HIDDEN MARKOV MODELS FOR RADIO LOCALIZATION OF MOVING TERMINALS IN LOS/NLOS CONDITIONS

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ABSTRACT

This paper deals with the problem of radio localization of moving terminals in wideband indoor applications with mixed line-of-sight/non-line-of-sight (LOS/NLOS) conditions. In dense multipath scenarios, the bias introduced by NLOS in angle and/or time of arrival estimates is reduced by employing a Hidden Markov Model (HMM) based algorithm. The proposed algorithm *jointly* tracks *both* the mobile station position *and* the LOS/NLOS conditions exploiting continuity information. Numerical results show that the HMM-based algorithm experiences non meaningful degradation in mixed LOS/NLOS propagation with dense multipath.

1. INTRODUCTION

Accurate localization in radio systems has received great attention over the last years. Without exploiting satellite-aided positioning systems (e.g., by Global Positioning System), several radio positioning techniques [1]-[2]-[3] have been proposed exploiting only local radio measurements while transmitting. These techniques are based on one or more measurement types such as angle (AOA - Angle of Arrival), time (TOA - Time Of Arrival) or time difference (TDOA - Time Difference of Arrival) of arrivals and power profile (RSS - Received Signal Strength).

In the next generation indoor wideband mobile systems, such as Ultra Wide Band (UWB) and Orthogonal Frequency Division Multiplexing (OFDM) systems, radio localization using time or/and angle based methods (TOA, TDOA and AOA) is a critical task due to high resolution and dense multipath effects. The local positioning problem is worsened by non-line-of-sight (NLOS) conditions due to signal blocking. To reduce the estimation bias introduced by the NLOS issue and alleviate multipath effects, here we propose to exploit *both* locality of the mobile station (MS) position *and* LOS/NLOS conditions for all links by using a HMM-based (Hidden Markov Model) [4] tracking algorithm here referenced as Detection/Tracking Algorithm (D/TA) [5]. The hidden status of each MS is characterized by its discretized position *and* LOS/NLOS conditions along the cell, both modeled as homogeneous first-order Markov chains. D/TA is a forward-only algorithm that can work in real time and it maximizes the a-posteriori probability of joint position-LOS/NLOS state for each MS exploiting all the independent RSS measurements (with respect to all access points - APs) available up to the current instant. With respect to other alternatives, such as the extended Kalman filter (EKF) [6], the D/TA algorithm does not rely on linearization and Gaussian assumptions but it has about the same computational complexity. For the sake of simplicity, only the single target D/TA will be presented; the interested reader can refer to [5] for multitarget extension. Notice that the HMM framework here presented may model either self-positioning or remote localization systems. Moreover, it may be employed in different scenarios and only observation probabilities have to be changed accordingly.

The paper is organized as follows: in the next section the localization problem is described, while Section 3 shows the HMM framework for joint tracking of MS position and sight condition. The DT/A method is recalled in Section 4 while numerical results are discussed in Section 5. Section 6 draws some conclusions.

2. PROBLEM FORMULATION

At time instant i, for $i \in \{0, 1, \ldots, I-1\}$, the mobile station is placed at the spatial location $\mathbf{q}_i = [q_i^{(x)}, q_i^{(y)}]$, with $q_i^{(x)} \in \mathcal{X} = \{0, \ldots, N_1 - 1\}$ and $q_i^{(y)} \in \mathcal{Y} = \{0, \ldots, N_2 - 1\}$ denoting the coordinates within a regular 2D grid $\mathcal{Q} = \mathcal{X} \times \mathcal{Y}$ of size $N_1 \times N_2$. The MS receives (or transmits) a radio signal from (or to) L fixed access points (AP) that are located in known positions $\mathbf{q}_{\mathrm{AP}\ell} = [q_{\mathrm{AP}\ell}^{(x)}, q_{\mathrm{AP}\ell}^{(y)}] \in \mathcal{Q}$, for $\ell \in \{1, \ldots, L\}$. The signal $\mathbf{r}_{i,\ell} \in \mathbb{R}^{M \times 1}$ measured over the ℓth MS-AP link is modeled as:

$$\mathbf{r}_{i,\ell} = [r_{i,\ell}(0) \cdots r_{i,\ell}(M-1)]^T = \mathbf{z}_{i,\ell} + \mathbf{w}_{i,\ell}, \tag{1}$$

