HMM-BASED TRACKING OF MOVING TERMINALS IN DENSE MULTIPATH INDOOR ENVIRONMENTS

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ABSTRACT

This paper deals with the problem of radio localization of moving terminals (MTs) for indoor applications with mixed line-of-sight/non-line-of-sight (LOS/NLOS) conditions. To reduce false localizations, a Bayesian approach is proposed to estimate the MT position. The tracking algorithm is based on a Hidden Markov Model (HMM) that permits to jointly track both the MT position and the sight condition. Numerical results show that the proposed HMM method improves the localization accuracy in LOS/NLOS indoor environments.

1. INTRODUCTION

In wireless communication systems, localization of moving terminals (MTs) is obtained through the estimation of propagation parameters related to the MT location [1] [2]. The estimation is performed by exchanging radio signals with L fixed access points (APs) placed in known positions. Typical parameters are: time of arrival (TOA), time difference of arrivals (TDOA), angle of arrival (AOA) and received signal strength intensity (RSSI). The relationship between these parameters and the MT position is given by analytical models or through field measurements. The most common approach for localization is the evaluation of the MT-APs distances (ranging) from estimates of the above mentioned parameters, then followed by tri- ($L = 3$) or multi- ($L > 3$) lateration.

In indoor environments characterized by dense multipath and/or NLOS conditions, false localizations arise as ranging results in *apparent* or biased distances due to propagation over secondary paths. Errors can be reduced by exploiting redundant measurements (large L), combining analytical models with maps of measurements (i.e., by a preliminary calibration step), or using Bayesian methods to track the MT trajectory instead of estimating one position at a time.

In this paper, we propose a HMM-based (Hidden Markov Model) [3] tracking algorithm that estimates the MT location at a given time instant exploiting all the measurements along the MT trajectory up to that instant. The method is based on the Detection/Tracking Algorithm (D/TA) [4], here adapted to the specific localization problem. It is a forward-only algorithm that can work in real-time by maximizing the a-posteriori probability of the HMM state given all the signals measured over the L links up to the current position. The measurements used for localization are the power delay profiles for the signals received over the L radio links. Notice that the RSSI-delay profile is more informative than the total RSSI, as it is a joint measurement of TOA and power. Furthermore, to improve the localization accuracy, we propose to track the MT position *directly* from RSSI-delay profiles rather than ranging and multi-lateration.

In order to cope with indoor propagation and reduce the estimate bias due to the multipath, the HMM is adapted to account for mixed LOS/NLOS situations. The hidden Markov state is defined as the combined set of the MT position *and* the L LOS/NLOS conditions for all the MT-AP links; in this way, the D/TA can jointly track *both* the position *and* the sight condition exploiting continuity information. With respect to other Bayesian estimators, such as the extended Kalman filter (EKF) [5], the DT/A algorithm does not rely on linearization and Gaussian assumptions still having about the same computational complexity. Furthermore, it may be easily adapted to incorporate any type of measurements such as DOAs estimated from antenna array receivers.

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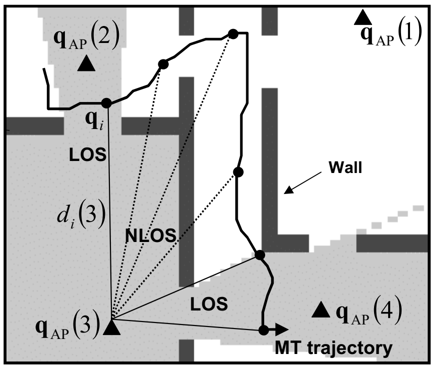

Figure 1: Localization of a MT from the radio signals exchanged with L fixed APs placed in known positions. Gray color indicates the LOS coverage for the ℓth AP.

The paper is organized as follows. The localization problem is described in Section 2. In Section 3 and 4 we propose the maximum likelihood estimate (MLE) of one position at a time and the HMM-based tracking of the position trajectory, respectively. Numerical results are discussed in Section 5. Section 6 draws some conclusions.

