A Graph-Based Algorithm for Robust Sequential Localization Exploiting Multipath for Obstructed-LOS-Bias Mitigation

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Abstract—This paper presents a factor graph formulation and particle-based sum-product algorithm (SPA) for robust sequential localization in multipath-prone environments. The proposed algorithm jointly performs data association, sequential estimation of a mobile agent position, and adapts all relevant model parameters. We derive a novel non-uniform false alarm (FA) model that captures the delay and amplitude statistics of the multipath radio channel. This model enables the algorithm to indirectly exploit position-related information contained in the multipath components (MPCs) for the estimation of the agent position without using any prior information such as floorplan information or training data. Using simulated and real measurements in different channel conditions, we demonstrate that the algorithm can provide high-accuracy position estimates even in fully obstructed line-of-sight (OLOS) situations and show that the performance of our algorithm constantly attains the posterior Cramér-Rao lower bound (P-CRLB), facilitating the additional information contained in the presented FA model. The algorithm is shown to provide robust estimates in both, dense multipath channels as well as channels showing specular, resolved MPCs, significantly outperforming state-of-the-art radio-based localization methods.

Index Terms—Obstructed line-of-sight, multipath, sum-product algorithm, probabilistic data association, message passing, belief propagation.

I. INTRODUCTION

LOCALIZATION of mobile agents using radio signals in environments such as indoor or urban territories is still a challenging task [1], [2], [3], [4]. These environments are characterized by strong multipath propagation and frequent obstructed line-of-sight (OLOS) situations, which can prevent the correct extraction of the line-of-sight (LOS) component (see Fig. 1). Radio channels resulting from multipath propagation are commonly represented as a superposition of a finite number of specular MPCs [5], [6], [7], [8]. However, cluttered environments with closely-spaced reflecting objects or with diffuse scatters (such as walls covered by shelves or irregular object shapes), along with the finite bandwidth of the measurement equipment, cause dense multipath propagation, which cannot be resolved into specular MPCs anymore [5], [9], [10], [11].

There exist many safety- and security-critical applications, such as autonomous driving [12], medical services [13], or keyless entry systems [14], where robustness of the position estimate is of critical importance.

A. State-of-the-Art Methods

New localization and tracking approaches within the context of 5G localization [15] that take advantage of large measurement apertures as ultra-wideband (UWB) systems [6], [16] or mmWave systems [17] seek to mitigate the effect of multipath propagation [18] (commonly referred to as “NLOS propagation”) and OLOS situations [8], [19], or even take

1We define robustness as the percentage of cases in which a system can achieve its given potential accuracy. I.e., a robust sequential localization algorithm can keep the agent’s track in a very high percentage of cases, even in challenging environments.
advantage of MPCs by exploiting inherent position information, turning multipath from impairment to an asset \cite{2, 20, 21, 22, 23}. Prominent examples of such approaches are multipath-based methods that estimate MPCs and associate them to virtual anchors representing the locations of the mirror images of an anchor on reflecting surfaces \cite{24}. The locations of virtual anchors are assumed to be known a priori \cite{25} or estimated jointly with the position of agents using multipath-based SLAM (MP-SLAM) \cite{21, 22, 26}. Jointly estimating the positions of virtual anchors and agents allows MP-SLAM to provide high-accuracy position estimates, even in OLOS situations, or to localize the agent with only a single anchor \cite{27}. However, it requires specular, resolved MPCs, which are consistent with the virtual anchor model \cite{28}. Other methods exploit cooperation among individual agents \cite{4, 27, 29, 30}, or perform robust signal processing against multipath propagation and clutter measurements in general. The latter comprise heuristics \cite{6, 31}, machine learning-based approaches \cite{19, 32, 33, 34} as well as Bayesian methods \cite{35, 36, 37}, and hybrids thereof \cite{38, 39, 40}. Heuristic methods, such as searching for the first amplitude to exceed a threshold value, are fast and easily implementable but suffer from low accuracy as well as a high probability of outage in low signal-to-noise-ratio (SNR) regions \cite{6}. In recent years, machine learning methods have grown increasingly popular. Early approaches \cite{19, 33} extract specific features from the radio channel applying model-agnostic supervised regression methods on these features. While these approaches potentially provide high accuracy estimates at low computational demand (after training), they suffer from their dependence on a large representative measurement database and can fail in scenarios that are not sufficiently represented by the training data. This is why recent algorithms facilitate deep learning and auto-encoding based methods to directly operate on the received radio signal and reduce the dependence on training data \cite{34, 41, 42}.

Multipath-based localization \cite{21, 22, 26, 36, 37, 43, 44}, multiobject-tracking \cite{45, 46, 47}, and parametric channel tracking \cite{48} are applications that pose common challenges, such as uncertainties beyond Gaussian noise, like missed detections and clutter, an uncertain origin of measurements, and unknown and time-varying number of objects to be localized and tracked. These challenges can be well addressed by Bayesian inference leveraging graphical models to perform joint detection and estimation. Since the measurement models of these applications are nonlinear, most methods typically rely on sampling techniques such as recursive Monte Carlo sampling or particle filtering, or use linearized Gaussian models \cite{49, 50}. Similarly, the probabilistic data association (PDA) algorithm \cite{45, 51} represents a low-complexity Bayesian method for robust localization and tracking with extension to multiple-sensors PDA \cite{52} and amplitude-information probabilistic data association (AIPDA) \cite{44, 53}. All these methods can be categorized as “two-step approaches”, in the sense that they do not operate on the received sampled radio signal, but use extracted measurements provided by a preprocessing step, providing a high level of flexibility and a significant reduction of computational complexity. In contrast, “direct positioning approaches” such as \cite{20, 54}, and \cite{55} directly exploit the received sampled signal, which can lead to a better detectability of low-SNR features, yet, they are computationally very demanding.

### B. Contributions

In this paper, we propose a particle-based SPA that sequentially estimates the position of a mobile agent by utilizing the position-related information contained in the LOS component as well as in MPCs.\(^2\) The proposed algorithm jointly performs probabilistic data association and estimation of the mobile agent state \cite{22, 46} together with all relevant model parameters, employing the SPA on a factor graph \cite{56}. Similar to other two-step approaches, it uses signal component delays and amplitudes estimated by a snapshot-based parametric channel estimation and detection algorithm (CEDA) as measurements. The proposed algorithm adapts in an online manner the time-varying component SNR \cite{44} as well as the detection probability of the LOS \cite{43, 57}. To this end, we propose a novel detection probability model that allows for both an exhaustive representation of the detection space and a smooth estimate of the SNR. The algorithm exploits a novel non-uniform “FA model”.\(^3\) Additionally, the model couples MPC measurements to the LOS measurement by a jointly inferred bias state. This enables the algorithm to utilize the position-related information contained in the MPCs without inferring specific map information, which can increase the accuracy and robustness of the agent’s position estimate in challenging environments, characterized by strong multipath propagation and temporary OLOS situations. The proposed algorithm is able to operate without any prior information (no floorplan information or training data are needed). It is demonstrated to provide robust estimates for specular, resolved multipath as well as dense, non-resolvable multipath, while offering sub-second runtime\(^4\) even in environments characterized by strong multipath propagation and, thus, a high number of measurements. The contributions of this paper are as follows.

\(^2\)Throughout this paper, MPCs denote all components of the received signal that are caused by the transmit signal, except the LOS component, i.e. “non-line-of-sight (NLOS) components”.

\(^3\)Typically the FA or clutter model for delay measurements is chosen to be a uniform distribution inside the observation region of the sensor \cite[Sec. 1-C]{46} \cite[Sec. 2.5.2]{51}. Since we do not distinguish between FAs and MPCs, the resulting distributions of delay and amplitude measurements are non-uniform with respect to delay, that explicitly models measurements originating from MPCs. More specifically, the introduced model represents the non-uniform distribution of delay measurements and corresponding delay-dependent distribution of amplitude measurements caused by MPCs and FAs in a joint manner. We refer to this part of the model using the terms “NLOS model” or “NLOS measurement model” throughout the paper. The presented NLOS model is derived from a stochastic radio signal model, which represents MPCs by their delay power spectrum (DPS), also referred to as power delay profile in the literature \cite{5, 9, 58, 59}.

\(^4\)The runtimes were determined on PC, see Sec. VII-D for details.
We derive a novel non-uniform NLOS model that is adapted to the distribution of the MPC delays and amplitudes corresponding to a stochastic radio signal model [9], [58], [59] and verify its potential in a numerical study.

We present a new factor graph and corresponding SPA in order to efficiently infer the marginal posterior distributions of all state variables of the introduced joint probabilistic model.

We show that the proposed algorithm is capable of overcoming even fully-OLOS situations and providing Cramér-Rao lower bound (CRLB)-level position accuracy using both synthetic and real radio signal measurements.

We analyze the influence of the individual features of our algorithm and compare it to a particle-based variant of the multi-sensor AIPDA algorithm, to the MP-SLAM algorithm presented in [22] and [44], and to the P-CRLB [60].

This work advances over the preliminary account of our conference publication [37] (and that of the related work [36]) by (i) applying an accurate, adaptive model for the joint distribution of delay and amplitude measurements instead of using heuristical models, (ii) sequentially inferring all parameters of the NLOS model together with the agent instead of using predetermined constants, (iii) improving the convergence behavior using a modified, “decoupled” SPA (see Sec. VI-A), (iv) demonstrating the performance of the proposed algorithm using simulated radio signals as well as real radio measurements obtained by (v) applying a CEDA, (vi) comparing to the MP-SLAM algorithm [22], [44] and (vii) providing the P-CRLB as a performance benchmark.