where $\mathbf{z}_{i,\ell} \sim \mathcal{N}(\mathbf{0}, \mathbf{C}_{i,\ell})$ represents the desired signal and $\mathbf{w}_{i,\ell} \sim \mathcal{N}(\mathbf{0}, \mathbf{C}_w)$ is AWGN with known covariance $\mathbf{C}_w = \sigma_w^2 \mathbf{I}_M$ ($\mathbf{I}_M$ is the unitary matrix of size $M \times M$). The signal $\mathbf{z}_{i,\ell}$, representative of arrivals in a dense multipath scenario, is non-stationary, white, with known covariance $\mathbf{C}_{i,\ell} = \mathrm{diag}[\sigma_z^2(\tau_{i,\ell}, \Delta\tau_{i,\ell}, 0), \ldots, \sigma_z^2(\tau_{i,\ell}, \Delta\tau_{i,\ell}, M-1)]$ where $\sigma_z^2(\tau, \Delta\tau, t)$ is an exponential power delay profile (PDP)

$$\sigma_z^2(\tau, \Delta\tau, t) = \sigma_z^2(\tau)\rho^{(t-\tau)} u(t - \tau - \Delta\tau), \tag{2}$$

decaying from the first arrival delay $\tau + \Delta\tau$ with attenuation factor $\rho \leq 1$ (recall that $u(t) = 1$ for $t \geq 0$ and $u(t) = 0$ elsewhere); this is also referred as filtered Poisson process [7]. The first arrival delay $\tau_{i,\ell} + \Delta\tau_{i,\ell}$ is the sum of the propagation time $\tau_{i,\ell}$ over the LOS distance $d_{i,\ell} = ||\mathbf{q}_i - \mathbf{q}_{\mathrm{AP}\ell}||$,

$$\tau_{i,\ell} = \langle d_{i,\ell}/c \rangle, \tag{3}$$

and the excess delay $\Delta\tau_{i,\ell} \geq 0$ experienced in the NLOS case. Here $\langle x \rangle$ denotes the nearest integer for the real value x, c is the propagation velocity (normalized by $\Delta q/\Delta t$ where Δq and Δt are the spatial and temporal sampling intervals assuming a regular and squared sampling grid). Clearly, it is $\Delta\tau_{i,\ell} = 0$ in case of LOS conditions, while in NLOS the additional delay $\Delta\tau_{i,\ell} > 0$ is modeled as a random variable with known distribution $f_{\Delta\tau}(\delta)$.

Notice that the PDP (2) depends on the path-loss law $\sigma_z^2(\tau) = \sigma_z^2(\tau_{\mathrm{ref}})(\tau/\tau_{\mathrm{ref}})^{-\alpha}$ where $\sigma_z^2(\tau_{\mathrm{ref}})$ is the power received at a reference distance $d_{\mathrm{ref}} = c\tau_{\mathrm{ref}}$ and α is the path-loss exponent

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(α=2 $\div$ 4). The SNR is defined as $\text{SNR}(\tau) = \sigma_z^2(\tau)/\sigma_w^2 = \text{SNR}_{\text{ref}} \cdot (\tau/\tau_{\text{ref}})^{-\alpha}$ where $\text{SNR}_{\text{ref}} = \sigma_z^2(\tau_{\text{ref}})/\sigma_w^2$.

In signal model (1) the delay $\tau_{i,\ell} + \Delta\tau_{i,\ell}$ represents an abrupt change or breakpoint (BP) between the two processes $\{r_{i,\ell}(t)\}_{t=1}^{\tau_{i,\ell}+\Delta\tau_{i,\ell}-1}$ and $\{r_{i,\ell}(t)\}_{t=\tau_{i,\ell}+\Delta\tau_{i,\ell}}^{M}$ that are characterized by different statistical properties. In fact, it is:

$$\text{Var}[r_{i,\ell}(t)] = \begin{cases} \sigma_w^2, & t < \tau_{i,\ell} + \Delta\tau_{i,\ell} \\ \sigma_w^2 + \sigma_z^2(\tau_{i,\ell})\rho^{t-\tau_{i,\ell}}, & t \geq \tau_{i,\ell} + \Delta\tau_{i,\ell} \end{cases} . \quad (4)$$

According to (3), in LOS conditions the BP event is linearly related to $d_{i,\ell}$; the MS-AP distance estimate can thus be obtained by simply detecting the BP position. After ranging from each of the $L \geq 3$ MS-AP links, the MS location $\mathbf{q}_i$ can be estimated through triangulation of the L distances. Nevertheless, this method leads to false locations in case of NLOS, as the BP depends on the fictitious distance $d_{i,\ell} + \Delta d_{i,\ell}$, where the bias $\Delta d_{i,\ell} = c\Delta\tau_{i,\ell} \geq 0$ is due to the propagation over reflected path.

