Direct Position Estimation of a Mobile Receiver in Multipath Environments via Adaptive Beamforming

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***Abstract*—The paper presents a novel direct position estimation approach to localize a mobile receiver in multipath environments, where the different paths are coherent hence standard AOA estimation methods fail. The proposed algorithm combines the angular information from signals transmitted by a set of static transmitters with the velocity information obtained from the onboard kinematic sensors. To this aim, the received signals are first decorrelated through spatial smoothing, then an adaptive beamforming strategy is applied to mitigate the detrimental effects of multipath propagation. Simulation results in a realistic multipath environment demonstrate that the proposed algorithm can achieve satisfactory localization performance, outperforming existing AOA-based (indirect) position estimation approaches.**

***Index Terms*—direct position estimation, array processing, direction of arrival, beamforming**

I. Introduction

Location estimation has received great attention in recent years and is still a very active research field. Different signals can be exploited to obtain position-related information, such as received signal strength (RSS), time (difference) of arrival (TOA/TDOA), or angle of arrival (AOA), both in static [1], [2] and mobile contexts [3]–[5]. Hybrid solutions that combine two or more of the above have also been considered to improve the accuracy of positioning [6], [7].

Unfortunately, the achievable accuracy in multipath scenarios often remains limited. RSS-based techniques in particular suffer from multipath-originated disturbances, namely fading and shadowing, yielding poor accuracy. Similarly, time information is very useful in line-of-sight (LOS) conditions, provided that large bandwidth and precise synchronization are available, but is significantly less reliable in presence of multipath propagation. On the other hand, the use of angular information is experiencing renewed interest thanks to the increasing availability of antenna arrays, as MIMO communication technologies are spreading e.g. in Wi-Fi (IEEE 802.11) and cellular (4G/5G) systems. This technological evolution, together with the wide availability of sensing modules (e.g., inertial navigation system (INS)) and computing capabilities in modern mobile devices, is paving the way for innovative localization paradigms in real-world scenarios including vehicles, robots, and generally indoor navigation.

A common approach to localization is to adopt indirect position estimation (IPE) techniques, in which position-related parameters (for instance, AOAs) are first estimated and then combined together to ultimately obtain the unknown position [8], [9]. In [10] a weighted least squares (WLS) IPE approach that exploits AOA measurements in conjunction with velocity information from an onboard INS has been proposed. Direct position estimation (DPE) techniques, conversely, aim at estimating the location directly from the raw signals, so improving the achievable performance especially under multipath propagation [11]. The most relevant DPE approaches that adopt antenna arrays consider a static scenario, i.e., a snapshot of the environment in which both the unknown position and all channel effects are assumed static. Moreover, the multipath is typically considered as a stochastic disturbance; in particular, in [12], [13] a single-path scenario is addressed. To mitigate the effects of multipath, the minimum-variance distortionless response (MVDR) beamformer is adopted in [14], [15], but still a single-path case is considered being the non-line-of-sight (NLOS) paths modeled as white Gaussian noise.

Aiming at advancing the state of the art in this respect, in the present work we investigate the problem of localizing a mobile receiver (MR) in presence of a coherent multipath environment (not regarded as stochastic disturbance). In particular, we derive a novel DPE algorithm based on the joint use of AOA and velocity information. To mitigate the detrimental effects caused by the presence of multiple paths in the received signal, a combination of spatial smoothing and adaptive beamforming is proposed. Moreover, mobility is exploited in the localization task to introduce an integration gain that is beneficial to the ultimate localization accuracy. Remarkably, the proposed algorithm does not assume any specific mobility model, i.e., it can be applied irrespective of the actual trajectory of the MR.