II. Notations and Definitions

Column vectors and matrices are denoted by boldface lowercase and uppercase letters. Random variables (RVs) are displayed in san serif, upright font, e.g., $x$ and $X$ and their realizations in serif, italic font, e.g., $x$ and $x$: $\hat{x}$ denotes the true value of $x$. The same notation applies for stochastic processes $x(t)$ and their realizations $x(t)$. $f(x)$ and $p(x)$ denote, respectively, the probability density function (PDF) or probability mass function (PMF) of a continuous or discrete RV. $(\cdot)^T$, $(\cdot)^*$ and $(\cdot)^H$ denote matrix transpose, complex conjugation and Hermitian transpose, respectively. $\|\|$ is the Euclidean norm. $|\cdot|$ represents the cardinality of a set. $\text{diag}(x)$ denotes a diagonal matrix with entries in $x$. $I_{n,n}$ is an identity matrix of dimension given in the subscript. $[X]_{n:n}$ denotes the $n$th diagonal entry of $X$. Furthermore, $1_a(x)$ denotes the indicator function that is $1_a(x) = 1$ if $x \in a$ and 0 otherwise, for $a$ being an arbitrary set and $\mathbb{R}^+$ is the set of positive real numbers. We predefine the following PDFs with respect to $x$:

The truncated Gaussian PDF is

$$f_{\text{TN}}(x; \mu, \sigma, \lambda) = \frac{1}{Q_1(\frac{\sigma}{\sqrt{2}})} \sqrt{\frac{2}{\pi \sigma}} e^{-\frac{(x-\mu)^2}{2 \sigma^2}} 1_{\mathbb{R}^+}(x - \lambda)$$

(1)

with mean $\mu$, standard deviation $\sigma$, truncation threshold $\lambda$ and $Q_1(\cdot)$ denoting the Q-function [61]. Accordingly, the Gaussian PDF is $f_{\text{N}}(x; \mu, \sigma) = f_{\text{TN}}(x; \mu, \sigma, -\infty)$. The truncated Rician PDF is [62, Ch. 1.6.7]

$$f_{\text{Trice}}(x; s, u, \lambda) = \frac{1}{Q_1(\frac{\sqrt{2} s}{\sqrt{\lambda}})} \frac{x}{s^2} e^{-\frac{(x^2 + u^2)}{2 s^2}} I_0(\frac{x u}{s^2}) 1_{\mathbb{R}^+}(x - \lambda)$$

(2)

with non-centrality parameter $u$, scale parameter $s$ and truncation threshold $\lambda$, $I_0(\cdot)$ is the 0th-order modified first-kind Bessel function and $Q_1(\cdot, \cdot)$ denotes the Marcum Q-function [61]. The truncated Rayleigh PDF is [62, Ch. 1.6.7]

$$f_{\text{Trayl}}(x; s, \lambda) = \frac{x}{s^2} e^{-\frac{x^2}{2 s^2}} 1_{\mathbb{R}^+}(x - \lambda)$$

(3)

with scale parameter $s$ and truncation threshold $\lambda$. This formula corresponds to the so-called Swirling I model [62]. Finally, we define the uniform PDF $f_U(x; a, b) = 1/(b - a) 1_{[a,b]}(x)$ and the uniform PMF $f_{UV}(x; \lambda) = 1/\lambda 1_{[0,\lambda]}(x)$.

III. Radio Signal Model

At each discrete time $n$, the mobile agent at position $\mathbf{p}_n$ transmits a signal $s(t)$ and each anchor $j \in \{1, \ldots, J\}$ at anchor position $\mathbf{p}_A(j) = [p_A(j), p_B(j)]^T$ acts as a receiver. The complex baseband signal received at the $j$th anchor is modeled as

$$r_n^{(j)}(t) = \mathbf{a}_n^{(j)} s(t - \tilde{\tau}_n^{(j)}) + \sum_{k=1}^{\tilde{K}_n^{(j)}} \mathbf{\alpha}_{n,k}^{(j)} s(t - \tilde{\tau}_{n,k}^{(j)}) + \mathbf{w}_n^{(j)}(t).$$

(4)

The first and second term describe the LOS component and the sum of $\tilde{K}_n^{(j)}$ specular MPCs with their corresponding complex amplitudes $\mathbf{a}_n^{(j)} \in \mathbb{C}$ and delays $\tilde{\tau}_n^{(j)} \in \mathbb{R}^+$, respectively. The delays are related to respective distances via $\tilde{\tau}_n^{(j)} = \mathbf{\tilde{d}}_n^{(j)} / c$ with $c$ being the speed of light. The third term represents an additive white Gaussian noise (AWGN) process $\mathbf{w}_n^{(j)}(t)$ with double-sided power spectral density $\tilde{N}_0/2$. The LOS distance is geometrically related to the anchor position via $\mathbf{\tilde{d}}_n^{(j)} \triangleq \mathbf{d}_{\text{LOS}}(\mathbf{p}_n) = |\mathbf{p}_n - \mathbf{p}_A(j)|$. We assume time synchronization between all anchors and the mobile agent.

However, our algorithm can be extended to an unsynchronized system along the lines of [2], [21], and [64].

The signal $r_n^{(j)}(t)$ in (4) is uniformly sampled with sampling frequency $f_s$ at corresponding sampling interval $T_s = 1/f_s$ and $N_s$ samples are collected, yielding a duration $T = N_s T_s$. By stacking the samples, we obtain the discrete time signal vector

$$\mathbf{r}_n^{(j)} = \mathbf{a}_n^{(j)} s(\tilde{\tau}_n^{(j)}) + \sum_{k=1}^{\tilde{K}_n^{(j)}} \mathbf{\alpha}_{n,k}^{(j)} s(\tilde{\tau}_{n,k}^{(j)}) + \mathbf{w}_n^{(j)} = \begin{bmatrix} r_n^{(j)} \\ \vdots \\ r_{N_s}^{(j)} \end{bmatrix}$$

(5)

where $s(\tau) \triangleq \{s(-(N_s-1)/2 T_s - \tau) \cdots s((N_s-1)/2 T_s - \tau)\}^T \in \mathbb{C}^{N_s \times 1}$ is the stacked signal vector containing the samples of the transmit signal $s(t)$. The measurement noise vector $\mathbf{w}_n^{(j)} \in \mathbb{C}^{N_s \times 1}$ is a zero-mean, circularly-symmetric complex Gaussian random vector with covariance matrix $\mathbf{\tilde{a}}^{(j)2} I_{N_s}$ and noise.

Note that state-of-the art UWB ranging devices (e.g., NXP SR040/SR150 or Qorvo DW1000/DW3000) can provide synchronized channel impulse responses (CIRs) using a two-way ranging protocol [63].
and the according normalized amplitude is 

where

ponent \[5\], \[9\], \[58\], \[59\]. Assuming uncorrelated scattering
width of

the MPCs are described by a zero-mean, circularly-symmetric
or scattering by unknown objects, since we assume that no
variance

between the LOS component and the dense multipath component \[59\]. In the
this model: The DPS typically exhibits an exponentially
decaying tail \[5\], \[9\] and a smooth onset \[9\], \[68\]. In particular,
when the LOS power is excluded, as is done in \(6\). Note that
\(\gamma_{tn}\) is mainly determined by the signal bandwidth and onset-
density of MPCs. For homogeneous deployment environments
the on-set density is well modeled as being invariant. There-
fore, \(\gamma_{tn}\) is assumed to be the same for all anchors.

For inference, we also define the normalized DPS
\(S_{D}(d/p_{n},\Omega^{(j)}_{sn}) = S_{D}(d/c; p_{n},\Omega^{(j)}_{sn}) / \Omega^{(j)}_{sn}\) and the dense-
multipath-to-noise ratio (DNR) \(\omega^{(j)}_{n} = \|s(\tau)\| \Omega^{(j)}_{sn}^{\frac{1}{2}} / \hat{\sigma}(\tau)\),
where the DNR denotes the square-root power ratio between
the dense multipath component and AWGN.

The proposed algorithm utilizes the position information
contained in \(S_{D}(\tau)\) to improve the position estimate without
explicitly exploiting map information.

\[ \hat{\sigma}(j)^{2} = \tilde{N}(j)/T, \]

\(\) The MPCs arise from reflection or scattering by unknown objects, since we assume that no
map information is available.

For a very large number of MPCs \(K_{n}\) and limited band-
width of \(s(t)\), the MPCs cannot be resolved anymore. Hence, the
MPCs are described by a zero-mean, circularly-symmetric complex Gaussian stochastic process \(v_{n}^{(j)}(\tau)\) \[65\], \[66\], \[67\]. The corresponding discrete time vector signal reads

\[ \mathbf{r}_{n}^{(j)} = \hat{\alpha}_{n,0}^{(j)} s(\hat{\tau}_{n,0}) + \sum_{\tau} s(\tau) v_{n}^{(j)}(\tau) d\tau + \mathbf{w}_{n}^{(j)} \quad (6) \]

with the second term denoting the dense multipath component \[5\], \[9\], \[58\], \[59\]. Assuming uncorrelated scattering
for \(v_{n}^{(j)}(\tau)\) \[9\], \[65\], the noise covariance matrix of \(\mathbf{r}_{n}^{(j)}\) is given by

\[ C_{n}^{(j)} = \int S_{D}(\tau) s(\tau)^{H} d\tau + \hat{\sigma}(j)^{2} I_{n} \quad (7) \]

where \(S_{D}(\tau)\) is the DPS. Using \(7\), the SNR of the LOS component is defined as \(6\) SNR
\(\mathbb{E}_{n}^{(j)} = |\hat{\alpha}_{n,0}^{(j)}|^{2} s(\hat{\tau}_{n,0})^{H} C_{n}^{(j)}^{-1} s(\hat{\tau}_{n,0})\)
and the according normalized amplitude is \(\hat{\alpha}_{n,0}^{(j)} \triangleq \text{SNR}_{n}^{(j)} \hat{\sigma}(j)\).