To avoid false locations we propose a tracking algorithm that estimates the sequence of positions $\mathbf{q}_0, \mathbf{q}_1, ..., \mathbf{q}_i$ by exploiting the whole set of observations $\mathbf{R}_i = [\mathbf{r}_0, \mathbf{r}_1, \ldots, \mathbf{r}_i]$, composed of all the signals measured over the L links up to the current instant i. Vector $\mathbf{r}_i = [\mathbf{r}_{i,1}^T, \ldots, \mathbf{r}_{i,L}^T]^T$ collects all the observations at the ith time. The proposed HMM method is based on the assumption that *both* the mobile position $\mathbf{q}_i$ *and* the L link sight conditions are Markov chains whose state is hidden in the measured signals $\mathbf{R}_i$ and must be jointly recovered. For the estimation of the MS location we propose a first-order HMM tracking algorithm [5] that can cope also with LOS/NLOS situations, by exploiting the memory introduced on the MS trajectory and the knowledge of the distribution $f_{\Delta\tau}(\delta)$ to compensate the bias $\Delta\tau_{i,\ell}$.

3. HMM FOR RADIO LOCALIZATION

3.1. Set of states and transition probabilities

Let the MS location $\mathbf{q}_i$ be defined in the discrete finite set $\mathcal{Q}$ consisting of $N_1 N_2$ positions $\mathbf{n} =[n_1, n_2]$, with $n_1 \in \mathcal{X}$, $n_2 \in \mathcal{Y}$. The MS movement within the 2D space is modeled as the following first-order homogeneous Markov model:

$$\mathbf{q}_i = \mathbf{q}_{i-1} + \mathbf{v}_i, \quad (5)$$

where $\mathbf{v}_i$ is the 2D discrete driving process with known distribution $f_{\mathbf{v}}(n_1, n_2) = P[\mathbf{v}_i = \mathbf{n}]$. The transitions between states are governed by the $N_1N_2 \times N_1N_2$ probabilities $a_{\mathbf{m},\mathbf{n}}^{(p)} = P[\mathbf{q}_i = \mathbf{n}|\mathbf{q}_{i-1} = \mathbf{m}] = f_{\mathbf{v}}(n_1 - m_1, n_2 - m_2)$ for $\mathbf{m} =[m_1, m_2]$, $\mathbf{n} =[n_1, n_2] \in \mathcal{Q}$. Examples of distribution $f_{\mathbf{v}}(n_1, n_2)$ are given in Fig. 1.

In addition to its position, at each time instant i the MS is characterized also by L sight conditions (LOS or NLOS) with respect to the APs. These binary conditions are here described by a set of L i.i.d. random processes $\mathbf{s}_i = [s_{i,1}, \ldots, s_{i,L}] \in \mathcal{S}^L$, with $\mathcal{S} =\{1, 2\}$. Each sight process, $s_{i,\ell} \in \mathcal{S}$, is $s_{i,\ell} = 1$ in case of LOS and $s_{i,\ell} = 2$ in case of NLOS. It is modeled as a 2-state first-order Markov chain with transition probabilities $a_{h,k}^{(s)} = P[s_{i,\ell} = k|s_{i-1,\ell} = h]$ for $h, k \in \mathcal{S}$. Notice that all probabilities $a_{h,k}^{(s)}$ depend only on two parameters: p_1 and p_2. The former is the probability $p_1 = a_{1,1}^{(s)}$ to remain in the LOS state while the latter is the probability $p_2 = a_{2,2}^{(s)}$ to remain in the NLOS state. In fact, due to probability normalization, it is: $a_{12}^{(s)} = 1 - p_1$ and $a_{21}^{(s)} = 1 - p_2$. Assuming independence between the L sight conditions, the transition probabilities for the overall sight process $\mathbf{s}_i$ are $a_{\mathbf{h},\mathbf{k}}^{(s)} = \prod_{\ell=1}^{L} a_{h_\ell,k_\ell}^{(s)}$ for any $\mathbf{h} = [h_1, \ldots, h_L]$, $\mathbf{k} = [k_1, \ldots, k_L] \in \mathcal{S}^L$. The sight process $\mathbf{s}_i$ is also assumed to be independent of the position process $\mathbf{q}_i$.