II. System Model

A. General scenario

We consider a general scenario with N_A fixed transmitters, referred to as anchors, placed at known locations $\boldsymbol{p}_A^b = \left[x_A^b \; y_A^b\right]^T$, $b = 1, \ldots, N_A$, and a MR with unknown position $\boldsymbol{p}(t) = [x(t) \; y(t)]^T$ (^{T} denoting transposition) at time t. Coordinates are expressed in a global Cartesian reference system. The MR is moving with a (generally non-constant) velocity and is equipped with a kinematic sensor. Anchors are transmit-only (typically with a single omnidirectional antenna) while the MR is receive-only and equipped with an M-element uniform linear antenna array (ULA). Each anchor broadcasts a known signal containing a train of N_p pulses (packet) with one-sided bandwidth B. Notice that, differently from the more conventional setup in which anchors receive the signal from the MR, perform some processing (e.g., AOA estimation), and then send such a local information to a central node for position estimation, in the considered scenario the whole localization procedure is performed at the MR. This has the advantage of not requiring further communications, considerably decreasing the bandwidth consumption. Moreover, antenna arrays are not needed on the anchors since the latter do not play any active role in the estimation task.

The MR executing the position estimation algorithm asynchronously collects and processes the impinging signals coming from the transmitting anchors nearby (assumed in the far field). More specifically, let $\boldsymbol{p}_0 = [x_0 \ y_0]^T \stackrel{\text{def}}{=} \boldsymbol{p}(t_0)$ be the (unknown) MR position at time instant t_0 when the localization procedure starts. Moreover, let $t_i, i \geq 1$, denote the instant corresponding to the center of the first pulse in the received packet transmitted from an anchor b_i. Since there is a univocal correspondence between the i-th received signal and the transmitting anchor b_i, we will use only t_i in the notation.

B. Flat and slow multipath channel

We assume a flat-slow multipath fading model, i.e., the symbol duration T is much larger than the channel delay spread and B exceeds the channel Doppler spread. This implies that the delays associated to the NLOS paths can be neglected and the complex channel gains remain constant over the channel coherence time T_c.

The received signal can be thus expressed as [16]

$$\boldsymbol{r}(t) = \gamma_i \sum_{m=0}^{D_i} \beta_i^m \boldsymbol{a}(\theta^m(t_i)) s(t) + \boldsymbol{n}(t), \quad t \in I_i \tag{1}$$

where the index $m = 0$ denotes the LOS path, $\beta_i^0 = 1$, $\theta^0(t_i) \stackrel{\text{def}}{=} \theta_i^{\text{LOS}}$ is the AOA of the LOS path at t_i, and $\boldsymbol{n}(t)$ is the additive white complex normal noise. As to I_i, it denotes the time support of the i-th received packet having duration that does not exceed T_c. As to γ_i and $\boldsymbol{a}(\cdot)$, they are the complex amplitude coefficient related to large-scale fading (or path-loss) and the ULA steering vector, respectively, while β_i^m and $\theta^m(t_i) \stackrel{\text{def}}{=} \theta_i^m$, $m > 0$, are the complex small-scale fading coefficient and the AOA of the m-th multipath component out of the D_i NLOS paths. The value of D_i can change at each time instant t_i and is typically unknown. Angles are expressed in the local reference system of the array which, for the sake of simplicity, is assumed oriented as the global reference system. Notice that the previous assumption is without loss of generality, since at each time instant the angle between the two reference systems can be obtained through the heading vector available from the onboard INS.

For the position estimation task, we can sample the signal received at time t_i only within an observation period short enough to ensure that the position and velocity of the MR remain approximately constants. Such a restriction makes the considered position estimation problem more challenging. We anticipate that the performance assessment will be conducted for values of B and N small enough to be in agreement with the assumption of flat-slow fading, for the realistic environment considered in the simulations.

