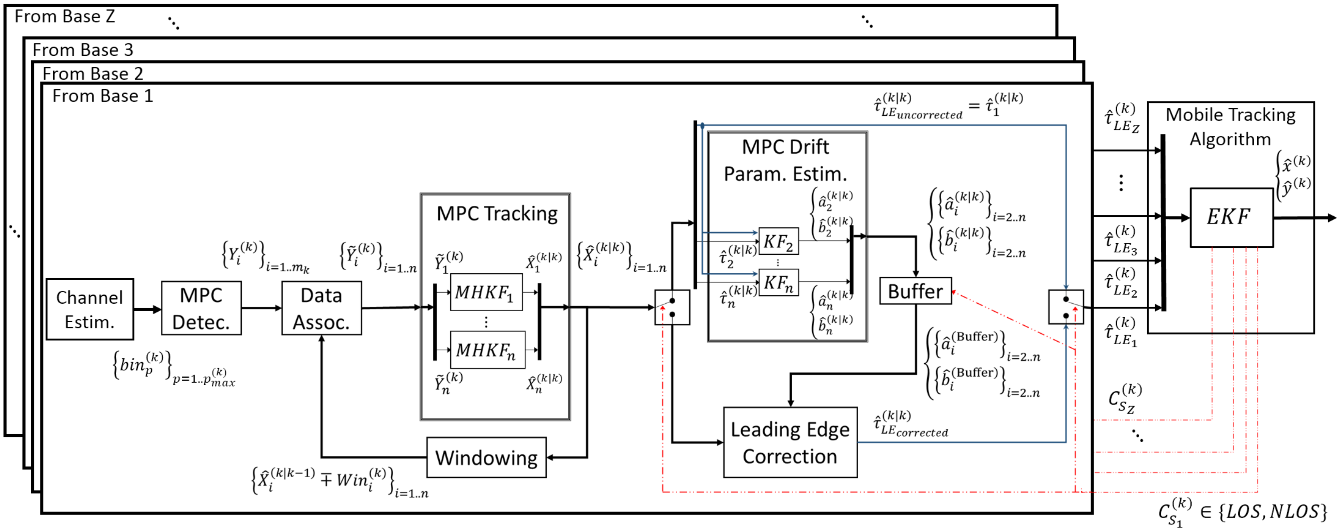

Fig. 3. Overall MPC-aided mobile tracking framework.

However, one can simply write the relationship between $\tau_{i,j}^{(k+1)}$ and $\tau_{LE_j}^{(k+1)}$. The idea is to estimate the time-invariant parameters of a linear function accounting for the temporal drift of any MPC relatively to the direct LE path:

$$\tau_{i,j}^{(k)} = a_{i,j} \cdot \tau_{LE_j}^{(k)} + b_{i,j} \tag{12}$$

Equation (12) still captures to some extent the time-invariance of α in (6). It can thus be used to provide the final mobile tracking EKF with corrected observations of $\tau_{LE_j}^{(k)}$. As long as $C_{S_j}^{(k)} = LoS$, $a_{i,j}$ and $b_{i,j}$ can be estimated as constant parameters by a side KF filter. Then, if $C_{S_j}^{(k)} = NLoS$ is detected (See e.g., the first paragraph of III), the latest estimated MPC drift parameters (stored in a buffer), $\hat{a}_{i,j}^{(Buffer)}$ and $\hat{b}_{i,j}^{(Buffer)}$, can be injected into (12) to determine one correction $\hat{\tau}_{LE_{i,j}}^{(k)}$ for each tracked secondary MPC i. Finally different rules can be applied (e.g., mean, median, weighted mean, majority voting) to combine the MPC contributions and issue the global correction $\hat{\tau}_{LE_j}^{(k)}$.

IV. Simulation Results

A. Multipath Tracking Performance

Using equation (12) to correct the value of $\hat{\tau}_{LE_{i,j}}^{(k)}$ in NLoS involves a good estimation of the parameters $a_{i,j}$ and $b_{i,j}$ over LoS periods. In addition, for the final correction $\hat{\tau}_{LE_j}^{(k)}$, it is necessary to track a large number of MPCs over sufficient time periods to capture beneficial space-time correlation effects.

For the evaluation of MPCs tracking, we use a semi-deterministic tool modeling the dynamic evolution of MPCs under mobility. The latter are first drawn as realizations of the IEEE 802.15.4a statistical channel model and then adjusted (in both amplitude and delay) according to the mobile trajectory [12]. Results are obtained over 100 simulation trials of 200 time steps each with a refresh period of $1/16$ s in both LoS and NLoS residential contexts. The maximum number n of MHKFs in parallel (See Fig. 3) is set to 20.

The MPC delay estimation error is defined as the time difference to the closest existing MPC at each time step, regardless of association issues. Table I reports such errors for characteristic values of their empirical Cumulative Density Functions (CDF) (i.e., median error regime at CDF=50% and worst-case error regime at CDF=90%) for different delay estimators: *Fingers*, local detected maxima (i.e., *MPC Detect.* outputs on Fig. 3), and tracked MPCs (i.e., *MHKF* outputs on Fig. 3). It can be noticed that the proposed parallel MHKF tracking architecture offers the best median estimation error in both LoS and NLoS channel configurations. One can also remark a very slight performance degradation in the worst-case error regime, even though still outperforming the *Fingers* approach. This is caused by pathological cases where two parallel MPCs are too close with respect to the receiver resolution (i.e., within 2 ns), leading to switch from one MPC to the next indifferently without detecting any change.