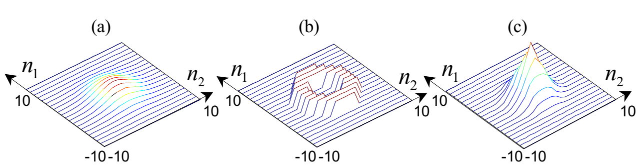

Fig. 1. Examples of distribution $f_{\mathbf{v}}(n_1, n_2)$ for random 2-D driving process $\mathbf{v}_i$. Notice that a large $f_{\mathbf{v}}(0, 0)$ value indicates that the MS is frequently still as shown in figures a) and c).

The complete HMM for localization is now defined including both the position *and* the sight processes. Namely, the HMM state is defined by the joint variable $\mathbf{O}_i = (\mathbf{q}_i, \mathbf{s}_i)$, that takes values in a discrete set of $2^L N_1N_2$ possible position/sight combinations. According to the independence assumption for $\mathbf{q}_i$ and $\mathbf{s}_i$, the probability of transition from $\mathbf{O}_{i-1} = (\mathbf{m}, \mathbf{h})$ to $\mathbf{O}_i = (\mathbf{n}, \mathbf{k})$ is $a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})}^{(ps)} = a_{\mathbf{m},\mathbf{n}}^{(p)} a_{\mathbf{h},\mathbf{k}}^{(s)}$ for $\mathbf{m}, \mathbf{n} \in \mathcal{Q}$ and $\mathbf{h}, \mathbf{k} \in \mathcal{S}^L$. A zero state $\mathbf{O}_i = \mathbf{0}$ is also introduced to indicate the absence of the MS signal (i.e., no MS detected), yielding the overall set $\mathcal{O}$ of $2^L N_1N_2 + 1$ position states. The $(2^L N_1N_2 + 1) \times (2^L N_1N_2 + 1)$ transition matrix $\mathbf{A}$ for the whole set of states, including the zero state, has elements defined as:

$$\begin{aligned} &a_{\mathbf{0},\mathbf{0}} = 1 - \theta && a_{\mathbf{0},(\mathbf{n},\mathbf{k})} = \theta/(2^L N_1N_2) \\ &a_{(\mathbf{m},\mathbf{h}),\mathbf{0}} = \nu && a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})} = (1 - \nu)a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})}^{(ps)}\Gamma_{\mathbf{m}} \end{aligned} \quad (6)$$

where $\mathbf{m}, \mathbf{n} \in \mathcal{Q}$ and $\mathbf{h}, \mathbf{k} \in \mathcal{S}^L$. Here, the parameters θ and ν represent the probabilities of trajectory initiation and termination, respectively. Notice that they are assumed to be independent of the specific non-zero state involved in the transition. The term $\Gamma_{\mathbf{m}}$ is used to normalize the rows of $\mathbf{A}$ to 1 so that $\mathbf{a}_{(\mathbf{m},\mathbf{h}),\mathbf{0}} + \sum_{\mathbf{n}\in\mathcal{Q},\mathbf{k}\in\mathcal{S}^L} \mathbf{a}_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})} = 1$ for any $(\mathbf{m}, \mathbf{h})$ (see [5] for further details on normalization strategies and edge effects due to the finite number of spatial positions).

3.2. Initial state distribution

The initial state distribution is defined by assigning the $2^L N_1N_2 + 1$ initial probabilities $\boldsymbol{\pi} = \{\pi_{\mathbf{0}}, \{\pi_{\mathbf{n},\mathbf{k}}\}\}$, where $\pi_{\mathbf{0}} = P[\mathbf{O}_0 = \mathbf{0}]$ and $\pi_{\mathbf{n},\mathbf{k}} = P[\mathbf{O}_0 = (\mathbf{n}, \mathbf{k})]$. If no *a-priori* knowledge of the initial position is given, we can simply impose a uniform initialization probability all over the $2^L MN + 1$ states, i.e. $\pi_{\mathbf{0}} = 1/2$ and $\pi_{\mathbf{n},\mathbf{k}} = 1/(2^{L+1}N_1N_2)$.