A. Delay Power Spectrum (DPS) Model

We choose to model the DPS \(S_{D}(\tau)\) as \[9\]

\[ \hat{\zeta}_{D}(\tau) = S_{D}(\tau; p_{n}, \hat{\gamma}_{n}, \hat{S}_{sn}) \]

\[ = \hat{\Omega}_{n}^{(j)} \frac{z_{\tau_{n}}^{(j)} + \sigma_{n}^{(j)}(1-e^{-\Delta_{\tau_{n}}})}{\hat{\gamma}_{n}} e^{-\Delta_{\tau_{n}} / \hat{\gamma}_{n}} 1_{B_{\tau}}(\Delta_{\tau_{n}}) \]

\( (8) \)

which is a double exponential function with \(\hat{\Omega}_{n}^{(j)}\) being the
DPS power. The rise time \(\hat{\gamma}_{n}\) and fall time \(\hat{\gamma}_{n}\) are shape
parameters. The distance difference \(\Delta_{\tau_{n}}(\tau; \cdot )\) is given by

\[ \Delta_{\tau_{n}}(\tau; p_{n}, \hat{\beta}_{n}^{(j)}; \cdot ) = c \tau - \hat{d}_{n}^{(j)}(\mathbf{p}_{n}) - \hat{\beta}_{n}^{(j)} \]

where \(\hat{d}_{n}^{(j)}\) is the NLOS bias, which denotes the difference
between the LOS distance \(\hat{d}_{n}^{(j)}(\mathbf{p}_{n})\) and the “onset distance”. \(\hat{\zeta}_{n}^{(j)} = \hat{\Omega}_{n}^{(j)} z_{\tau_{n}}^{(j)} \hat{S}_{sn}^{(j)}\) collects the NLOS shape parameters for
each time \(n\) and anchor \(j\). Experimental evidence motivates this model: The DPS typically exhibits an exponentially

\[ \text{Note that the presented SNR model takes into account the interference between the LOS component and the dense multipath component \[59\]. In the absence of the dense multipath component this reduces to the familiar SNR \(|\hat{\alpha}_{n,0}^{(j)}|^{2} s(\hat{\tau}_{n,0})^{2} / \hat{\sigma}^{(j)}\).} \]

\[ \text{decaying tail \[5\], \[9\] and a smooth onset \[9\], \[68\]. In particular, when the LOS power is excluded, as is done in \(6\). Note that} \]

\(\) \(\gamma_{tn}\) is mainly determined by the signal bandwidth and onset-
density of MPCs. For homogeneous deployment environments
the on-set density is well modeled as being invariant. Therefore, 
\(\gamma_{tn}\) is assumed to be the same for all anchors.

For inference, we also define the normalized DPS
\(S_{D}(d/p_{n},\Omega^{(j)}_{sn}) = S_{D}(d/c; p_{n},\Omega^{(j)}_{sn}) / \Omega^{(j)}_{sn}\) and the dense-
multipath-to-noise ratio (DNR) \(\omega^{(j)}_{n} = \|s(\tau)\| \Omega^{(j)}_{sn}^{\frac{1}{2}} / \hat{\sigma}(\tau)\),
where the DNR denotes the square-root power ratio between
the dense multipath component and AWGN.

The proposed algorithm utilizes the position information
contained in \(S_{D}(\tau)\) to improve the position estimate without
explicitly exploiting map information.

\[ \text{B. Parametric Channel Estimation} \]

By applying a suitable snapshot-based channel estimation and detection algorithm (CEDA) \[5\], \[69\], \[70\], and \[71\] to
the observed discrete signal vector \(r_{n}^{(j)}\), one obtains, at each
time \(n\) and anchor \(j\), a number of \(M_{n}^{(j)}\) measurements denoted by \(z_{n,m}^{(j)}\) with \(m \in M_{n}^{(j)} = \{1, \ldots , M_{n}^{(j)}\}\). Each
\(z_{n,m}^{(j)} = [z_{dn,m}^{(j)} z_{an,m}^{(j)}]^{T}\) contains a distance measurement 
\(z_{dn,m}^{(j)} \in [0, d_{\text{max}}]\) with maximum distance \(d_{\text{max}} = c \tau_{n}\),
and a normalized amplitude measurement \(z_{an,m}^{(j)}\). The CEDA
decomposes the discrete signal vector \(r_{n}^{(j)}\) into individual, decorrelated components according to \(5\),
reducing the number of dimensions (as \(M_{n}^{(j)}\) is usually much smaller than \(N_{n}\)).
It thus can be said to compress the information contained in
\(r_{n}^{(j)}\) into \(z_{n}^{(j)} = [z_{n,1}^{(j)} \ldots z_{n,M_{n}^{(j)}}^{(j)}]^{T}\). See the supplementary
material \[72\], Sec. V) for further details. The stacked vector 
\(z_{n}^{(j)} = [z_{n,1}^{(j)} \ldots z_{n,M_{n}^{(j)}}^{(j)}]^{T}\) is used as noise measurement by the
proposed algorithm.

\[ \text{IV. System Model} \]

We consider a mobile agent to be moving along an unknown
trajectory as depicted in Fig. 1. The current state of the agent is
described by the state vector \(x_{n} = [p_{n}^{T} v_{n}^{T}]^{T}\), which is composed of the agent’s position \(p_{n} = [p_{xn} p_{yn}]^{T}\) and velocity 
\(v_{n} = [v_{xn} v_{yn}]^{T}\). We also introduce the following additional state variables, which represent all RV inferred along with \(x_{n}\):
First, we define the augmented agent state \(\bar{x}_{n} = [x_{n}^{T} \gamma_{n}^{T}]^{T}\), which collects all RVs that are \textit{common} for all anchors. Second, we define the anchor state \(y_{n}^{(j)} = [u_{n}^{(j)} \omega_{n}^{(j)} b_{n}^{(j)} \gamma_{n}^{(j)}]^{T}\) collecting all \textit{continuous} RVs, which are modeled separately
for each anchor. Third, there are two discrete RVs $q_{n \mid n}$ and $a_{n \mid n}$, which denote the LOS probability and association variable, respectively, and are modeled separately for all anchors. For the sake of clarity, all RVs constituting the system model are summarized and described in Table I.

At each time $n$ and for each anchor $j$ the CEDA provides the currently observed measurement vector $z_{n \mid n}$, with fixed $M_{n \mid n}$, according to Sec. III-B. Before the measurements are observed, they are random and represented by the vector $z_{n \mid m} = [z_{n \mid m \mid 1} \ldots z_{n \mid M_{n \mid m}}]^T$. In line with Sec. III-B we define the nested random vectors $z_{n \mid j} = [z_{n \mid 1 \mid j} \ldots z_{n \mid M_{n \mid j}}]^T$ and $z_n = [z_{1 \mid j} \ldots z_{T \mid j}]^T$. Also the number of measurements $M_{n \mid j}$ is a RV. The vector containing all measurement numbers is defined as $M_n = [M_{n \mid 1} \ldots M_{n \mid J}]^T$. Each measurement $z_{n \mid m}$ either originates from the LOS or is due to an MPC. It is also possible that a measurement $z_{n \mid m}$ did not originate from any physical component, but from FAs of the CEDA. The presented model only distinguishes between “LOS measurements” originating from the LOS and “NLOS measurements”, i.e., measurements due to MPCs or FAs.

A. LOS Measurement Model

The LOS likelihood function (LHF) of an individual distance measurement $z_{n \mid m}$ is given by

$$f_L(z_{n \mid m} \mid p_n, u_{n \mid m}) = f_N(z_{n \mid m} - a_{n \mid m}, \sigma_d(u_{n \mid m}))$$  \hspace{1cm} (9)

with mean $a_{n \mid m} \cdot p_n$ and variance $\sigma_d^2(u_{n \mid m})$. The variance is determined based on the Fisher information given by

$$\sigma_d^2(u_{n \mid m}) = \frac{\beta_{\text{bw}}}{\pi} u_{n \mid m}^2,$$

where $\beta_{\text{bw}}$ is the root mean squared bandwidth [1], [2] and $u_{n \mid m}$ is the normalized amplitude at anchor $j$. The LOS LHF $f_L$ the normalized amplitude measurement $z_{n \mid m}$ is modeled as $\gamma$ [44], [48]

$$f_L(z_{n \mid m} \mid u_{n \mid m}) = f_{\text{TrInc}}(z_{n \mid m} \mid u_{n \mid m}, \gamma)$$ \hspace{1cm} (10)

with $f_{\text{TrInc}}$ being a truncated Rician PDF (2). $\gamma$ is the detection threshold of the CEDA, which is a constant to be chosen. As for the distance LHF, the scale parameter is determined based on the Fisher information given as $\sigma_d^2(u_{n \mid m}) = 1/2 + u_{n \mid m}^2$ [48]. Note that this expression reduces to $1/2$ if the AWGN noise variance $\sigma_d^2$ is assumed to be known or $N_s$ to grow indefinitely (see [48] for a detailed derivation). Note that for (10) the Marcum-Q function in (2) represents the detection probability $p_D(u_{n \mid m})$ (see Sec. IV-D).