2. PROBLEM FORMULATION

We consider the localization problem illustrated in Fig. 1. The spatial location of a moving terminal (MT) has to be estimated from the radio signals exchanged by the MT with L fixed APs placed in known positions. Let $\mathbf{q}_i$ be the 2D spatial coordinates of the MT at time i, for $i = 0, 1, \ldots, I-1$ (I defines the number of location estimates performed by the tracking system). In addition, $\mathbf{q}_{\mathrm{AP}}(\ell)$ denotes the fixed 2D spatial coordinates of the ℓth AP for $\ell = 1, \ldots, L$. To simplify, we constrain $\mathbf{q}_i$ and $\mathbf{q}_{\mathrm{AP}}(\ell)$ to be defined on a regular squared grid $\mathcal{Q}$ (with assigned spatial sampling interval Δq), composed of $N_1 N_2$ points $\mathbf{n} = [n_1, n_2]$ with $n_1 \in \{0, \ldots, N_1 - 1\}$ and $n_2 \in \{0, \ldots, N_2 - 1\}$. The real-valued discrete-time signal vector $\mathbf{r}_i(\ell) = [r_i(0;\ell) \ \cdots \ r_i(M-1;\ell)]^{\mathrm{T}}$, measured at the ith time instant over the ℓth MT-AP link (with sampling time interval Δt), is modelled as a non-stationary zero-mean white Gaussian process. It is the superposition of two signals

$$\mathbf{r}_i(\ell) = \mathbf{x}(\mathbf{q}_i, \mathbf{q}_{\mathrm{AP}}(\ell), s_i(\ell)) + \mathbf{w}_i(\ell). \tag{1}$$

The term $\mathbf{w}_i(\ell) \sim \mathcal{N}(\mathbf{0}, \sigma_0^2 \mathbf{I}_M)$ is AWGN ($\mathbf{I}_M$ is the unitary matrix of size M), while $\mathbf{x}(\mathbf{q}_i, \mathbf{q}_{\mathrm{AP}}(\ell), s_i(\ell))$ is the radio signal transmitted over the dense multipath channel linking $\mathbf{q}_{\mathrm{AP}}(\ell)$ to $\mathbf{q}_i$. Its power-delay-profile (PDP) depends on the sight condition $s_i(\ell)$

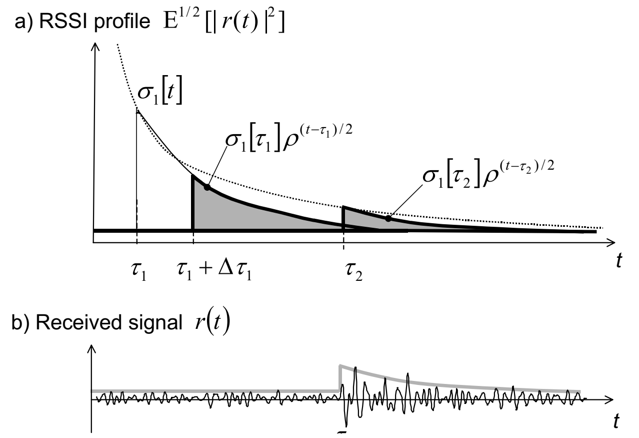

Figure 2: Signal model: a) RSSI delay profile; b) Measured signal.

over the ℓth link, here indicated as $s_i(\ell) = 0$ for LOS and $s_i(\ell) = 1$ for NLOS. The power of the signal sample $r_i(t;\ell)$ varies along the delay axis t according to the filtered Poisson process model [6]

$$\mathrm{Var}(r_i(t;\ell)) = \begin{cases} \sigma_0^2, & t < \bar{\tau}_i(\ell) \\ \sigma_0^2 + \sigma_1^2(\tau_i(\ell))\rho^{t-\tau_i(\ell)}, & t \geq \bar{\tau}_i(\ell) \end{cases}, \quad (2)$$

decaying exponentially with attenuation factor $\rho < 1$ from the first arrival delay $\bar{\tau}_i(\ell)$ (see Fig. 2). The first arrival delay

$$\bar{\tau}_i(\ell) = \tau_i(\ell) + s_i(\ell) \cdot \Delta\tau_i(\ell)$$

equals the propagation time $\tau_i(\ell) = \lfloor d_i(\ell)/c \rceil$ over the MT-AP distance $d_i(\ell) = d(\mathbf{q}_i, \mathbf{q}_{\mathrm{AP}}(\ell))$ in case of LOS ($s_i(\ell) = 0$), while it is increased by $\Delta\tau_i(\ell) > 0$ in case of NLOS ($s_i(\ell) = 1$). The excess delay$\Delta\tau_i(\ell)$ will be modeled as a random variable with distribution $f_\Delta(\delta)$. Here $\lfloor x \rceil$ denotes the nearest integer for the real value x while c is the propagation velocity normalized by $\Delta q/\Delta t$. According to the path-loss law, the signal power $\sigma_1^2(\tau)$ received at distance $d = c\tau$ is given by