At the receiver, $\boldsymbol{r}(t)$ is passed through a matched filter, whose output is then sampled at a rate $f_s = 1/T$, resulting in the following sequence of received samples

$$\boldsymbol{y}_{i,n} = \gamma_i \sum_{m=0}^{D_i} \beta_i^m \boldsymbol{a}(\theta_i^m) c_{i,n} + \boldsymbol{\nu}_{i,n}, \quad n = 0, \ldots, N-1 \tag{2}$$

where $c_{i,n}$ is the discrete symbol related to the n-th sample taken at $t_{i,n} = t_i + nT$ and $\boldsymbol{\nu}_{i,n} \sim \mathcal{CN}_M(\boldsymbol{0}, \sigma^2 \boldsymbol{I}_M)$ the filtered thermal noise, with σ^2 denoting the noise power and $\boldsymbol{I}_M$ the $M \times M$ identity matrix.

Without loss of generality, the symbols are assumed known at the receiver. Hereafter, we denote with $\boldsymbol{Y}_i = [\boldsymbol{y}_{i,0} \cdots \boldsymbol{y}_{i,N-1}]$ the $M \times N$ matrix containing samples of the i-th observation. It is worth noting that the AOA of the LOS path θ_i^{LOS} directly relates the position of anchor b_i to the MR position through

$$\theta_i^{\text{LOS}} = \operatorname{atan2}\left(y_A^{b_i} - y(t_i), x_A^{b_i} - x(t_i)\right) \tag{3}$$

with $\operatorname{atan2}(y, x)$ the four-quadrant inverse tangent.

For a sufficiently high anchors send rate, the time interval between any two consecutive observations is relatively short ($\leq$ 100 ms). As a consequence, the (arbitrary) MR trajectory over $[t_0, t_k], k \geq 1$, can be approximated by the following kinematic model

$$\boldsymbol{p}(t_k) = \begin{bmatrix} x(t_k) = x_0 + \sum_{i=1}^k v_x(t_{i-1})(t_i - t_{i-1}) \\ y(t_k) = y_0 + \sum_{i=1}^k v_y(t_{i-1})(t_i - t_{i-1}) \end{bmatrix} \tag{4}$$

where a velocity vector $\boldsymbol{v}(t_i) = [v_x(t_i) \ v_y(t_i)]^T$ is considered for $t \in [t_i, t_{i+1})$, read from the onboard sensor at time t_i. Differently from most existing approaches, the proposed algorithm adds one more dimension to the localization procedure, namely the variation in time that allows us to exploit mobility in the position estimation task. In particular, each collected $\boldsymbol{Y}_i$ brings a new position-related information that can help the MR to identify its most probable trajectory, as discussed below.

III. A Novel DPE Algorithm based on Adaptive Beamforming and Mobility

Compared to the DPE approaches proposed in [12]–[15], which model the multipath as an additive white Gaussian contribution, in this work we explicitly take into account the structure of the NLOS paths (see eq. (1)). Since such components are scaled and delayed versions of the transmitted signal, they give rise to the problem of coherence among the received paths, which makes standard array processing techniques such as beamforming inapplicable. Notice that this scenario is different from the emerging contexts of mmWave MIMO positioning; indeed, at mmWave frequencies the multipath is generally sparse and can be more easily resolved thanks to the high angular resolution [17]. Furthermore, the algorithms in [12]–[15] are devised for static scenarios, while in our case we are facing a dynamic context where both position and channel parameters change over time.

To end up with a novel DPE algorithm for coherent environments under MR mobility, we propose a two-step approach:

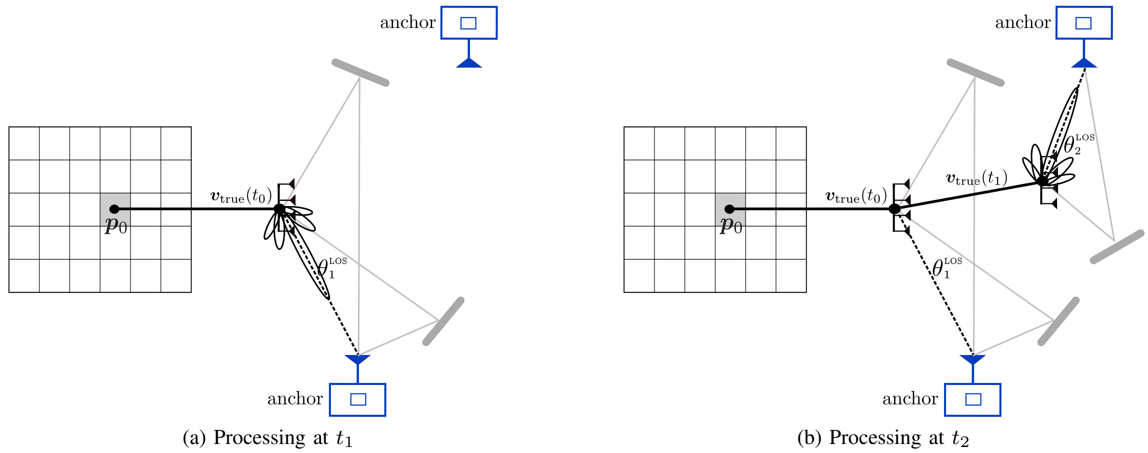


Fig. 1: Processing steps of the proposed DPE algorithm for the ideal case $\tilde{\boldsymbol{p}}_0 = \boldsymbol{p}_0$.

1) adoption of the forward-backward spatial smoothing (FBSS) technique to decorrelate the received signals;
2) adaptive beamforming exploiting the directional response of the ULA to identify the most probable LOS.

Spatial smoothing (SS) is a technique to decorrelate signals for some array structures [18]. In particular, an M-element ULA can be divided into S virtual overlapped subarrays with each subarray composed of $P < M$ sensors and shifted by one with respect to the previous one. As a result, the full array is divided into $S = M - P + 1$ subarrays. Each set of subarray data is denoted by $\boldsymbol{y}_{i,n}^{(j)}, j = 1, \ldots, S$, and contains the P components of $\boldsymbol{y}_{i,n}$ from j to $j + P - 1$, respectively. The full set of available data is thus given by

$$\boldsymbol{y}_{i,n}^{(1)} = \left[y_{i,n}^1 \cdots y_{i,n}^P\right]^T, \ldots, \boldsymbol{y}_{i,n}^{(S)} = \left[y_{i,n}^S \cdots y_{i,n}^{S+P-1}\right]^T \quad (5)$$

where $y_{i,n}^l$ denotes the l-th entry of $\boldsymbol{y}_{i,n}$. The forward-only (FO) matrix is then obtained by using the averaged sample covariance matrix $\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{F}} \in \mathbb{C}^{P \times P}$, which is defined as

$$\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{F}} = \frac{1}{S} \sum_{j=1}^{S} \hat{\boldsymbol{R}}_{Y_iY_i}^{(j)} \quad (6)$$

with $\hat{\boldsymbol{R}}_{Y_iY_i}^{(j)} = (1/N)\boldsymbol{Y}_i^{(j)}\boldsymbol{Y}_i^{(j)H}$ denoting the j-th subarray sample covariance matrix and $\boldsymbol{Y}_i^{(j)} \overset{\text{def}}{=} [\boldsymbol{y}_{i,0}^{(j)} \cdots \boldsymbol{y}_{i,N-1}^{(j)}]$. After SS has been performed, a forward-backward (FBSS) strategy can be employed to decorrelate the received signal in a stronger way. More precisely, by exploiting the translational invariance property of $\boldsymbol{a}(\cdot)$, the forward-backward sample covariance matrix can be used in place of (6)

$$\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{FB}} = \frac{\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{F}} + \boldsymbol{J}(\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{F}})^*\boldsymbol{J}}{2}. \quad (7)$$

where $\boldsymbol{J}$ is an exchange matrix, whose elements are zero except for ones on the antidiagonal. Without loss of generality, we consider the first subarray as the reference subarray, and denote its steering vector as $\boldsymbol{a}^{(1)}(\cdot)$. The optimum weight vector $\boldsymbol{w}_{\text{FB}} \in \mathbb{C}^{P \times 1}$ of an adaptive beamformer that exploits the decorrelated matrix $\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{FB}}$ to steer the array response toward a given direction of interest θ is given by [19]

$$\boldsymbol{w}_{\text{FB}}(\theta) = \frac{(\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{FB}})^{-1}\boldsymbol{a}^{(1)}(\theta)}{\boldsymbol{a}^{(1)H}(\theta)(\hat{\boldsymbol{R}}_{Y_iY_i}^{\text{FB}})^{-1}\boldsymbol{a}^{(1)}(\theta)}. \quad (8)$$