B. NLOS Measurement Model

The NLOS LHF of an individual normalized amplitude measurement $z_{n \mid m}$ is given as

$$f_{\text{NL}}(z_{n \mid m} \mid \gamma) = f_{\text{TrRayl}}(z_{n \mid m} \mid u_{n \mid m}, \gamma)$$ \hspace{1cm} (11)

where $f_{\text{TrRayl}}$ is a truncated Rayleigh PDF (3) and

$$s_n^2(z_{n \mid m} \mid p_n, \theta_n) = \frac{1}{2} \left( c_n^2(z_{n \mid m} \mid p_n, \gamma) + 1 \right) \hspace{1cm} (12)$$

is the NLOS scale function. We used $\theta_n = [\theta_n^1 \theta_n^2 \theta_n^3]^T$ and $\gamma_n = [\omega_n^1 \omega_n^2 \omega_n^3]^T$ for notational brevity. See the supplementary material [72, Sec. I] for details about the derivation of (11). The shape of (11) with respect to $z_{n \mid m}$ is shown in Fig. 2a. The NLOS LHF of the distance measurement $z_{n \mid m}$ is given by

$$f_{\text{NL}}(z_{n \mid m} \mid p_n, \theta_n) = Q_2(p_n, a_{n \mid m})$$ \hspace{1cm} (13)

where $Q_2(p_n, a_{n \mid m}) = \int_0^\infty \exp \left( -\frac{1}{2} a_{n \mid m}^2 (2 s_n^2(z_{n \mid m} \mid p_n, \theta_n)) \right) d\gamma$

is the normalization constant ensuring integration to 1. The exponential term in (13) corresponds to the probability that at time $n$ for anchor $j$ a NLOS measurement at distance $z_{n \mid m}$ is generated. The shape of (13) with respect to $z_{n \mid m}$ for different values of $\gamma$ is shown in Fig. 2b. Note that (13) approaches a uniform PDF when $\gamma$ or $\omega_n^1$ approach zero.

The presented NLOS measurement model is valid independently of the DPS model chosen in (8). However, (8) is a reasonable choice as it is physically motivated [9] and is of moderate computational complexity.

C. Data Association Model

At each time $n$ and for each anchor $j$, the measurements, i.e., the components of $z_{n \mid m}$ are subject to data association
uncertainty. Thus, it is not known which measurement $z_{n,m}^{(j)}$ originated from the LOS, or which one is due to an “NLOS measurement”, i.e., measurements originating from MPCs or FAs. Based on the concept of PDA [51], we define the association variable $a_{n}^{(j)}$ as

$$a_{n}^{(j)} = \begin{cases} m \in M_{n}^{(j)}; & z_{n,m}^{(j)} \text{ is the LOS measurement in } z_{n}^{(j)} \\ 0, & \text{no LOS measurement in } z_{n}^{(j)} \end{cases}.$$  

(14)

Assuming the number of NLOS measurements to follow a uniform distribution (so called “non-parametric model”), the joint PMF of $a_{n}^{(j)}$ and $M_{n}^{(j)}$ can be shown to be [51]

$$p(a_{n}^{(j)}, M_{n}^{(j)}|u_{n}^{(j)}, q_{n}^{(j)}) = \frac{p_{E}(u_{n}^{(j)}, q_{n}^{(j)})}{M_{n}^{(j)} M_{n,\text{max}}}, \quad a_{n}^{(j)} \in M_{n}^{(j)}$$

$$1 - p_{E}(u_{n}^{(j)}, q_{n}^{(j)}) \quad a_{n}^{(j)} = 0$$

(15)

where $p_{E}(u_{n}^{(j)}, q_{n}^{(j)})$ is the probability that there is a LOS measurement for the current set of measurements defined in Sec. IV-D and $M_{n,\text{max}}$ is an irrelevant constant. Incorporating $a_{n}^{(j)}$ into the model, we define the overall distance LHF as

$$f(z_{n,m}^{(j)}|\xi_{En}^{(j)}) = \begin{cases} f_{L}(z_{n,m}^{(j)}|p_{n}, u_{n}^{(j)}) , & a_{n}^{(j)} = m \\ f_{NL}(z_{n,m}^{(j)}|p_{n}, \xi_{n}^{(j)}) , & a_{n}^{(j)} \neq m \end{cases}$$

(16)

where we used $\xi_{n}^{(j)} = [p_{n}, u_{n}^{(j)}, a_{n}^{(j)} \xi_{n}^{(j)}]^T$ for brevity. The shape of (16) is depicted in Fig. 3a. Further, the overall amplitude LHF is given by

$$f(z_{n,m}^{(j)}|\xi_{En}^{(j)}) = \begin{cases} f_{L}(z_{n,m}^{(j)}|u_{n}^{(j)}) , & a_{n}^{(j)} = m \\ f_{NL}(z_{n,m}^{(j)}|p_{n}, \xi_{n}^{(j)}, \xi_{En}^{(j)}) , & a_{n}^{(j)} \neq m \end{cases}$$

(17)

which is shown in Fig. 3b. Using the common assumption of the measurements to be independent for different values of $n$ [46], the joint LHF for all measurements per anchor $j$ and time $n$ is

$$f(z_{n,m}^{(j)}|\xi_{En}^{(j)}) = \prod_{m=1}^{M_{n}^{(j)}} f(z_{n,m}^{(j)}|\xi_{En}^{(j)}) f(z_{n,m}^{(j)}|\xi_{En}^{(j)})$$

(18)

D. LOS Existence Probability Model

We model the LOS existence probability given in (15) as $p_{E}(u_{n}^{(j)}, q_{n}^{(j)}) = p_{D}(u_{n}^{(j)}) q_{n}^{(j)}$. The probability of detection $p_{D}(u_{n}^{(j)})$ is the probability that at time step $n$ and anchor $j$ the agent generates a radio signal component whose amplitude is high enough so that it leads to an LOS measurement. It is modeled by the counter probability of a Rician cumulative distribution function (CDF) given as

$$p_{D}(u_{n}^{(j)}) = Q \left( \frac{u_{n}^{(j)}}{\sigma_{u}(u_{n}^{(j)})}, \gamma \right)$$

(19)

by assuming that the proposed algorithm is applied after a generalized likelihood ratio test detector. $q_{n}^{(j)}$ is the probability of the event that the LOS is not obstructed, which is referred to as LOS probability in the following, and acts as a prior probability to the detection event. According to [43], [57], and [74], we model $q_{n}^{(j)}$ as discrete RV that takes its values from a finite set $Q = \{\lambda_{1}, \ldots, \lambda_{Q}\}$, where $\lambda_{i} \in (0, 1]$. The LOS probabilities for different sensors $j$ are assumed to be independent. The proposed LOS existence probability model $p_{E}(u_{n}^{(j)}, q_{n}^{(j)})$ correctly incorporates the detection process into the system model via $p_{E}(u_{n}^{(j)})$ excluding a detection of measurements with $z_{n,m}^{(j)}$ below $\gamma$ and it can cope with amplitude model mismatch by correcting the amplitude-related probability of detection with $q_{n}^{(j)}$. With respect to implementation (see Sec. VI-B.1) this means that our model allows for smooth sequential inference of slow amplitude variations (e.g., due to path loss) via $p_{D}(u_{n}^{(j)})$, while $q_{n}^{(j)}$ ensures a complete representation of the probability space, covering rapid amplitude variations (e.g., due to OLOS).

E. State Transition Model

We model the evolution of $\bar{x}_{n}$ and $y_{n}^{(j)}$ and $q_{n}^{(j)}$ over time $n$ as independent first-order Markov processes, which are defined by the joint state transition PDF

$$f(\bar{x}_{n}, y_{n}^{(j)}, q_{n}^{(j)}|\bar{x}_{n-1}, y_{n-1}^{(j)}, q_{n-1}^{(j)})$$

$$= f(\bar{x}_{n}|\bar{x}_{n-1}) \prod_{j=1}^{J} f(y_{n}^{(j)}|y_{n-1}^{(j)}) p(q_{n}^{(j)}|q_{n-1}^{(j)}).$$

(20)

with $f(\bar{x}_{n}|\bar{x}_{n-1})$ and $f(y_{n}^{(j)}|y_{n-1}^{(j)})$ being the respective state transition PDFs. For the discrete RV $q_{n}^{(j)}$ the first-order Markov process model results in a conventional Markov chain, with $[Q_{n}^{(j)}]_{k} = p(q_{n}^{(j)} = \lambda_{k}|q_{n-1}^{(j)} = \lambda_{k})$ being the elements of the transition matrix.