3.3. Observation probabilities

The observation employed in the HMM framework is the vector $\mathbf{r}_i \in \mathbb{R}^{ML\times 1}$. We assume the L observations $\{\mathbf{r}_{i,\ell}\}_{\ell=1}^{L}$ conditioned to the non-zero state $\mathbf{O}_i = (\mathbf{n}, \mathbf{k})$ to be statistically independent; the observation probability density function (pdf) $b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i) = P[\mathbf{r}_i|\mathbf{O}_i = (\mathbf{n}, \mathbf{k})]$ can be calculated as:

$$b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i) = \prod_{\ell=1}^{L} P[\mathbf{r}_{i,\ell}|\mathbf{q}_i = \mathbf{n}, s_{i,\ell} = k_\ell] . \quad (7)$$

Let us first consider the LOS case ($s_{i,\ell} = 1$), the ℓth conditioned pdf in (7) is:

$$P[\mathbf{r}_{i,\ell}|\mathbf{q}_i = \mathbf{n}, s_{i,\ell} = 1] = \Lambda(\mathbf{r}_{i,\ell}, \langle\|\mathbf{n} - \mathbf{q}_{\text{AP}\ell}\|/c\rangle, 0) \quad (8)$$

where $\Lambda(\mathbf{r}, \tau, \Delta\tau)$ is the likelihood function for the generic observation $\mathbf{r} = [r(0), \ldots, r(M - 1)]^T$, LOS delay τ and NLOS

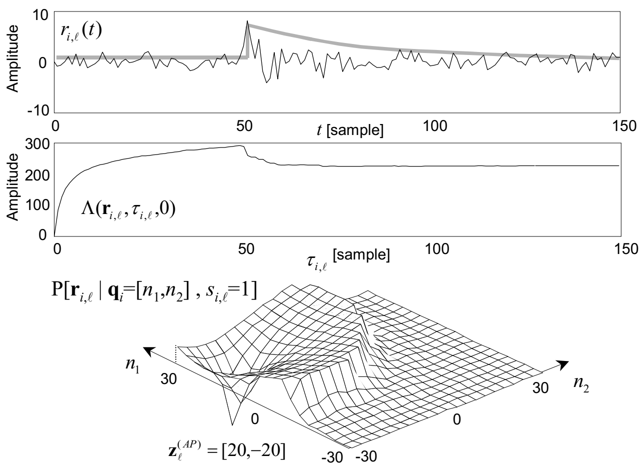

Fig. 2. Example of observation for LOS. From top to bottom: a) measured signal (solid line indicates $\sigma_z^2(\tau=50,\Delta\tau=0,t)$ with $\rho=0.99$); b) observation pdf as a function of the delay; c) observation pdf as a function of the position.

additional delay $\Delta\tau$. Being $\phi(x)=\exp(-x^2/2)/\sqrt{2\pi}$ the normal function, from model (1) we get:

$$\Lambda(\mathbf{r},\tau,\Delta\tau)=\prod_{t=0}^{\tau+\Delta\tau-1}\frac{\phi\left(\frac{r(t)}{\sigma_0}\right)}{\sigma_0}\prod_{t=\tau+\Delta\tau}^{M-1}\frac{\phi\left(\frac{r(t)}{\sigma_1(\tau,\Delta\tau,t)}\right)}{\sigma_1(\tau,\Delta\tau,t)},\quad(9)$$

where $\sigma_0^2=\sigma_w^2$ and $\sigma_1^2(\tau,\Delta\tau,t)=\sigma_w^2+\sigma_z^2(\tau,\Delta\tau,t)$ denote, respectively, the signal power within the backward ($t<\tau+\Delta\tau$) and the forward ($t\geq\tau+\Delta\tau$) sections of the measurement $\mathbf{r}$ for the breakpoint instant $\tau+\Delta\tau$. An example of conditioned pdf for LOS is given in Fig. 2.