Let $\mathcal{Y} = \{\boldsymbol{Y}_1, \ldots, \boldsymbol{Y}_K\}$ denote the set of observations collected up to the current time instant t_K. Assuming that the velocities of the MR are known — noisy measurements from the onboard INS will be used in the performance assessment in Sec. IV — the position estimation problem reduces to determining the MR (initial) position $\boldsymbol{p}_0$ in presence of many nuisance parameters due to multipath propagation. In this respect, it is worth highlighting that the proposed methodology is meant for observation periods short enough to prevent the accumulation of inertial errors, which would be detrimental to the ultimate position estimation accuracy. The main idea behind the proposed approach consists in using a compressed version of the observations $\mathcal{Y}$, denoted as $\mathcal{O} = \{\boldsymbol{o}_1(\theta_1), \ldots, \boldsymbol{o}_K(\theta_K)\}$, where each compressed observation $\boldsymbol{o}_i$ is obtained from the received samples $\boldsymbol{Y}_i^{(1)}$ by applying a beamformer towards a look direction θ_i, i.e.,

$$\boldsymbol{o}_i(\theta_i) = (\boldsymbol{w}_{\text{FB}}^H(\theta_i)\boldsymbol{Y}_i^{(1)})^T, \quad i = 1, \ldots, K. \quad (9)$$

Notice that the novel set of compressed observations $\mathcal{O}$ is parameterized as a function of the look directions $\{\theta_1, \ldots, \theta_K\}$ and depends on both MR position and velocity information. The DPE problem can be thus formulated as

$$\hat{\boldsymbol{p}}_0 = \arg\max_{\tilde{\boldsymbol{p}}_0} \sum_{i=1}^{K} \|\boldsymbol{o}_i(\tilde{\theta}_i)\|^2. \quad (10)$$

For a given trial position $\tilde{\boldsymbol{p}}_0$, each look direction $\tilde{\theta}_i$ can be readily determined by reconstructing $\tilde{\boldsymbol{p}}_i$ through (4) and using (3). Intuitively, the proposed approach aims at measuring the total energy accumulated over time for each trial position $\tilde{\boldsymbol{p}}_0$. In Fig. 1, we report a pictorial representation of the processing steps up to $K = 2$ performed by the proposed DPE algorithm for the ideal case $\tilde{\boldsymbol{p}}_0 = \boldsymbol{p}_0$. As it can be noticed, the look directions $\tilde{\theta}_i$ are perfectly aligned with the actual LOS directions $\{\theta_1^{\text{LOS}}, \ldots, \theta_K^{\text{LOS}}\}$ over the whole trajectory, and the adaptive beamforming guarantees maximum gain towards the useful signal directions, while mitigating the undesired NLOS contributions which are treated as interferers. A similar behavior should be expected for $\tilde{\boldsymbol{p}}_0 \approx \boldsymbol{p}_0$, up to minor errors in the pointing directions $\tilde{\theta}_i$. Conversely, for $\tilde{\boldsymbol{p}}_0 \neq \boldsymbol{p}_0$, the beamformer will point towards directions that do not contain any useful signal, possibly suppressing the LOS paths. In such cases, the cumulative energy collected along the MR trajectory should be reasonably lower than that measured when $\tilde{\boldsymbol{p}}_0 \approx \boldsymbol{p}_0$. In practice, since the energy is estimated only from a finite number of noisy samples, significant deviations from its actual value may be expected, especially in presence of a high number of multipath components.