V. PROBLEM FORMULATION AND FACTOR GRAPH

In this section we formulate the sequential estimation problem of interest and present the joint posterior and the factor graph underlying the proposed algorithm.
A. Problem Statement

The problem considered is the sequential estimation of the agent state $x_n$. This is done in a Bayesian sense by calculating the minimum mean-squared error (MMSE) [73] of the augmented agent state

$$\hat{x}_{n}^{\text{MMSE}} = \int \hat{x}_n f(\hat{x}_n | z) \, d\hat{x}_n,$$

(21)

with $\hat{x}_{n}^{\text{MMSE}} = [\hat{x}_{n}^{\text{MMSE}}, \hat{v}_{n}^{\text{MMSE}}]^T$ and $\hat{x}_{n}^{\text{MMSE}} = [\hat{p}_{n}^{\text{MMSE}} T \hat{v}_{n}^{\text{MMSE}}]^T$. Furthermore, we also calculate

$$\hat{y}_{n}^{(j)\text{MMSE}} = \int y_{n}^{(j)} f(y_{n}^{(j)} | z) \, dy_{n}^{(j)},$$

(22)

$$\hat{q}_{n}^{(j)\text{MMSE}} = \sum_{\lambda_{n} \in \mathbb{Q}} \lambda_{n} p(q_{n}^{(j)} = \lambda_{n} | z)$$

(23)

with $\hat{y}_{n}^{(j)\text{MMSE}} = [\hat{u}_{n}^{(j)\text{MMSE}}, \hat{z}_{n}^{(j)\text{MMSE}}] T$, $\hat{b}_{n}^{(j)\text{MMSE}}, \hat{z}_{n}^{(j)\text{MMSE}} T$. Furthermore, we also calculate

$$\hat{x}_{n}^{\text{MMSE}} = \int \hat{x}_n f(\hat{x}_n | z) \, d\hat{x}_n,$$

(21)

with $\hat{x}_{n}^{\text{MMSE}} = [\hat{x}_{n}^{\text{MMSE}}, \hat{v}_{n}^{\text{MMSE}}]^T$ and $\hat{x}_{n}^{\text{MMSE}} = [\hat{p}_{n}^{\text{MMSE}} T \hat{v}_{n}^{\text{MMSE}}]^T$. In order to obtain (21), (22), and (23), the respective marginal posterior PDFs need to be calculated. By direct marginalization of the joint posterior PDF is computationally infeasible [46], we perform message passing by means of the SPA rules on the factor graph that represents a factorized version of the joint posterior of our statistical model discussed in Sec. IV.

B. Joint Posterior and Factor Graph

For each $n$, let $y_n = [y_n^{(1)} T \ldots y_n^{(J)} T]^T$, $a_n = [a_n^{(1)} T \ldots a_n^{(J)} T]^T$, and $q_n = [q_n^{(1)} T \ldots q_n^{(J)} T]^T$. Furthermore, let $z = [z_1 T \ldots z_n T]^T$, $\bar{x} = [\bar{x}_1 T \ldots \bar{x}_n T]^T$, $a = [a_1 T \ldots a_n T]^T$, $y = [y_0 T \ldots y_n T]^T$, $q = [q_0 T \ldots q_n T]^T$, and $M = [M_1 T \ldots M_n T]^T$. We now assume that the measurements $z$ are observed and thus fixed. Applying Bayes’ rule as well as some commonly used independence assumptions [25], [46] the joint posterior for all states up to time $n$ and all $J$ anchors can be derived up to a constant factor as

$$f(\bar{x},a,y,q,M|z)$$

$$\propto f(z|\bar{x},a,y,q) f(\bar{x},a,y,q) f(a|y,q) f(\bar{x}) p(q) f(y)$$

$$\propto f(\bar{x}_0) \prod_{j=1}^{J} p(q_{n}^{(j)}) f(y_{n}^{(j)}) \prod_{n=1}^{n} f(\bar{x}_n|\bar{x}_{n-1}) \Psi(y_{n}^{(j)} | y_{n-1}^{(j)}) \times \sum_{\lambda_{n} \in \mathbb{Q}} \lambda_{n} p(q_{n}^{(j)} = \lambda_{n} | z)$$

(24)

VI. SUM-PRODUCT ALGORITHM

A. Marginal Posterior and Sum-Product Algorithm (SPA)

The marginal posterior can be calculated efficiently by passing messages on the factor graph according to the SPA [56]. For the proposed algorithm, we specify not to send messages backward in time. This makes the factor graph in Fig. 4 an acyclic graph. For acyclic graphs the SPA yields exact results for the marginal posteriors [56]. At time $n$, the following calculations are performed for all $J$ anchors. The prediction messages are given as

$$\eta(\bar{x}_n) = \int \Phi(\bar{x}_n|\bar{x}_{n-1}) \hat{f}_x(\bar{x}_{n-1}) \, d\bar{x}_{n-1}$$

(26)

$$\phi(y_{n}^{(j)}) = \int \Phi(y_{n}^{(j)}|y_{n-1}^{(j)}) \hat{f}_y(y_{n-1}^{(j)}) \, dy_{n-1}^{(j)}$$

(27)

$$\psi(q_{n}^{(j)}) = \sum_{q_{n-1}^{(j)}} \Psi(q_{n}^{(j)}|q_{n-1}^{(j)}) \hat{p}_q(q_{n-1}^{(j)})$$

(28)

where $\hat{f}_x(\bar{x}_{n-1})$, $\hat{f}_y(y_{n-1}^{(j)})$ and $\hat{p}_q(q_{n-1}^{(j)})$ are messages of the previous time $n - 1$. The measurement update messages are given by

$$\xi^{(j)}(\bar{x}_n) = \int \phi(y_{n}^{(j)}) \sum_{q_{n-1}^{(j)}} \psi(q_{n}^{(j)})$$

(29)
\[
\chi^{(j)}(\bar{x}_n) = \eta(\bar{x}_n) \prod_{j=1}^{J} \xi^{(j)}(\bar{x}_n) / \xi^{(j)}(\bar{x}_n) \\
\nu(y_n^{(j)}) = \sum_{q_n^{(j)}=1}^{M_n^{(j)}} \psi(q_n^{(j)}) \int \chi^{(j)}(\bar{x}_n) \\
\times \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}) d\bar{x}_n \\
\beta(q_n^{(j)}) = \int \phi(y_n^{(j)}) \chi^{(j)}(\bar{x}_n) \\
\times \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}) d\bar{x}_n dy_n^{(j)}. \\
\]  
(30)

Finally, we calculate the marginal posteriors as \( f(\bar{x}_n | z) \propto \hat{f}_x(\bar{x}_n) \prod_{j=1}^{I} \xi^{(j)}(\bar{x}_n) \), \( f(y_n^{(j)} | z) \propto \hat{f}_y(y_n^{(j)}) = \phi(y_n^{(j)}) \nu(y_n^{(j)}) \) and \( p(q_n^{(j)} | z) \propto \hat{p}_q(q_n^{(j)}) = \psi(q_n^{(j)}) \beta(q_n^{(j)}) \).

We additionally compare the performance of the above approximate computation. Our implementation that provides approximate computation. Our implementation the LOS LHF of the normalized amplitude distributions to factorize as

\[
\chi^{(j)}(\bar{x}_n) = \eta(\bar{x}_n) \prod_{j=1}^{J} \xi^{(j)}(\bar{x}_n) \\
\nu(y_n^{(j)}) = \sum_{q_n^{(j)}=1}^{N_n} \psi(q_n^{(j)}) \int \chi^{(j)}(\bar{x}_n) \\
\times \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}) d\bar{x}_n \\
\beta(q_n^{(j)}) = \int \phi(y_n^{(j)}) \chi^{(j)}(\bar{x}_n) \\
\times \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}) d\bar{x}_n d\bar{y}_n^{(j)}. \\
\]  
(31)

An approximation of the message \( \beta(q_n^{(j)}) \) in (32) is given as

\[
\beta(q_n^{(j)}) \approx \sum_{i=1}^{I} w^{(i)}_x \nu^{(i)}_y \\
\times \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}). \\
\]  
(35)

### i) Belief Calculation and State Estimation

The above approximate messages are further used for calculating the non-normalized weights corresponding to the beliefs \( \hat{f}_x(\bar{x}_n) \) and \( \hat{f}_y(y_n^{(j)}) \) for all \( j \in J \) as \( \bar{w}_x^{(i)} = w_x^{(i)} \prod_{j=1}^{I} w^{(i)}_x^{(j)} \) and \( \bar{w}_y^{(i)} = w_y^{(i)} \prod_{j=1}^{I} w^{(i)}_y^{(j)} \) respectively.

After normalization, i.e., \( \bar{w}_x^{(i)} = \bar{w}_x^{(i)} / \sum_{i=1}^{F} \bar{w}_x^{(i)} \) and \( \bar{w}_y^{(i)} = \bar{w}_y^{(i)} / \sum_{i=1}^{F} \bar{w}_y^{(i)} \), an approximation of the MMSE state estimates \( \hat{x}_n^{(i)} \) and \( \hat{y}_n^{(i)} \) in (21), (22) and (23) as given in \( \hat{x}_n^{(i)} \approx \sum_{i=1}^{F} \bar{x}_n^{(i)} \bar{w}_x^{(i)} \) and \( \hat{y}_n^{(i)} \approx \sum_{i=1}^{F} \bar{y}_n^{(i)} \bar{w}_y^{(i)} \).

To avoid particle degeneracy [49], a resampling step\(^8\) is performed as a preparation for the next time step \( n+1 \) leading to equally weighted particles \( \{\bar{x}_n^{(i)}, w^{(i)}_x^{(n)} = 1/F\}_{i=1}^{F} \) and \( \{\bar{y}_n^{(i)}, w^{(i)}_y^{(n)} = 1/F\}_{i=1}^{F} \) for all \( j \in J \) representing the beliefs \( \hat{f}_x(\bar{x}_n) \) and \( \hat{f}_y(y_n^{(j)}) \).