$$\sigma_1^2(\tau) = \sigma_1^2(\tau_{\mathrm{ref}})(\tau/\tau_{\mathrm{ref}})^{-\alpha} \quad (3)$$

where $\sigma_1^2(\tau_{\mathrm{ref}})$ is the power received at the reference distance $d_{ref} = c\tau_{\mathrm{ref}}$ and α is the path-loss exponent (typical values are $\alpha = 2 \div 4$). The SNR is here defined as $\eta(\tau) = \sigma_1^2(\tau)/\sigma_0^2 = \eta(\tau_{\mathrm{ref}}) \cdot (\tau/\tau_{\mathrm{ref}})^{-\alpha}$. An example of path-loss profile is illustrated in Fig. 2; since $\ell = \mathbf{1}$, the AP index is dropped.

The RSSI delay profile (2) is characterized by an abrupt change (or break-point event - BP) for $\tau = \bar{\tau}_i(\ell)$. In case of LOS ($s_i(\ell) = 0$), the BP position $\bar{\tau}_i(\ell) = \tau_i(\ell)$ and the corresponding RSSI peak power $\sigma_1^2(\tau_i(\ell))$ are related to the MT-AP distance $d_i(\ell) = c \cdot \tau_i(\ell)$. It is therefore possible to estimate the MT location $\mathbf{q}_i$ by a separate estimation (or ranging) of each distance $d_i(\ell)$ from the measurement $\mathbf{r}_i(\ell)$ for $\ell = 1, \ldots, L$, then followed by a tri- or multi-lateration (for $L = 3$ or $L > 3$, respectively) of $\{d_i(\ell)\}_{\ell=1}^{L}$. This approach is the mostly adopted in the literature, though the measurement used for ranging is usually the total RSSI and not the RSSI-delay profile.

On the contrary, we propose here to estimate $\mathbf{q}_i$ *directly* from the compound measurement $\mathbf{r}_i = [\mathbf{r}_i^{\mathrm{T}}(1), \ldots, \mathbf{r}_i^{\mathrm{T}}(\ell)]^{\mathrm{T}} \in \mathbb{R}^{ML\times 1}$. At first, in Sec. 3, we consider the local MLE of $\mathbf{q}_i$ from $\mathbf{r}_i$. The shortcoming of this "memory-less" approach is the high number of false localizations that occur in NLOS conditions. In fact, in NLOS situations, the BP depends on the fictitious distance $d_i(\ell) + \Delta d_i(\ell)$, where the bias $\Delta d_i(\ell) = c \cdot \Delta\tau_i(\ell) > 0$ is due to the propagation over reflected path. To overcome this problem, in Sec. 4, we propose a tracking approach that estimates the position $\mathbf{q}_i$ from the whole set $\mathbf{R}_i = [\mathbf{r}_0, \mathbf{r}_1, \ldots, \mathbf{r}_i]$ of signals measured up to the current time instant i, by exploiting the continuity of the MT trajectory. To take care also of mixed LOS/NLOS conditions, the proposed HMM method is based on the assumption that *both* the mobile position $\mathbf{q}_i$ *and* the L sight conditions are Markov chains whose state is hidden in the measured signals $\mathbf{R}_i$ and must be jointly recovered.