IV. Simulation Model and Results

In this section, we conduct a simulation analysis to assess the performance of the proposed DPE algorithm. We consider, as a reference scenario, a MR equipped with an $M = 64$ element ULA, and a varying number of anchors available in range that broadcast signals with a rate $R = 10$ Hz. To reproduce a realistic multipath environment, several phenomena and non-idealities are included in the simulation model. The performance are evaluated using the root mean squared error (RMSE) metric, computed on 500 Monte Carlo trials.

A. Simulation Model

In the following, we describe the models used in the simulation analysis.

1) Channel Model: As a representative example of mobile communications, we consider a carrier frequency $f_c = 5.9$ GHz and a transmit power $P_{T,dB} = 18$ dBm. Following [16], the path loss at distance d from the transmitter is computed from the well-known formula

$$L_{PL,dB} = 10\eta \log_{10} \frac{d}{d_0} \tag{11}$$

where the path loss exponent is set to $\eta = 4$ and the reference distance $d_0 = 1$ m. To simulate a challenging multipath environment, we set the channel coherence bandwidth $B_c = 250$ kHz and the channel Doppler spread $B_D = 512$ Hz [20]. As to the power of the additive noise at the receiver, we set its value based on the noise figure $N_0 B = k_B T_0 B$, with T_0 the standard noise temperature and k_B the Boltzmann constant.

The NLOS components are generated according to the Clarke's model [21]; more precisely, the reflected paths originate from local scatterers that are uniformly distributed in the environment, i.e., $\theta_i^m \sim \mathcal{U}(0, 2\pi)$. The power of each NLOS component is computed according to an exponentially decaying power delay profile (PDP) function [16]. The environment is characterized by the presence of a varying number of NLOS components D_i, uniformly distributed between 1 and 10. We also take into account possible LOS obstructions and set 10% of the links to the NLOS class, while we recall that the algorithm always assumes the existence of a direct path.

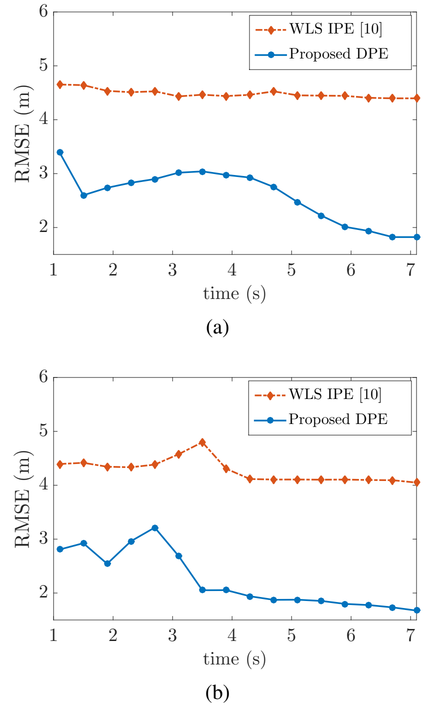


Fig. 2: RMSE on position estimation for (a) single anchor and (b) two anchors localization scenarios.

2) Mobility Model and Velocity Measurements: The MR moves along a non-linear trajectory with a velocity profile characterized by an accelerated motion for one third of the path (from 12 to 25 km/h in modulus), followed by a constant velocity motion at modulus 25 km/h for the second third, and ending with a deceleration until reaching the initial speed of 12 km/h, covering a total path of about 7 seconds.