The resulting problem complexity scales only linearly in the number of particles \( I \) and in the number of measurements \( M_n^{(j)} \). For computational efficiency of the particle-based implementation the LOS LHF of the normalized amplitude measurement (10) is approximated by a truncated Gaussian PDF, i.e.,

\[
\hat{f}_L(z_n^{(j)} | u_n^{(j)}) = f_{L_n}(z_n^{(j)}; \sigma_u(u_n^{(j)}), u_n^{(j)}, \gamma). \\
\]

### ii) Measurement Update

The non-normalized weights representing the messages \( \xi^{(j)}(\bar{x}_n) \) and \( \nu(y_n^{(j)}) \) in (29) and (31) are calculated by

\[
w^{(i)}_x | y_n^{(j)} = w^{(i)}_y | y_n^{(j)} = \sum_{q_n^{(j)}=1}^{N_n} \psi(q_n^{(j)}) \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}) \\
\times \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}). \\
\]  
(33)

\[
w^{(i)}_y | y_n^{(j)} = w^{(i)}_y | y_n^{(j)} = \sum_{a_n^{(j)}=0}^{M_n^{(j)}} \hat{g}(z_n^{(j)}; p_n, y_n^{(j)}; a_n^{(j)}; q_n^{(j)}). \\
\]  
(34)

\(8\)We suggest to use “systematic” resampling for efficiency [49].
uniform PMF $\tilde{f}(i)(y^{(i)}_0) = f_{UD}(y^{(i)}_0)Q$ taking all values of $Q$ with equal probability. We assume the velocity vector $v_0$ to be zero mean, Gaussian, with covariance matrix $\sigma_v^2 I_2$ and $\sigma_v = 6$ m/s, as we do not know in which direction we are moving.

The remainder of the states are initialized heuristically, by assuming an initial measurement vector $z_0$ containing $M_0^{(i)}$ measurements to be available. The normalized amplitude PDFs are initialized as $\tilde{f}(i)(y^{(i)}_0) = f_{TRayl}(y^{(i)}_0; z_{0,\text{max}}^{(i)}), 0.05 z_{0,\text{max}}^{(i)} \gamma)$ where $z_{0,\text{max}}^{(i)}$ is the maximum normalized amplitude measurement in $z^{(i)}_0$. The position state is initialized as $f(p_0) \sim \prod_{j=1}^{f} \prod_{n=1}^{M_f} f(\tilde{z}_{i,m}^{(j)}|p_{\text{init}}, z_{0,\text{max}}^{(j)}) f(p_{\text{init}})$, where the proposal distribution $f(p_{\text{init}})$ is drawn uniformly on two-dimensional discs around each anchor $j$, which are bounded by the maximum possible distance $d_{\text{max}}$ and a sample is drawn from each of the $J$ discs with equal probability. The DNR PDFs are initialized as $\tilde{f}(\omega^{(j)}_0) = f_{TRayl}(\omega^{(j)}_0; \omega^{(j)}_{\text{init}}, 0.05 \omega^{(j)}_{\text{init}} \gamma)$, where $\omega^{(j)}_{\text{init}}$ is determined as described in the supplementary material [72, Sec. II].

3) Normalization of the NLOS Distance Likelihood: As discussed in Sec. IV-B, the NLOS LHF in (13) must be normalized by $Q_0(p_n, \zeta^{(j)}_n)$. However, $Q_0(p_n, \zeta^{(j)}_n)$ cannot be determined analytically and, being a function of $p_n$ and $\zeta^{(j)}_n$, it needs to be calculated for each individual particle (see Sec. VI-B.1). Thus, we need an efficient numerical approximation. For details see the supplementary material [72, Sec. III].

VII. RESULTS

We validate the proposed model and analyze the performance gain caused by the features of the proposed algorithm using both synthetic data obtained using numerical simulation and real radio measurements. The performance is compared with the P-CRLB and that of the AIPDA. For synthetic measurements with geometry related multipath, we also compare to the MP-SLAM algorithm presented in [22] and [44].

A. Common Analysis Setup

The following setup and parameters are commonly used for all analyses presented.

The PDF of the joint anchor state $x_n$ is factorized as $f(x_n|z_{n-1}) = f(x_n|w_{n-1}) f(\gamma_{tn}|\gamma_{tn-1})$, where the agent motion, i.e. the state transition PDF $f(x_n|w_{n-1})$ of the agent state $x_n$, is described by a linear, constant velocity and stochastic acceleration model [62, p. 273], given as $x_n = A x_{n-1} + B w_n$, with the acceleration process $w_n$ being i.i.d. across $n$, zero mean, and Gaussian with covariance matrix $\sigma_a^2 I_2$, $\sigma_a$ is the acceleration standard deviation, and $A \in \mathbb{R}^{4 \times 4}$ and $B \in \mathbb{R}^{4 \times 2}$ are defined according to [62, p. 273], with sampling period $\Delta T$. The state transition of the rise distance $\gamma_{tn}$, i.e., the state transition PDF $f(\gamma_{tn}|\gamma_{tn-1})$, is $\gamma_{tn} = \gamma_{tn-1} + \varepsilon_{\gamma_n}$, where the noise $\varepsilon_{\gamma_n}$ is i.i.d. across $n$, zero mean, Gaussian, with variance $\sigma_{\gamma_n}^2$. Similarly, the state transition model of the joint anchor state $y^{(i)}_n$, i.e. the state transition PDF $f(y^{(i)}_n|y^{(i)}_{n-1})$, is chosen as $y^{(i)}_n = y^{(i)}_{n-1} + \varepsilon^{(i)}_n$, where the noise vector $\varepsilon^{(i)}_n$ is i.i.d. across $n$ and $j$, zero mean, jointly Gaussian, with covariance matrix $\begin{bmatrix} \sigma_a^2 & \sigma_a^2 \omega_n^2 & \sigma_a^2 \gamma_n^2 & \sigma_a^2 \gamma_n \omega_n \end{bmatrix}$ and the individual state-transition variances (STV) $\sigma_{\gamma_n}^2, \sigma_{\omega_n}^2, \sigma_{\gamma_n}^2$ and $\sigma_{\omega_n}^2$. Unless noted differently the STVs are set as $\sigma_{\gamma_n} = 2 m^2 s^{-2}$, $\sigma_{\omega_n} = 0.05 \omega_n^{(i)\text{MMSE}}$, $\sigma_{\omega_n} = 0.05 \omega_n^{(i)\text{MMSE}}$, $\sigma_{\gamma_n} = 0.5 \gamma_n^{(i)\text{MMSE}}$, $\sigma_{\omega_n} = 0.5 \gamma_n^{(i)\text{MMSE}}$. While $\sigma_{\gamma_n}$ is set according to the maximum agent acceleration [62], for the STV of all other parameters we use values relative to the root mean squared error (RMSE) estimate of the previous time step $n-1$ as a heuristic. Note that this choice allows no tuning of the STV to be required for all experiments presented, even though the propagation environments are considerably different. We used $5 \cdot 10^4$ particles before the first resampling operation and 5000 particles for inference during the track. We set the detection threshold as low as $\gamma = 1.77 (5 \text{d}B)$ for all simulations, which allows the algorithm to facilitate low-energy MPCs (this choice is further discussed in Sec. VII-B).

The set of possible LOS probabilities is chosen as $Q = \{0.01, 0.33, 0.66, 1\}$. The state transition matrix $Q^{(j)} \triangleq Q$ is set as follows: $Q^{(j)}_{1,1} = 0.9$, $Q^{(j)}_{4,4} = 0.95$, $Q^{(j)}_{2,1} = 0.1$ and $Q^{(j)}_{3,4} = 0.05$. For $2 \leq k \leq 3$, $Q^{(j)}_{k,k} = 0.85$, $Q^{(j)}_{k+1,k} = 0.05$ and $Q^{(j)}_{k+1,k+1} = 0.1$. For all other tuples $(i, k)$, $Q^{(j)}_{i,k} = 0$ in order to encourage high LOS probabilities [57]. For the numerical approximation of $Q_0(p_n, \zeta^{(j)}_n)$ as discussed in Sec. VI-B.3, we used $K_5 = 30$. The results are shown in terms of the RMSE of the estimated agent position $\hat{p}_n^{(i)\text{RMSE}} = \sqrt{\mathbb{E}[\|p^{(i)\text{MMSE}} - p_n\|^2]}$, evaluated using a numerical simulation with 500 realizations. For each of the scenarios investigated, we consistently analyze the influence of the individual features of our algorithm according to Table II. It shows the algorithm variants implemented and the corresponding features that are enabled for an algorithm (x) or not ( ). When “$y^{(i)}_n$ tracking” is deactivated, we set $q_0^{(i)} = 0.999$ for all $n, j$. When we use “decoupled SPA”, the suboptimal message passing scheme presented in Sec. VI-A is used. Not applying the “uninform-$f_h$,” means (12) is replaced by $s_n^{(i)} \triangleq 1/2$, and for AL4 and AL5 we use $5 \cdot 10^4$ particles instead of 5000. Note that AL1 represents a multi-sensor variant of the conventional AIPDA. The MP-SLAM algorithm is implemented according to [22] and [44] using the measurements $\tilde{z}_{m,n}$, i.e., distance and amplitude measurements, as an input. For consistency, the state transition PDFs and initial state distributions of the agent state and normalized amplitude state are set as described in Sec. VII-A and VI-B.2. For convergence, we had to use $5 \cdot 10^4$ particles.
and an anchor driving noise of $\sigma_{\text{An}} = 0.02$ m, other parameters are $P_a = 0.999$, $\mu_{n,1} = 0.05$. The mean number of false alarms was approximated as $\mu_{\text{FA}} = N_s e^{-\gamma^2}$ (see [44] for definitions). For stability we increased the delay measurement variances of all virtual anchors (not the physical anchors) by a factor of 2 with respect to the Fisher information-based value.