3. LOCAL ESTIMATION

At each time instant, the MT state is characterized by the position-sight value $\mathbf{O}_i = (\mathbf{q}_i, \mathbf{s}_i)$, where $\mathbf{q}_i \in \mathcal{Q}$ is the spatial location and $\mathbf{s}_i = [s_i(1), \ldots, s_i(\ell)] \in \mathcal{S}$ are the LOS/NLOS sight conditions with respect to the L APs. The sight set $\mathcal{S} = \{0,1\}^L$ is composed of 2^L possible sight combinations, while $\mathbf{O}_i$ can assume $2^L N_1 N_2$ possible position-sight values. The local MLE $\hat{\mathbf{O}}_i = (\hat{\mathbf{q}}_i, \hat{\mathbf{s}}_i)$ from the L-link measurement $\mathbf{r}_i$ is the maximizer in $(\mathbf{n}, \mathbf{k})$ of the conditioned pdf $b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i) = P(\mathbf{r}_i|\mathbf{O}_i = (\mathbf{n}, \mathbf{k}))$ for $\mathbf{n} = [n_1, n_2] \in \mathcal{Q}$, $\mathbf{k} = [k_1, \ldots, k_L] \in \mathcal{S}$ and $k_\ell = \{0, 1\}$. Assuming the observations $\{\mathbf{r}_i(\ell)\}_{\ell=1}^{L}$ conditioned to $\mathbf{O}_i = (\mathbf{n}, \mathbf{k})$ as statistically independent, the likelihood function simplifies to

$$b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i) = \prod\nolimits_{\ell=1}^{L} P(\mathbf{r}_i(\ell)|\mathbf{q}_i = \mathbf{n}, s_i(\ell) = k_\ell). \quad (4)$$

In the LOS case ($s_i(\ell) = 0$), the ℓth conditioned pdf in (4) is

$$P(\mathbf{r}_i(\ell)|\mathbf{q}_i = \mathbf{n}, s_i(\ell) = 0) = \Lambda(\mathbf{r}_i(\ell), \lfloor d(\mathbf{n}, \mathbf{q}_{\mathrm{AP}}(\ell))/c \rceil, 0) \quad (5)$$

where $\Lambda(\mathbf{r}, \tau, \Delta\tau)$ is the likelihood function for a generic observation $\mathbf{r} = [r(0), \ldots, r(M-1)]^{\mathrm{T}}$, LOS delay τ and NLOS additional delay $\Delta\tau$. Being $\phi(x) = \exp(-x^2/2)/\sqrt{2\pi}$ the normal function, from model (1) we get

$$\Lambda(\mathbf{r}, \tau, \Delta\tau) = \prod_{t=0}^{\tau+\Delta\tau-1} \frac{\phi\left(\frac{r(t)}{\sigma_0}\right)}{\sigma_0} \prod_{t=\tau+\Delta\tau}^{M-1} \frac{\phi\left(\frac{r(t)}{\sqrt{\sigma_0^2+\sigma_1^2(\tau)\rho^{t-\tau}}}\right)}{\sqrt{\sigma_0^2+\sigma_1^2(\tau)\rho^{t-\tau}}}. \quad (6)$$

Assuming $f_\Delta(\delta)$ known, for NLOS condition ($s_i(\ell) = 1$), it is

$$P(\mathbf{r}_i(\ell)|\mathbf{q}_i = \mathbf{n}, s_i(\ell) = 1) = \sum_{\delta} f_\Delta(\delta)\Lambda\left(\mathbf{r}_i(\ell), \left\lfloor \frac{d(\mathbf{n}, \mathbf{q}_{\mathrm{AP}}(\ell))}{c} \right\rceil, \delta\right).$$

4. BAYESIAN ESTIMATION: HMM TRACKING

The HMM framework is here defined by selecting as Markov state the joint position-sight variable $\mathbf{O}_i$. The state is hidden in the L-link observation $\mathbf{r}_i$, whose conditioned probability density functions (pdf) $b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i)$ can be calculated as in Sect. 3. The overall HMM set $\boldsymbol{\lambda} = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$ is defined by assigning the state transition probabilities $\mathbf{A}$, the observation probabilities $\mathbf{B}$, and the initial state probabilities $\boldsymbol{\pi}$.

The transition probabilities are calculated by modelling both the position $\mathbf{q}_i$ and the sight $\mathbf{s}_i$ as independent first-order homogeneous Markov processes. The MT movement within the 2D space is generated by equation

$$\mathbf{q}_i = \mathbf{q}_{i-1} + \mathbf{v}_i \quad (7)$$

where $\mathbf{v}_i$ is the 2D discrete driving process with known distribution $f_v(n_1, n_2) = P(\mathbf{v}_i = \mathbf{n})$. The transitions between states are ruled by the $N_1N_2 \times N_1N_2$ probabilities

$$a_{\mathbf{m},\mathbf{n}}^{(p)} = P(\mathbf{q}_i = \mathbf{n}|\mathbf{q}_{i-1} = \mathbf{m}) = f_v(n_1 - m_1, n_2 - m_2) \quad (8)$$

for $\mathbf{m} = [m_1, m_2]$, $\mathbf{n} = [n_1, n_2] \in \mathcal{Q}$ (see examples in Fig. 3).