TABLE I
MPC DELAY ESTIMATION ERROR

	LoS		NLoS	
	50%	90%	50%	90%
Fingers	0.2389	0.5653	0.2389	0.7486
Detected MPCs	0.2139	0.4661	0.2062	0.4705
MHKF	0.1588	0.5024	0.1721	0.5108

Fig. 4 shows the empirical CDFs of the absolute time variations $\delta^{(k)}$ between two successive estimated MPC delays between time steps $k-1$ and k. The idea is to evaluate the capability to capture the MPC space-time correlation over mobility. The *MHKF* approach is now compared to two variants of the *Fingers* approach, whose outputs are ordered according to the detected bins' amplitudes or to their delays (for better fairness). It is thus rather clear that the proposed solution better captures MPC continuity over mobility with most of the estimated delay transitions below 1ns (and definitely lower than 2ns, in compliance with the considered pedestrian mobility). Other basic *Fingers* approaches are simply bounded to the bin shift and quantization effect for errors below 1 ns, but they can experience much larger transitions up to 50 ns.

Fig. 5 represents the empirical joint Probability Density Function (PDF) of MPC's Life Time (LT) and MPC's Cumu-

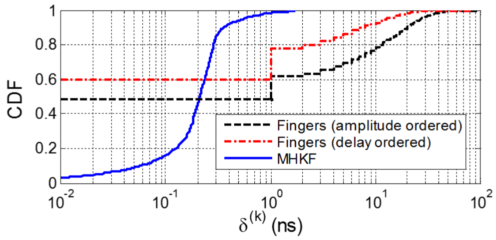

Fig. 4. CDF of time variations between consecutive estimated MPC delays.

lative Tracking Time (CTT). Our proposal globally enables to shift the dominating density modes towards the right upper corners of the plots (i.e., thus capturing simultaneously longer CTTs and longer LTs) in LoS and NLoS contexts. This contributes to improve the LE correction procedure in case of sudden LoS-to-NLoS transitions.

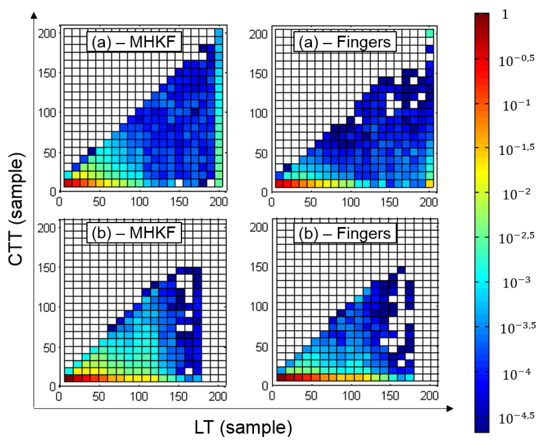

Fig. 5. 2D joint PDF of MPC's Life Time (LT) and Cumulative Tracking Time (CTT) for *MHKF* and *Fingers* in residential LoS (a) and NLoS (b).

B. *Mobile Tracking Performance*

We now consider a 14mx14m square room with $Z = 3$ bases and one mobile user. The channel model is simplified so that the received signal consists of a direct path (in LoS) and four secondary MPCs resulting from single-bounce reflections on the walls (in both LoS and NLoS). At the start and the end of the simulated trajectory (of 2D coordinates (7m,1m)), all bases are in LoS whereas the channel status is gradually changed to NLoS at the three bases, as materialized by the shadowed areas on Fig. 6. When only one base is in NLoS, the location error of the nominal EKF filter increases significantly due to the incorporation of strongly biased delay observations (blue). Over the same portion of trajectory, the benefits from NLoS detection and subsequent measurement bias mitigation by adjusting the observation covariance (black) is rather significant. Nevertheless, as soon as the NLoS configurations are generalized with respect to the other bases (i.e., up to the 3 bases), the covariance-based outliers mitigation (i.e. after NLoS detection through innovation monitoring) tends to reject all the input measurements and experiences poor Geometric Dilution of Precision (GDoP), thus making the filter diverge even more rapidly than the solution with no prior NLoS detection. At the end of the trajectory, the classical innovation monitoring approach keeps on rejecting reliable measurements even in systematic LoS contexts due to the previous divergence. On the contrary, our MPC-aided strategy maintains a reasonable location error comparable to systematic LoS (lower than 0.5m over the full trajectory) whatever the channel status.

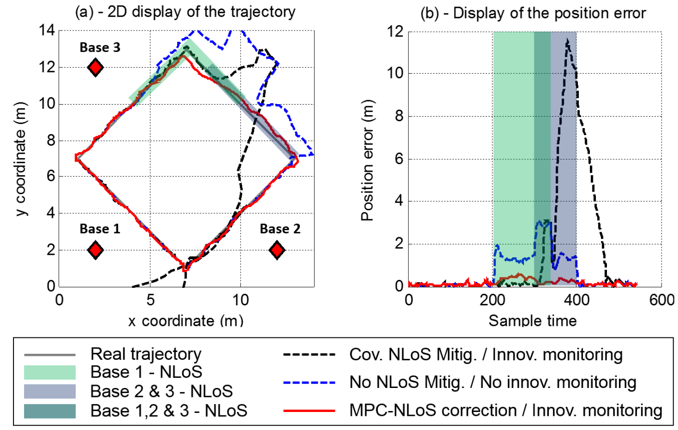

Fig. 6. Example of 2D estimated square trajectory.

V. Conclusion

In this paper, under practical IR-UWB receiver constraints, we have presented a low-complexity algorithmic framework to effectively track time-variant MPCs, correct estimated LE delays after NLoS detection, and finally assist mobile position estimation in case of generalized obstructions with respect to fixed bases. The provided simulation-based results show that the proposed solution can finely capture MPCs' space-time correlation under mobility, and finally contributes to maintain a constant quality of the localization service in harmful indoor environments. Pending field experiments with the devices described herein will allow performance analysis on real data.

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