On the other hand, for NLOS condition, it is:

$$P[\mathbf{r}_{i,\ell}|\mathbf{q}_i=\mathbf{n},s_{i,\ell}=2]=\sum_{\delta>0}f_\Delta(\delta)\Lambda\left(\mathbf{r}_{i,\ell},\langle\|\mathbf{n}-\mathbf{q}_{\mathrm{AP}\ell}\|/c\rangle,\delta\right).\quad(10)$$

For large SNR, we can use the following approximation: $\sigma_1^2(\tau,\Delta\tau,t)=\sigma_1^2(\tau)\rho^{t-\tau}$, for $t\geq\tau+\Delta\tau$, with $\sigma_1^2(\tau)=\sigma_w^2+\sigma_z^2(\tau)$. For $\Delta\tau=0$ equation (9) reduces to:

$$\Lambda(\mathbf{r},\tau,0)\approx\frac{\beta(M-\tau)}{(\sqrt{2\pi}\sigma_0)^M}\exp\left[-\frac{E_0(\tau)}{2\sigma_0^2}-\frac{E_1(\tau)}{2\sigma_1^2(\tau)}\right]\quad(11)$$

where $\beta(x)=(\rho^{-\frac{x-1}{4}}\frac{\sigma_0}{\sigma_1(\tau)})^x$. Terms $E_0(\tau)=\sum_{t=0}^{\tau-1}r^2(t)$ and $E_1(\tau)=\sum_{t=\tau}^{M-1}r^2(t)\rho^{\tau-t}$ denote the signal energy for the backward and forward section, respectively. For $\Delta\tau>0$ it is $\Lambda(\mathbf{r},\tau,\Delta\tau)=\Lambda(\mathbf{r},\tau,0)\cdot\Gamma(\mathbf{r},\tau,\Delta\tau)$ with

$$\Gamma(\mathbf{r},\tau,\Delta\tau)\approx\frac{\exp\left[-\frac{E_0(\tau+\Delta\tau)-E_0(\tau)}{2\sigma_0^2}-\frac{\rho^{-\Delta\tau}E_1(\tau+\Delta\tau)-E_1(\tau)}{2\sigma_1^2(\tau)}\right]}{\beta(\Delta\tau)}.\quad(12)$$

Notice that for the zero-state the conditioned pdf $b_{\mathbf{0}}(\mathbf{r}_i)=P[\mathbf{r}_i|\mathbf{O}_i=\mathbf{0}]$ is defined as:

$$b_{\mathbf{0}}(\mathbf{r}_i)=\frac{1}{(\sqrt{2\pi}\sigma_w)^{LM}}\exp\left[-\frac{1}{2\sigma_w^2}\sum_{\ell=1}^{L}\sum_{t=0}^{M-1}r_{i,\ell}^2(t)\right].\quad(13)$$

In the followings, the HMM parameter set is indicated according the compact notation $\lambda=(\mathbf{A},\mathbf{B},\boldsymbol{\pi})$ where $\mathbf{B}$ is the observation density set defined as $\mathbf{B}=\{b_{\mathbf{0}}(\cdot),\{b_{\mathbf{n},\mathbf{k}}(\cdot)\}\}$.

4. DETECTION/TRACKING ALGORITHM

The maximum likelihood estimate (MLE) $\widehat{\mathbf{O}}_i=(\widehat{\mathbf{q}}_i,\widehat{\mathbf{s}}_i)$ may be directly obtained by maximizing the likelihood function (7):

$$\hat{\mathbf{O}}_i=\underset{(\mathbf{n},\mathbf{k})\in\mathcal{O}}{\arg\max}\prod_{\ell=1}^{L}P\left[\mathbf{r}_{i,\ell}|\mathbf{q}_i=\mathbf{n},s_{i,\ell}=k_\ell\right].\quad(14)$$

MLE is a local estimate based on the ith measurement vector $\mathbf{r}_i$ only. On the contrary, the HMM tracking algorithm considers all measurements ($\mathbf{R}_i$) observed up to the ith instant. Given the set of HMM parameters λ (supposed known), the D/TA [5] estimates the position-sight state $\mathbf{O}_i=(\mathbf{q}_i,\mathbf{s}_i)$ at the ith instant by maximizing the a-posteriori probability $\gamma_i(\mathbf{n},\mathbf{k})=P[\mathbf{O}_i=(\mathbf{n},\mathbf{k})|\mathbf{R}_i,\lambda]$: $\hat{\mathbf{O}}_i=\underset{(\mathbf{n},\mathbf{k})\in\mathcal{O}}{\arg\max}\gamma_i(\mathbf{n},\mathbf{k})$. From Bayes' theorem it is:

$$\gamma_i(\mathbf{n},\mathbf{k})=\mu_i b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i)\,P\left[\mathbf{O}_i=(\mathbf{n},\mathbf{k})|\mathbf{R}_{i-1},\lambda\right],\quad(15)$$

where μ_i is a normalization term such that $\gamma_i(\mathbf{0})+\sum_{\mathbf{n},\mathbf{k}}\gamma_i(\mathbf{n},\mathbf{k})=1$. The conditioned pdf $b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i)$ is obtained as described in Section 3.3, while the a-priori pdf $P[\mathbf{O}_i=(\mathbf{n},\mathbf{k})|\mathbf{R}_{i-1},\boldsymbol{\lambda}]$ can be calculated from the a-posteriori pdf for the previous instant $i-1$ through the transition probabilities of the Markov chain:

$$P\left[\mathbf{O}_i=(\mathbf{n},\mathbf{k})|\mathbf{R}_{i-1},\lambda\right]=\sum_{(\mathbf{m},\mathbf{h})\in\mathcal{O}}a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})}\gamma_{i-1}(\mathbf{m},\mathbf{h}).\quad(16)$$

At the first step ($i=0$), the initialization of the a-posteriori probabilities is obtained as: $\gamma_0(\mathbf{n},\mathbf{k})=\mu_0\,b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_0)\,\pi_{(\mathbf{n},\mathbf{k})}$, $\gamma_0(\mathbf{0})=\mu_0\,b_{\mathbf{0}}(\mathbf{r}_0)\,\pi_{\mathbf{0}}$.

5. SIMULATION RESULTS

The localization performance is evaluated by simulating a MS moving within a circular area (e.g. diameter $D=60$) and exchanging signals with $L=3$ equidistant APs placed on the border of the layout (the area close to each AP is not used). The changes of the MS location over the time are simulated according to a Gaussian-shaped pdf $f_{\mathbf{v}}(n_1,n_2)$ (as in Fig. 1a). The sight conditions $\{s_{i,\ell}\}_{\ell=1}^3$ are simulated by means of three independent first-order Markov chains. Measurements have length $M=150$; the first arrival delay $\tau_{i,\ell}$ is obtained from (3) and the additional NLOS delay $\Delta\tau_{i,\ell}$ (for $s_{i,\ell}=2$) has exponential distribution $f_{\Delta\tau}(\delta)\sim\exp(1/\sigma_{\Delta\tau})$ with $\sigma_{\Delta\tau}=10$. The signal power $\sigma_z^2(\tau,\Delta\tau,t)$ is calculated according to the path-loss law, with exponent $\alpha=2.4$, $\mathrm{SNR}_{\mathrm{ref}}=40$ dB at $d_{\mathrm{ref}}=2$. An exponential PDP is simulated with $\rho=0.99$. The algorithm performances are evaluated in terms of root mean square error (RMSE) of the location estimate as a function of the spatial position over a trajectory of $I=30000$ time samples. For a given position $\mathbf{q}\in\mathcal{Q}$, the RMSE is evaluated as $\mathrm{RMSE}(\mathbf{q})=[\sum_{j\in N(\mathbf{q})}||\mathbf{q}-\hat{\mathbf{q}}_j||^2/I(\mathbf{q})]^{\frac{1}{2}}$, where $N(\mathbf{q})$ is the ensemble of all instants in which the trajectory flows across $\mathbf{q}$ and $I(\mathbf{q})$ is its cardinality.

An example is shown in Fig. 3. Here the trajectory has been made smoother and shorter ($I=50$) for visualization purposes. The figure compares the true trajectory (thick line) with the estimated ones (markers) obtained by a local MLE (left figure) and the

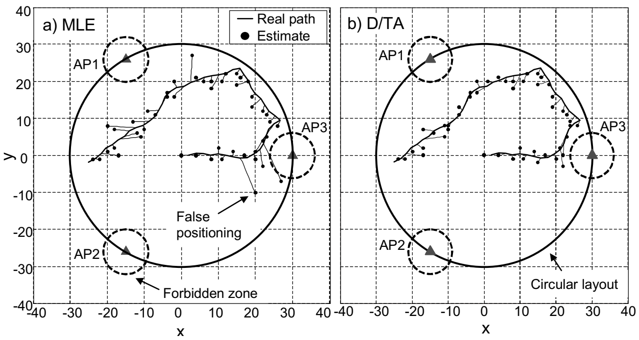

Fig. 3. Examples of localization with local MLE (left) and D/TA (right): the solid line indicates the true trajectory while the markers show the estimated one.