Each sight process $s_i(\ell)$ is modeled as a 2-state first-order homogeneous Markov chain with transition probabilities $a_{h,k}^{(s)} = P(s_i(\ell) = k|s_{i-1}(\ell) = h)$ for $h, k \in \{0, 1\}$. The probability

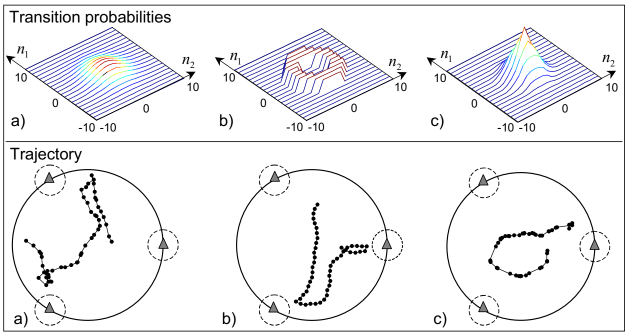

Figure 3: Examples of distribution $f_v(n_1, n_2)$ for random 2-D driving process $\mathbf{v}_i$. Notice that a large $f_v(0, 0)$ value indicates that the MS is frequently still as shown in figures a) and c).

to remain in the LOS or NLOS state is, respectively, $p_0 = a_{0,0}^{(s)}$ or $p_1 = a_{1,1}^{(s)}$. Due to probability normalization, it is also $a_{0,1}^{(s)} = 1-p_0$ and $a_{1,0}^{(s)} = 1-p_1$. For the APs independence, 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 $\mathbf{h} = [h_1, \ldots, h_L]$ and $\mathbf{k} = [k_1, \ldots, k_L] \in \mathcal{S}$. 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

$$a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})}^{(ps)} = a_{\mathbf{m},\mathbf{n}}^{(p)} a_{\mathbf{h},\mathbf{k}}^{(s)} \tag{9}$$

for $\mathbf{m}, \mathbf{n} \in \mathcal{Q}$ and $\mathbf{h}, \mathbf{k} \in \mathcal{S}$. A zero state $\mathbf{O}_i = \mathbf{0}$ is also introduced to indicate the lack of the MT signal (i.e., no MT detected), yielding the overall set $\mathcal{O}$ of $2^L N_1 N_2 + 1$ position states. The $(2^L N_1 N_2 + 1) \times (2^L N_1 N_2 + 1)$ transition matrix $\mathbf{A}$ for the whole set of states, including the zero state, has elements defined as: $a_{\mathbf{0},\mathbf{0}} = 1 - \theta$, $a_{\mathbf{0},(\mathbf{n},\mathbf{k})} = \theta/(2^L N_1 N_2)$, $a_{(\mathbf{m},\mathbf{h}),\mathbf{0}} = \nu$, $a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})} = (1-\nu) a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})}^{(ps)} \Gamma_{\mathbf{m}}$ for $\mathbf{m}, \mathbf{n} \in \mathcal{Q}$ and $\mathbf{h}, \mathbf{k} \in \mathcal{S}$. The parameters θ and ν represent the probabilities of, respectively, trajectory initiation and termination while $\Gamma_{\mathbf{m}}$ is a factor used to normalize the transition probabilities between non-zero states.

Notice that the observation pdf set $\mathbf{B} = \{b_0(\cdot), b_{\mathbf{n},\mathbf{k}}(\cdot)\}$ must also include the zero-state conditioned pdf $b_0(\mathbf{r}_i) = P(\mathbf{r}_i | \mathbf{O}_i = \mathbf{0})$

$$b_0(\mathbf{r}_i) = \frac{1}{(\sqrt{2\pi}\sigma_0)^{LM}} \exp\left[-\frac{1}{2\sigma_0^2} \sum_{\ell=1}^{L} \sum_{t=0}^{M-1} r_i^2(t;\ell)\right]. \tag{10}$$

The initial state distribution for the HMM is defined by assigning the $2^L N_1 N_2 + 1$ initial probabilities $\boldsymbol{\pi} = \{\pi_{\mathbf{0}}, \{\pi_{(\mathbf{n},\mathbf{k})}\}\}$, where $\pi_{\mathbf{0}} = P(\mathbf{O}_0 = \mathbf{0})$ and $\pi_{(\mathbf{n},\mathbf{k})} = P(\mathbf{O}_0 = (\mathbf{n}, \mathbf{k}))$.