As a performance benchmark, we provide the CRLB on the position error variance considering all visible LOS measurements of a single time step $n$, which we refer to as the snapshot-based positioning CRLB (SP-CRLB) [7], [59], [76], [77]. Furthermore, we provide the corresponding posterior Cramér-Rao lower bound (P-CRLB) [60] that additionally considers the dynamic model of the agent state and the “P-CRLB-LOS”, which is the P-CRLB assuming the LOS component to all anchors is always available and, thus, provides a lower bound for the proposed estimator. See the supplementary material [72, Sec. VI] for further details.

### B. Analysis on Synthetic Measurements

For the synthetic setup, we investigate the scenario shown in Fig. 5. The agent moves along a trajectory, with two distinct direction changes, where the agent velocity is set to vary around a magnitude of 0.8 m/s. It is observed at $N = 190$ discrete time steps $n \in \{1, \ldots, N\}$ at a constant observation rate of $\Delta T = 100$ ns, resulting in a continuous observation time of 19 s. We simulate three anchors, A1-A3, which are placed in close vicinity to each other. The limited directional diversity of the anchors (corresponding to a poor geometric dilution of precision (GDOP) [78]), poses a challenging setup for delay measurement-based position estimation. Note that the environment setup shown in Fig. 5, i.e., walls and resulting obstructions, are only used in Sec. VII-B.2. For all synthetic radio measurements involving the proposed CEDA (see [72, Sec. VI]), we choose the transmitted complex baseband signal $s(t)$ to be of root-raised-cosine shape with a roll-off factor of 0.6 and a duration of 2 ns (bandwidth of 500 MHz). The signal is critically sampled, i.e., $T_s = 1.25$ ns, with a total number of $N_s = 161$ samples, amounting to a maximum distance of $d_{\text{max}} = 60$ m.

#### 1) Synthetic Measurements With Stochastic Multipath:

In this section we present results using synthetic measurements generated by simulating the MPCs as zero mean stochastic process. More specifically, we compare results obtained by simulating the radio signal according to (6) and applying the CEDA to results obtained using fully synthetic measurements, which are generated according to Sec. IV without involving the CEDA. For fully synthetic measurements the average number of NLOS measurements per time $n$ and anchor $j$ prior to the simulated detection process was approximated as $N_c$. Detection further reduces the prior number of NLOS events by the mean NLOS detection probability. We simulate two OLOS situations clearly separated in time, a partial one at $n \in [75, 104]$, where only the LOS to anchor A2 is blocked, and a full one at $n \in [115, 144]$, where the LOS to all anchors is blocked. The following true system parameters are used, which are set constant for all time steps $n$ and anchors $j$:

- The normalized amplitude is set to $u_n = [\sqrt{19.5} \text{dB} \ \sqrt{20.5} \text{dB} \ \sqrt{20.5} \text{dB}]^T$
- The parameters of the DPS are set to $\omega_n = 25$ dB, $\gamma_n = 0.7$ m, $\gamma_{\text{fn}} = 6$ m, $\delta_n = 0.7$ m.

We start by validating the system model presented in Sec. IV. For this experiment the relatively defined STV are set with respect to the true values instead of the RMSE values, given as $\sigma_u = 0.05 \tilde{u}_n$, $\sigma_\omega = 0.05 \tilde{\omega}_n$, $\sigma_b = 0.05 \tilde{b}_n$, $\sigma_\gamma = 0.05 \tilde{\gamma}_n$, $\sigma_{\gamma_n} = 0.5 \tilde{\gamma}_n$. Fig. 6, 7, 8a and 8b show the results of the performed numerical simulations. Fig. 6 shows MMSE estimates of all state variables as a function of time $t'$ and compares to the respective true values. The MMSE estimates are determined according to (21)-(23) using both fully synthetic measurements and CEDA-based measurements. Fig. 7 compares distance-model-agnostic, bin-based estimates (BBEs) of scale parameter and relative measurement frequency with the presented model functions, i.e., with the NLOS scale function (12) and the NLOS distance LHF (13). Each of the functions is determined both ways, using the MMSE estimates of $\tilde{\omega}_n$ of the last time step, given as $\tilde{\omega}_n^{(\text{MMSE})}$ and using the respective true values used for simulation $\tilde{\omega}_n^{(i)}$. The BBEs are determined using all NLOS measurements (the LOS measurements are removed) of the last 20 time steps, given as $\{\tilde{\omega}_n m \mid m \in M_n^{(i)} \setminus \tilde{a}_n, n \in \{180, \ldots, 200\}\}$ for details about the BBEs see the supplementary material [72, Sec. IV]. This analysis is complemented by Figs. 8a and 8b which show the position RMSE $\epsilon_{\text{RMSE}}$ in two ways. First, as a function of the discrete observation time $n$ and, second, as the cumulative frequency of the RMSE evaluated over the whole time span. Fig. 6 demonstrates that using CEDA-based measurements the MMSE estimates of the parameters of the NLOS LHF (i.e., the MMSE estimates corresponding to $\tilde{\omega}_n^{(i)}$) are slightly biased, in particular the DNR estimate $\hat{\omega}_n^{(\text{MMSE})}$. This effect is a consequence of the asymptotic bandwidth assumption used in the derivation of the NLOS likelihood model (see [72, Sec. I]).

However, as in Fig. 6 the model functions parameterized with the MMSE values accurately fit the BBEs, the MMSE estimate of the agent position $\tilde{\mu}_n^{(\text{MMSE})}$ in Fig. 6 remains unbiased and, thus, the positioning performance in Figs. 8a and 8b using...
Fig. 6. MMSE estimates (determined using fully synthetic measurements and CEDA-based measurements) and true values of all state variables v.s. discrete time $n$ for the experiment described in Sec. VII-B.1. We show the mean MMSE estimate and the corresponding range from minimum to maximum value. Anchor state variables are only shown for anchor A1. Different shades of gray represent different numbers of anchors in OLOS according to Fig. 5.

Fig. 7. Bin-based estimates (BBEs) of (a) the Rayleigh scale parameter of the amplitude measurements and (b) the relative frequency of the distance measurements compared to (a) the NLOS scale function and (b) the NLOS distance LHF. All values are shown as a function of the difference of the distance measurement and the corresponding LOS component distance, given as $z_{\text{d},m}^{(1)} - d_{\text{LOS}}^{(1)}$ for anchor A1.

"CEDA-based measurements" is identical to the performance using "fully synthetic measurements" up to random deviations.

In addition, in Figs. 8a and 8b we compare to fully synthetic measurements with (i) known initial state distributions, slightly lowering the RMSE around $n = 0$, and (ii) assuming the parameters of $\zeta^{(j)}$ to be known constants, leading to a significant increase of performance at the end of the full OLOS situation as the bias information does not vanish over discrete time $n$. With CEDA-based measurements we also compare to results where (i) we calculate the relatively defined STV using the RMSE values of the respective last time step $n - 1$ according to Sec. VII-A and where (ii) we use a uniform delay intensity function $f_{\text{NL}}(z_{\text{d},m}^{(j)}) = 1/d_{\text{max}}$ showing no significant degradation of performance. The latter result suggests that for low values of $\gamma$, the information provided in (13) is insignificant (c.f. Fig. 2b). Therefore, in what follows, we keep the uniform delay intensity function leading to a considerable reduction of runtime since $Q_0(p_n, \zeta^{(j)})$ does not need to be calculated (see also Sec. VI-B.3 and Sec. VII-D). Next, we investigate the influence of the individual features of our algorithm as described in Sec. VII-A and Table II. Figs. 8c and 8d show the RMSE of this experiment as a function of $t'$ as well as the cumulative frequency of the RMSE. The RMSE of the multi-sensor AIPDA (AL1) mostly attains the P-CRLB during LOS and partial OLOS situations. A reason for that is that the angle, which the remaining anchors A1 and A3 span with respect to the agent is sufficiently large to provide a reasonable position estimate. However, AL1 shows a slightly increased RMSE around $n = 80$ due to the agent direction change and significantly deviates from the very beginning of the full OLOS situation, losing the track in every single realization. Comparing the curves of AL2-AL5, one can conclude that every single algorithm feature investigated lowers the RMSE significantly when activated. The RMSE of the proposed algorithm AL5 constantly attains the P-CRLB, which indicates no lost track, even falling below the P-CRLB in full OLOS situations. This is possible as it leverages the additional position information contained inside the MPCs via the non-uniform NLOS LHF, which is not considered by the P-CRLB model. In contrast, AL2 loses a large percentage of tracks after the full OLOS situation, because NLOS measurements significantly contribute to the LOS based position hypotheses due to the insufficient representation of the existence probability by the amplitude state particles (see Sec. IV-D). While AL3 constantly attains the P-CRLB during the LOS situation as well the partial OLOS situation, it loses the track for every realization in full OLOS. After a short amount of time in which AL3 can maintain the agent position through the agent state transition model and the decreasing
Fig. 8: Performance of different algorithm variants in terms of the RMSE of the estimated agent position (a), (c) as a function of the discrete observation time \( n \), and (b), (d) as the cumulative frequency in inverse logarithmic scale, determined from numerical simulation of stochastic multipath according to Sec. VII-B.1. Different shades of gray represent different numbers of anchors in OLOS according to Fig. 5.

