

Probabilistic 5G Indoor Positioning Proof of Concept with Outlier Rejection

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Abstract—The continuously increasing bandwidth and antenna aperture available in wireless networks laid the foundation for developing competitive positioning solutions relying on communications standards and hardware. However, poor propagation conditions such as non-line of sight (NLOS) and rich multipath still pose many challenges due to outlier measurements that significantly degrade the positioning performance.

In this work, we introduce an iterative positioning method that reweights the time of arrival (ToA) and angle of arrival (AoA) measurements originating from multiple locators in order to efficiently remove outliers. In contrast to existing approaches that typically rely on a single locator to set the time reference for the time difference of arrival (TDoA) measurements corresponding to the remaining locators, and whose measurements may be unreliable, the proposed iterative approach does not rely on a reference locator only. The resulting robust position estimate is then used to initialize a computationally efficient gradient search to perform maximum likelihood position estimation.

Our proposal is validated with an experimental setup at 3.75 GHz with 5G numerology in an indoor factory scenario, achieving an error of less than 50 cm in 95% of the measurements. To the best of our knowledge, this paper describes the first proof of concept for 5G-based joint ToA and AoA localization.

Index Terms—Indoor positioning, probabilistic localization, 5G positioning, ToA positioning, AoA positioning

I. INTRODUCTION

Positioning using radio signals has been extensively studied in literature, and will gain further importance due to the emergence of integrated sensing and communication (ISAC) [1]. Location information is a key enabler of many applications, e. g., in the areas of security or healthcare [2]. The possibility of deploying 5th generation (5G) systems as private networks makes indoor positioning using 5G signals a particularly interesting task and an attractive technology for enterprise customers. Especially in factory scenarios, accurate positioning will be of crucial importance as it paves the way for fully automated factories, e. g., by enabling asset tracking or robot navigation [3].

In addition to an accurate localization performance overall, the prevention of outliers is pivotal for a positioning system.

This requirement becomes especially challenging in indoor environments, where multipath components due to non-line of sight (NLOS) propagation frequently occur. Those effects can create outliers in the time of arrival (ToA) and angle of arrival (AoA) measurements, that are the basis for many localization systems, leading to severely impacted position estimates. One way of coping with this issue is, instead of employing ToA-only or AoA-only solutions, to jointly use ToA and AoA measurements to increase the robustness of a system, as done e. g., in [4]–[6]. More recently, [7] has investigated the performance of probabilistic joint ToA/AoA positioning in indoor environments. None of these previous works, however, effectively mitigates the impact of multipath propagation, e. g., by detecting and rejecting such components beforehand.

Similarly to [7], in this work, we are focusing on probabilistic positioning algorithms due to their excellent performance under appropriate probability distributions assumptions. However, such techniques exhibit the drawback of either prohibitive complexity of multi-dimensional grid search or the requirement of a proper initial search point, that enables gradient-based optimization with its light requirements in terms of computational complexity. Moreover, the performance of maximum likelihood (ML) algorithms can be enhanced by removing outliers, created e. g., due to the already mentioned multipath propagation, and by weighting the remaining measurements based on the confidence in them. In literature, various approaches based on time difference of arrival (TDoA) exist that could be employed to determine an initial search point, e. g., [8]–[11]. However, [8]–[10] require the definition of a reference locator, which has the drawback that the reference itself could exhibit an outlier measurement. On the other hand, [11] avoids the definition of a reference locator, but can not detect outliers and does not provide the possibility of assigning weights to the measurements.

In this paper, we present an experimental 5G positioning system based on joint ToA/AoA probabilistic positioning with robust initialization that overcomes the aforementioned drawbacks. Through an iteratively reweighted least squares (IRLS) technique, our proposal can reject outliers, mitigating the effects of multipath propagation. Moreover, through this iterative approach, we can assign weights to the remaining measurements according to the confidence in them. Our initialization routine effectively acts as a pre-filtering method to im-

prove the performance of the investigated ML positioning algorithms. We show that with joint ToA/AoA ML positioning in conjunction with initialization, we achieve a two-dimensional (2D) error of at most ca. 50 cm for 95% of the measurements conducted in a real-world indoor environment operating at 3.75 GHz carrier frequency with 5G numerology [12] and 100 MHz bandwidth. To the best of the authors' knowledge, this work demonstrates the first joint ToA/AoA positioning proof of concept operating with 5G signals.

The rest of the paper is structured as follows: in Section II, we explain how ToA and AoA measurements are taken by locators. Section III introduces the probabilistic positioning algorithms. The main part of this work is our robust initialization routine that is presented in Section IV. In Section V, we briefly explain the experimental setup that will be used in Section VI to compare our proposal's performance versus other baselines. Conclusions are drawn in Section VII.