Given the complete HMM parameter set $\boldsymbol{\lambda}$, the D/TA estimates the position-sight state $\mathbf{O}_i$ based on all the measurements $\mathbf{R}_i$ collected up to the ith instant, by maximizing the a-posteriori pdf

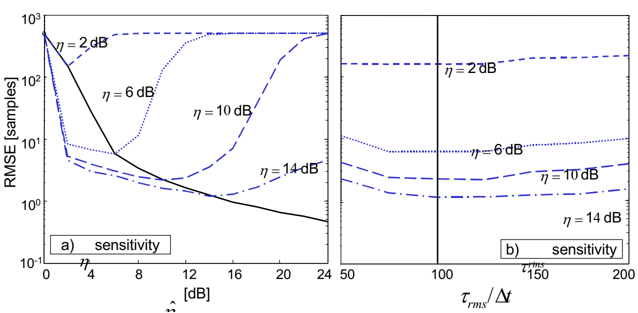

Figure 4: Sensitivity for the delay/range estimate vs. the SNR $\hat{\eta}$ and the PDP factor $\hat{\rho} = \exp(-\Delta t/\tau_{\mathrm{rms}})$ used for tracking: a) RMSE vs. SNR; b) RMSE vs. τ_{rms}. HMM parameters used: $\eta = 2, 6, 10, 14$ dB and $\tau_{\mathrm{rms}} = 100\Delta t$. RMSE is normalized by Δt.

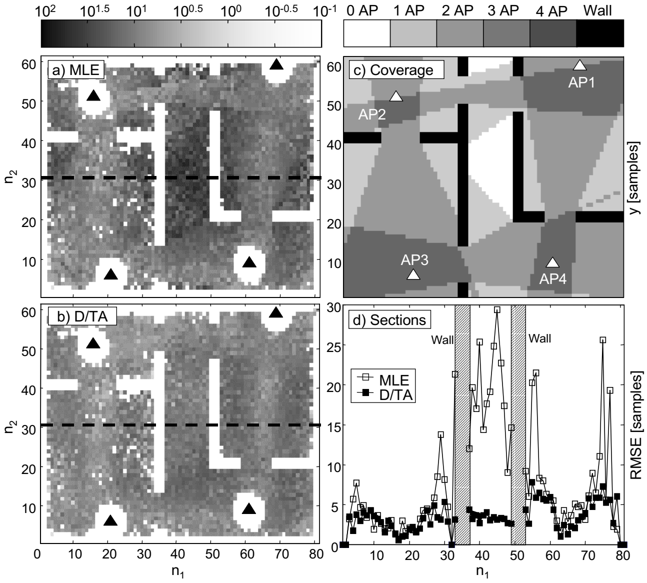

Figure 5: a-b) RMSE as a function of the spatial position for the ML estimate (a) and the D/TA (b). c) AP coverage. d) RMSE of figures (a) and (b) along the section $n_1 = 31$ (plotted as black dashed line in figures (a) and (b)). The RMSE performance is drawn for each spatial position $\mathbf{q} = [n_1, n_2]$ in mixed LOS/NLOS conditions. Notice that, as shown in figure (c), there is no area with coverage 4 and that a large portion lacks of coverage.

$\gamma_i(\mathbf{n}, \mathbf{k}) = P(\mathbf{O}_i = (\mathbf{n}, \mathbf{k}) \mid \mathbf{R}_i, \boldsymbol{\lambda})$ with respect to $(\mathbf{n}, \mathbf{k})$. The a-posteriori pdf is calculated according to the forward recursion [3]

$$\gamma_i(\mathbf{n}, \mathbf{k}) \propto b_{\mathbf{n},\mathbf{k}}(\mathbf{r}_i) \sum_{(\mathbf{m},\mathbf{h}) \in \mathcal{O}} a_{(\mathbf{m},\mathbf{h}),(\mathbf{n},\mathbf{k})}\, \gamma_{i-1}(\mathbf{m}, \mathbf{h}). \tag{11}$$