Fig. 9: A single measurement realization and the respective MMSE estimates using the proposed algorithm (AL5) for geometry-related synthetic measurements (see Sec. VII-B.2). We show MMSE estimates in (a) distance domain \( \hat{d}^{(1)}_{n,0,\text{MMSE}} \), (c) amplitude domain \( \hat{u}_{n,\text{MMSE}} \), \( \hat{\omega}_{n,\text{MMSE}} \), (d) LOS probability domain \( \hat{q}^{(1)}_{n,\text{MMSE}} \), and (b) amplitude as a function of distance domain for \( n \in \{130, \ldots, 136\} \). The measurements in (b) correspond to the upper and in (c) to the left axis. Note that in (a) and (c) only measurements for every third time \( n \) are shown (i.e., \( n \in \{1, 4, 7, \ldots\} \)).

LOS probability, it identifies MPCs as the LOS component due to their coherent appearance and large amplitude, which is not covered by the uniform NLOS model, and loses the track. AL4 shows a seemingly random performance degradation, which is due to the insufficient representation of the high dimensional joint state by the particle filter and some resulting lost tracks, which AL5 overcomes by decoupling the anchor states (see Sec. VI). However, the discrepancy between AL4 and AL5 can be dissolved by using a sufficiently high number of particles (see AL4’ and AL5’), at the cost of significantly increasing the runtime (see Sec. VII-D).

2) Synthetic Measurements With Geometry-Related Multipath: In this section, we discuss results using synthetic measurements based on the simple floorplan shown in Fig. 5. The measurements are obtained by simulating a radio signal according to (5), consisting of the LOS component and specular MPCs, and using the proposed CEDA. The MPC delays are calculated out of the floorplan (i.e., W1-W5) using the mirror images (virtual anchors) up to the third order [24]. The SNR of the LOS component as well as the MPCs [48] are set to 20 dB at a distance of 1 m and are assumed to follow free-space path loss. The SNR of the individual MPCs are additionally attenuated by 3 dB after each reflection (e.g., 6 dB for a second-order reflection). As depicted in Fig. 5, for this experiment the anchors are obstructed by an obstacle (W5), which leads to partial and full OLOS situations in the center of the investigated trajectory. Figs. 9, 10a, and 10b show results of the performed numerical simulation. Fig. 9 provides
a graphical representation of the measurement space, showing a single measurement realization $z$ together with the corresponding MMSE estimates of the proposed algorithm (AL5). The MMSE estimates are determined according to (21)-(23).

In particular, Fig. 9a shows that (i) the MMSE estimate of the LOS delay $\hat{\tau}_{\text{LOS}}^{(j)\text{MMSE}}$ accurately represents the dynamic behavior of the multipath energy, decreasing rapidly when the strongest, first MPC is covered, while the SNR estimate $\hat{\omega}_{\text{SNR}}^{(j)\text{MMSE}}$ remains stable. For visualization, Fig. 9b shows the NLOS scale function at time $n = 133$ parametrized with the respective MMSE estimates of all NLOS function parameters. Fig. 9d shows the LOS existence probability $q_{\text{LOS}}^{(1)}$ well representing the OLOS situation. Figs. 10a and 10b show the RMSE as a function of the discrete observation time $n$ as well as the cumulative frequency of the RMSE. Again, we investigate the influence of the individual features of our algorithm according to Sec. VII-A and Table II. Comparing the presented curves, we again observe AL5 to significantly outperform AL1-AL5, with the qualitative performance differences being almost identical to those of Sec. VII-B.1. The only significant dissimilarity is the seemingly smaller deviation between AL4 and AL5. This is because AL4 does not lose any tracks during initialization, as the average energy and distance to the LOS component of the measurements of the first time step $n = 0$ are significantly lower in this scenario, leading to a better coverage of the state space by the particle filter.

Finally, we only observe a slightly more unstable local behavior of AL4. The MP-SLAM algorithm (AL6) achieves a significantly reduced RMSE during the first part of the OLOS situation, due to geometric information provided by the specular MPCs, outperforming the proposed method (AL5). However, the investigated scenario is geometrically ambiguous as there is little directional change in the agent movement \cite{28}. Also there are many low-SNR components, which disappear and reappear, due to the obstacle (W5). This is why AL6 follows ambiguous paths for many realizations (i.e., it loses the track), leading to a significantly reduced performance after the full OLOS situation. We additionally added AL6*, which represents the numerical results after removing 20.6\% (103 realizations) of diverged tracks. This result demonstrates the dramatically increased accuracy that can be obtained using MP-SLAM.

C. Performance for Real Radio Measurements

For further validation of the proposed algorithm, we use real radio measurements collected in a laboratory hall of NXP Semiconductors, Gratkorn, Austria. The hall, shown in Fig. 11a, features a wide, open space and includes a demonstration car (Lancia Thema 2011), furniture, and metallic surfaces, thereby representing a typical multipath-prone industrial environment. An agent is assumed to move along a pseudo-random trajectory (selected out of a grid of agent positions), obtained in a static measurement setup. We selected $N = 195$ measurements, assuming an observation rate of $\Delta T = 170\,\text{ms}$. The agent velocity is set to vary around a magnitude of 0.35 m/s. This leads to a corresponding continuous observation time 33.15 s. At each selected position, a radio signal was transmitted from the assumed agent position, which was received by 4 anchors. The agent was represented by a polystyrene build, while the anchor antennas were mounted on the demonstration car. The agent as well as the anchors were equipped with a dipole antenna with an approximately uniform radiation pattern in the azimuth plane and zeros in the floor and ceiling directions. The radio signal was recorded by an M-sequence correlative channel sounder with frequency range
$3 - 10$ GHz. Within the measured band, the actual signal band was selected by a filter with root-raised-cosine impulse response $s(t)$, with a roll-off factor of 0.6, a two-sided 3-dB bandwidth of $B = 499.2$ MHz and a center frequency of $7.9872$ GHz (corresponding to channel 9 of IEEE 802.15.4a), and critically sampled with $T_s = 1/(1.6B)$. We used $N_s = 161$ samples, amounting to a maximum distance of $d_{\text{max}} = 60$ m for the CEDA. We created two full OLOS situations at $n \in [80, 92]$ and $n \in [159, 170]$ using an obstacle consisting of a metal plate covered with attenuators as shown in Fig. 11b. A floor plan showing the track, the environment (i.e., the car, other reflecting objects and walls), the antenna positions, and OLOS conditions with respect to all antennas is shown in Fig. 11c. The metal surface of the car strongly reflected the radio signal, leading to a radiation pattern of $270^\circ$ for A1 and A2 and $180^\circ$ for A3 and A4. Thus, during large parts of the trajectory the LOS of 2 or 3 out of 4 anchors is not visible at the track starting point, the position estimate obtained by trilateration is ambiguous. In the scenario presented, the relative antenna position with respect to the car can be assumed to be known. Thus, for this experiment, we used the antenna pattern as prior information for initialization of the position state. For the numerical evaluation presented, we added AWGN to the real radio signal obtained. We set $\|P_{\text{raw}}^{(j)}\|^2/\sigma_j^2 = 20$ dB, where $\|P_{\text{raw}}^{(j)}\|^2$ is the average energy of the real measured signal per anchor $j$. Figs. 10c and 10d show the RMSE as a function of the discrete observation time $n$ as well as the cumulative frequency of the RMSE. Again, we analyze the influence of the individual features of our algorithm according to Sec. VII-A and Table II and observe AL5 to significantly outperform the other algorithm variants. Different to Sec. VII-B.2 all presented algorithms fail to reach the P-CRLB over parts of the track. The exact consistency in progression of the RMSE curves suggests unmodeled effects (e.g., diffraction at the vehicle body) as well as inaccuracies in the reference as a probable reason.

### D. Runtime

Table III shows the average runtime of the proposed algorithm (A5) and compares it to the runtime of the multi-sensor AIPDA (AL1) and that of the MP-SLAM algorithm (AL6). All runtimes are estimated using Matlab implementations executed on an AMD Ryzen Threadripper 1900X 8-Core Processor with up to 4 GHz for all scenarios investigated. We also show the average number of measurements (over all anchors and time steps) $M_{\text{mean}}$, the number of anchors $J$ and the number of particles, which determine the algorithm complexity per time step. The runtime of our algorithm (AL5) is of the same order of magnitude than that of the multi-sensor AIPDA (AL1), which is in the range of tens of milliseconds for all scenarios investigated. In contrast, the runtime of the MP-SLAM algorithm (AL6) is significantly higher, since it requires joint data association between all map features [22] and a higher number of particles for numerical stability.

### VIII. Conclusion

We have presented a particle-based sum-product algorithm (SPA) that sequentially estimates the position of a mobile agent using range and amplitude measurements provided by a snapshot-based channel estimation and detection algorithm (CEDA). We introduced a novel non-line-of-sight (NLOS) model that is adapted to the delay power spectrum (DPS) of the multipath radio channel. We analyzed the performance...
of the proposed algorithm using both numerically simulated and real measurements in different channel conditions and showed that the additional information provided by the NLOS model can support the estimation of the agent position. Our algorithm significantly outperformed the conventional AIPDA filter and consistently attained the P-CRLB in partial OLOS situations (i.e., no lost tracks). While multipath-based SLAM (MP-SLAM) can naturally outperform our algorithm in channels showing resolved, specular MPCs, we demonstrate the proposed algorithm to offer a significantly smaller number of lost tracks at reduced execution time in a geometrically ambiguous scenario.

A possible direction for future research includes extending the model to multiple biases with respect to several MPCs using joint probabilistic data association and dynamic MPC initialization [46], [48] or to several MPC clusters by using data association with extended objects [47].

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