D/TA (right figure). The errors of the estimate can be appreciated from the lines that connect the true and the estimated positions. False positioning for NLOS occurs only using local MLE.

Fig. 4 shows the RMSE of the estimate as a function of the position $\mathbf{q} \in \mathcal{Q}$ for both the local MLE (Fig. 4a-4b) and the D/TA (Fig. 4c-4d), in case of LOS only ($p_1 = 1$, $p_2 = 0$; Fig.4a-4c) and for LOS/NLOS conditions ($p_1 = p_2 = 0.7$; Fig. 4b-4d). In the MLE-LOS map the error increases in proximity of the APs, while it is uniform in the middle of the layout. This effect is due to false positioning errors occurring when one or more measurements $\mathbf{r}_{i,\ell}$ refer to a distant AP. These problems are solved by the D/TA which yields a uniform error map all over the layout. The advantage of the D/TA (especially in mixed LOS/NLOS conditions) is more evident in Fig. 4e and 4f that show the $\{x = 0\}$ sections of the maps in Fig. 4a-4b-4c-4d. The local MLE yields very poor performance, with RMSE ranging from 0 to 30, while the D/TA error is stable under 5, in both LOS and mixed LOS/NLOS cases.

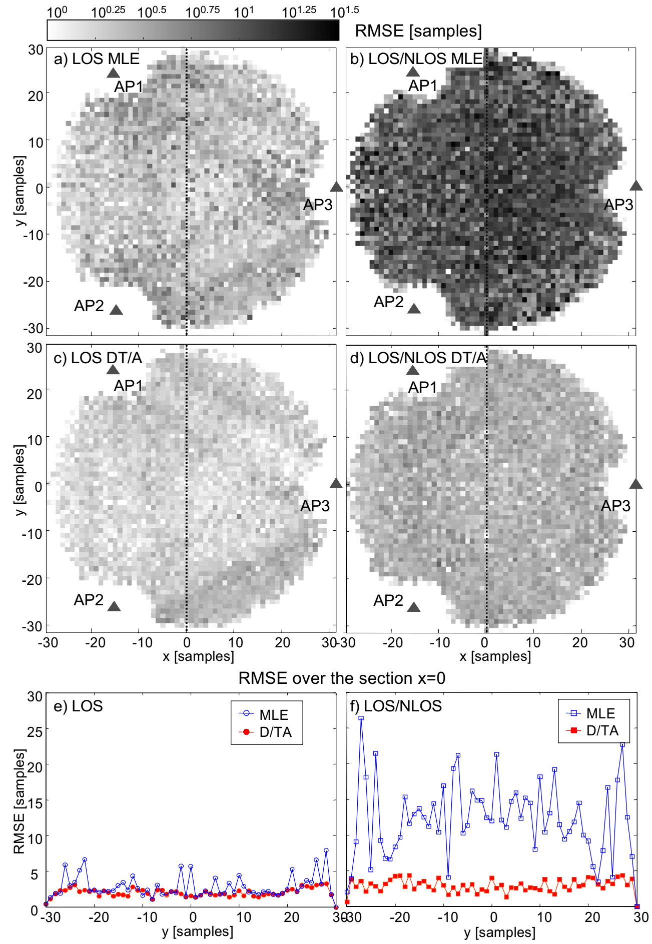

Fig. 4. RMSE of the position estimate for local MLE and global D/TA. The dashed lines in figures a)-b)-c)-d) indicate section $x = 0$. Figures a) and c) refer to RMSE performances of MLE and DT/A estimates, respectively. Performances are drawn for each spatial position $\mathbf{q} = [x, y]$ in LOS conditions only. Figures b) and d) show RMSE performances obtained for MLE (b) and DT/A (d) estimates in mixed LOS/NLOS environment. Figures e) and f) compare the RMSE performances for varying y along the section $x = 0$ in LOS and LOS/NLOS situations.

6. CONCLUSIONS

A novel approach based on HMM has been proposed to track location of moving terminals. The proposed algorithm alleviates the LOS/NLOS problem in dense multipath conditions by adding, for each radio link, the sight state. Simulations show that performances achieved when accounting for LOS/NLOS conditions are similar to those in ideal LOS-only propagation environment.

7. REFERENCES

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