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

5. PERFORMANCE ANALYSIS

At first, in Fig. 4, we investigate the robustness of the local MLE to mismodeling. As a single AP ($L = 1$) is considered in LOS conditions only, localization reduces to the estimation of the MT-AP distance $d_i(1)$ (i.e., ranging) or, equivalently, of the TOA $\tau_i(1)$. The estimation is obtained by maximizing with respect to $\tau_i(1)$ the likelihood function $\Lambda(\mathbf{r}_i(1), \tau_i(1), s_i(1) = 0)$. We analyze the sensitivity of the MLE to the SNR $\eta = \eta(\tau_{\mathrm{ref}})$ and the decaying PDP factor ρ by generating measurements with fixed parameters η and ρ and by estimating the TOA with $\hat{\eta} \neq \eta$ or $\hat{\rho} \neq \rho$. A set of $I = 1000$ measurements $\mathbf{r}_i(1)$ is generated with $M = 1000$ samples each (obtained by sampling a continuous-time signal of duration 100 ns at a $f_s = 1/\Delta t = 10$ GHz rate), with PDP $\rho = 0.9$, $\tau_i(1) = \tau_{\mathrm{ref}} = M/2\ \forall i$, and $\eta \in \{2, 6, 10, 14\}$ dB. In Fig. 4a the root mean square error (RMSE) of the TOA estimate is evaluated for $\hat{\rho} = \rho$ and $\hat{\eta}$ ranging from 0 to 24 dB. On the other hand, Fig. 4b shows the RMSE for $\hat{\eta} = \eta$ and $\hat{\rho} = \exp(-\Delta t/\tau_{\mathrm{rms}})$ with τ_{rms} ranging from 5 to 20 ns (i.e., from 50 to 200 time samples). Minimum RMSE is always reached for true values $\hat{\eta} = \eta$ or $\hat{\rho} = \rho$, as it is shown by the solid line indicating the locus of the RMSE minima. It can be noticed that the RMSE around $\hat{\eta} \approx \eta$ is quite flat: good performances can be obtained even for rough estimates of the model parameters (mostly for large η).

The performances of the localization algorithms are evaluated by simulating a MT moving within the rectangular indoor environment shown in Fig. 1 having dimensions 30×40 m (i.e., $N_1 = 61$ and $N_2 = 81$ at a sampling step of $\Delta q = 50$ cm), $L = 4$ APs, walls and doors located as indicated in the figure (the area close to each

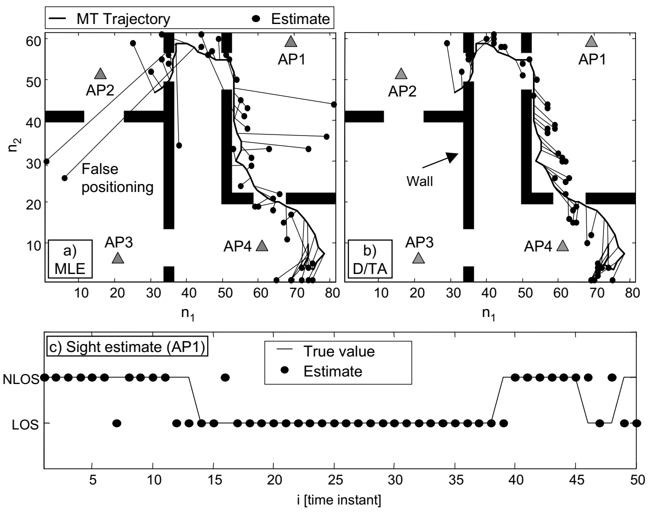

Figure 6: Examples of localization and sight estimation in mixed LOS/NLOS condittions: a) local MLE positioning; b) D/TA positioning; c) true sight condition and sight estimate using DT/A shown for MT-AP1 link.