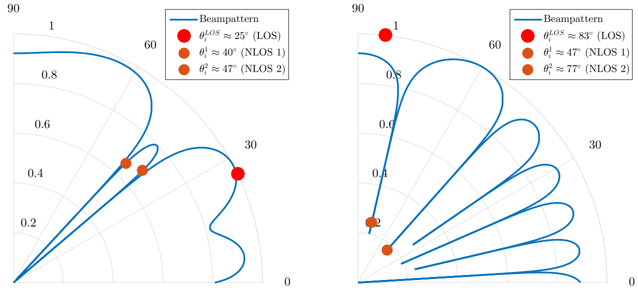
The velocity measurements obtained from the onboard INS at each time t_i are modeled as

$$\hat{\boldsymbol{v}}(t_i) = \boldsymbol{v}(t_i) + \boldsymbol{\epsilon}_v(t_i) \tag{12}$$

where $\boldsymbol{v}(t_i)$ is the actual velocity vector and $\boldsymbol{\epsilon}_v(t_i) = [\epsilon_{v,x}(t_i) \;\; \epsilon_{v,y}(t_i)]^T$ is the error vector whose entries are Gaussian-distributed zero-mean random variables having standard deviation $0.1 v_x(t_i)$ and $0.1 v_y(t_i)$ along the x and y axis, respectively.

B. Single-anchor Localization

We start by investigating a minimal scenario in which the MR executing the proposed DPE algorithm aims at localizing itself by exploiting only a single anchor available in range and placed 100 m distant. In this setup, the received signal-to-noise ratio (SNR) starts from about 7 dB and increases up to 40 dB as the MR approaches the anchor. In Fig. 2a, we report the RMSE of the MR position estimation as a function of the time. As it can be seen, the MR initially estimates its position with an error of about 3.5 m. Interestingly, the RMSE tends to decrease as soon as the DPE algorithm integrates new measurements, achieving a final accuracy of about 1.8 m. This notable improvement can be related to the ability of the



(a) (b)

Fig. 3: Array beampattern after adaptive beamforming towards (a) $\theta_i^{\mathrm{LOS}} \approx 25^\circ$ and (b) $\theta_i^{\mathrm{LOS}} \approx 83^\circ$.

algorithm to identify the most probable MR trajectory thanks to the proposed integration mechanism over time.

For comparison, we implemented a modified version of the AOA-based WLS algorithm proposed in [10], which we recall is an IPE approach. In particular, for the AOA estimation step, the smooth-MUSIC algorithm has been used in place of the MUSIC algorithm (inapplicable due to coherency). The results clearly demonstrate that the WLS cannot provide satisfactory performance in multipath environments.

C. Multiple-anchors Localization

To further investigate the algorithms performance, we consider a different scenario in which an additional anchor is available in range, initially distant 30 m from the MR. From Fig. 2b, it can be noticed that the presence of a second anchor brings noticeable advantages compared to the single-anchor case. In particular, the RMSE of the DPE algorithm quickly drops between 3 and 4 seconds, and keeps on diminishing over time. Conversely, the WLS algorithm exhibits almost the same unsatisfactory performance of the single-anchor case, meaning that it is not able to get rid of multipath despite the more information collected during the motion.

As a final remark, we observe that the RMSE of both algorithms experience a sudden increase as the MR crosses one of the anchors between 2 and 3 seconds. This behavior is linked to an intrinsic issue with signals impinging from directions close to the endfire of the array ($\approx 90^\circ$): in this angular region, the adaptive beamformer is not able to guarantee maximum gain in the desired direction, as shown in Fig. 3. This aspect opens up a new research question on how to design a proper mechanism that can be integrated in the proposed DPE algorithm to mitigate such detrimental effects.

V. Conclusion

We have proposed a novel DPE algorithm to localize a MR moving in a multipath environment. It leverages mobility information together with an adaptive beamforming strategy to get rid of multipath and reconstruct the MR trajectory over time. The performance assessment, carried out by simulating a realistic multipath environment, has shown that the proposed DPE algorithm can provide good localization accuracy, significantly outperforming an existing IPE competitor. From the results, it also emerged that the DPE algorithm loses accuracy when the received signals impinge with AOAs close to the endfire of the array. In this respect, it could be interesting to investigate whether a different processing can help to mitigate such an issue that typically arises in AOA-based methods.

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