AP is not used). Changes of the MT location over the time are simulated according to a conic-shaped pdf $f_v(n_1, n_2)$ (as in Fig. 3c). The sight conditions $\{s_i(\ell)\}_{\ell=1}^4$ are determined according to the coverage map in Fig. 5c and tracked using four independent first-order Markov chains. Measurements are sampled at $f_s = 1$ GHz and have length $M = 150$. The first arrival delay $\tau_i(\ell)$ is calculated from the MT-AP distance and, for NLOS, from an exponentially distributed excess delay $\Delta\tau_i(\ell)$ with $f_{\Delta\tau}(\delta) \propto \exp(-\delta/\sigma_{\Delta\tau})$ and $\sigma_{\Delta\tau} = 10$. The signal power $\sigma_1^2(\tau)$ is derived according to the path-loss law, with $\alpha = 2.4$ and $\eta(\tau_{\text{ref}}) = 40$ dB at $d_{\text{ref}} = 2$. An exponential PDP is simulated with $\rho = 0.9$. The algorithm performances are evaluated in terms of RMSE of the location estimate as a function of the spatial position over a trajectory of $I = 30000$ time intervals. For a given position $\mathbf{q}_i \in \mathcal{Q}$, the RMSE is evaluated as $\text{RMSE}(\mathbf{q}_i) = [\sum_{j \in I(\mathbf{q}_i)} ||\mathbf{q}_i - \hat{\mathbf{q}}_j||^2 / N(\mathbf{q}_i)]^{\frac{1}{2}}$, where $I(\mathbf{q}_i)$ is the set of all instants in which the trajectory flows across $\mathbf{q}_i$ and $N(\mathbf{q}_i)$ is its cardinality. The sight transition probabilities p_0 and p_1 used for tracking were estimated by a preliminary training phase performed on the specific environment. In this case, a trajectory of $I = 20000$ steps was simulated and used to calculate the relative frequencies of transition from LOS to NLOS and viceversa, yielding $p_0 \simeq p_1 \simeq 0.9$ (independent of the MT position).

Fig. 5 shows the RMSE of the estimate as a function of the position $\mathbf{q}_i \in \mathcal{Q}$ for both the local MLE (Fig. 5a) and the D/TA (Fig. 5b), in case of mixed LOS/NLOS sight. In the MLE map, the error is shown to increase in poorly covered areas (such as the central corridor and the corners of the rooms), while it is uniform in areas with good AP coverage. 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. 5d, which shows the sections of the maps in Fig. 5a-b evaluated for $n_2 = 31$. The local MLE yields very poor performance, with RMSE ranging from 0 to 30. On the other hand, the D/TA error is stable around 5, yielding a high performance gain with respect to MLE, especially in the corridor area where the sight tracking capability of the D/TA is more effective.

An example of trajectory estimation is shown in Fig. 6 where the path has been generated smoother and shorter ($I = 50$) for visualization purposes only. The figure compares the true trajectory (thick line) with the estimated ones (markers) obtained by the local MLE (left) and the D/TA (right). The estimate errors can be appreciated by looking at the lines that connect the true and the estimated

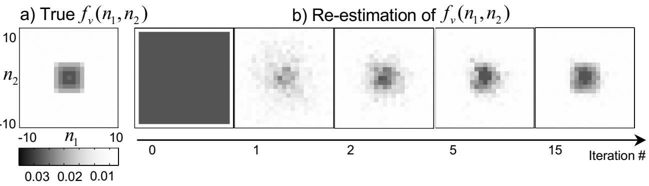

Figure 7: Re-estimation of the HMM transition probabilities $f_v(n_1, n_2)$: a) true probabilities (used to generate the observations); b) estimated probabilities at iteration number $k = 0, 1, 2, 5, 15$ ($k = 0$ is the initialization step).

positions. False positioning for NLOS conditions (e.g. in the central corridor) occurs only using local MLE.

The Baum-Welch re-estimation algorithm [3] can be used for the estimation of the HMM parameters from field data. This is described in Fig. 7 for the re-estimation of the position-transition probabilities $f_v(n_1, n_2)$. A set of 100 training trajectories of length $I = 1000$ are generated according to the transition probabilities $f_v(n_1, n_2)$ shown in Fig. 3c. The transition probabilities are considered as unknown during the tracking phase and they are therefore estimated by an iterative procedure. Since no a-priori information is available on $f_v(n_1, n_2)$, at first iteration a uniform pdf $f_v^{(0)}(n_1, n_2)$ is used to track the MT trajectory. On the basis of the estimated sequence of positions and $f_v^{(0)}(n_1, n_2)$, a new pdf $f_v^{(1)}(n_1, n_2)$ is calculated and used to track again the trajectory. The process is iterated till convergence. Fig. 7b shows that few iterations are enough to approach the true distribution.

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 false localizations in mixed LOS/NLOS conditions are highly reduced with respect to local estimation methods.

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