II. TOA AND AOA ESTIMATION

We consider a positioning system with K locators with indices in the set $\mathcal{K} = \{1, 2, \dots, K\}$, aiming at localizing a user equipment (UE), whose unknown three-dimensional (3D) location is denoted by $\mathbf{x} = [x, y, z]$. The known 3D position of the k -th locator is given by the vector $\mathbf{p}_k = [x_k, y_k, z_k]$. Its 3D orientation is defined by a 3×3 matrix $\mathbf{\Omega}_k$, which contains the orthogonal unit vectors corresponding to the locator's orientation w. r. t. the reference coordinate system.

Each locator independently provides estimates of the ToA, corresponding to a distance estimate \hat{d}_k . Note that to enable TDoA-based approaches, we require all locators to be synchronized with each other, but not with the UE. Therefore, the ToA estimates include an unknown transmit time. The estimated azimuth and elevation AoAs of the UE from each locator are parametrized using a directional statistics approach [13].

The ToA and AoA measurements serve as inputs to our positioning algorithms, which will be described in Sections III and IV. While ToA and AoA estimation are not the focus of this work due to space reasons, we refer the interested reader to [14]. The approach of this previous work allows us to obtain estimates of the three parameters of interest by utilizing multi-dimensional Multiple Signal Classification (MUSIC) in a computationally efficient manner. Managing computational complexity is critical, as a typical 5G signal parametrization comes with a high number of subcarriers [12] and, thus, leads to a large number of samples to be processed.

III. PROBABILISTIC POSITIONING ALGORITHMS

In order to locate the UE, we consider the ToA-only, AoA-only, and joint ToA/AoA ML techniques described below.

A. ToA Maximum Likelihood Positioning

We model the ToA estimation error as a zero-mean Gaussian random variable such that the log-likelihood (LL) function of

the K locators is given as

$$\begin{aligned} \mathcal{L}_T(\mathbf{x}, \tau) &= \sum_{k \in \mathcal{K}} \ln p(\hat{d}_k | \mathbf{x}, \tau) \\ &= - \sum_{k \in \mathcal{K}} w_{T,k} \cdot \frac{(\hat{d}_k - \|\mathbf{p}_k - \mathbf{x}\| - \tau \cdot c)^2}{2} \end{aligned} \quad (1)$$

where $w_{T,k}$ is the weight of the k -th locator, corresponding to the inverse variance of the ToA estimate σ_k^{-2} , and the constant term has been omitted. Furthermore, τ denotes the unknown transmit time and c the speed of light. A position estimate only relying on ToA measurements is obtained by maximizing the joint LL function of the K locators [15]

$$(\hat{\mathbf{x}}_T, \hat{\tau}_T) = \arg \max_{\mathbf{x}, \tau} \mathcal{L}_T(\mathbf{x}, \tau). \quad (2)$$

Note that solving (2) also yields an estimate of the transmit time $\hat{\tau}_T$ as an additional nuisance parameter.

B. AoA Maximum Likelihood Positioning

Similarly to the ToA approach, a position estimate can also be obtained solely based on AoA measurements. We use the von Mises-Fisher (VMF) distribution to model angular uncertainties, as in [13]. The LL function (the constant term has been omitted) of the K locators is written as

$$\begin{aligned} \mathcal{L}_\angle(\mathbf{x}) &= \sum_{k \in \mathcal{K}} \ln \text{VMF}(\mathbf{u}_k | \hat{\mathbf{u}}_k, \kappa_k) \\ &= \sum_{k \in \mathcal{K}} \kappa_k \hat{\mathbf{u}}_k^T \mathbf{\Omega}_k^T \frac{\mathbf{x} - \mathbf{p}_k}{\|\mathbf{x} - \mathbf{p}_k\|} \end{aligned} \quad (3)$$

where $\hat{\mathbf{u}}_k \in \mathbb{R}^3$ is a unit vector representing the mean direction in the locator's reference frame $\mathbf{\Omega}_k$, obtained by the estimated AoAs. The concentration parameters κ_k reflect the reliability of the angular measurements and are set according to $\kappa_k = \kappa_{\max} w_{\angle,k}$, where κ_{\max} is the maximum concentration parameter, which characterizes the minimum spread of the AoA estimates and is hardware specific. The weights $w_{\angle,k}$ are obtained according to reliability information of the angular measurements as described in [16].

Analogously to (2), maximizing (3) yields an AoA-based position estimate

$$\hat{\mathbf{x}}_\angle = \arg \max_{\mathbf{x}} \mathcal{L}_\angle(\mathbf{x}). \quad (4)$$

C. Joint ToA/AoA Maximum Likelihood Positioning

As the third algorithm, we consider ML positioning using ToA and AoA in a joint fashion. Assuming ToA and AoA estimates to be independent, (1) and (3) are combined to obtain a more robust joint ToA/AoA ML position estimate [13]

$$\begin{aligned} (\hat{\mathbf{x}}_\cap, \hat{\tau}_\cap) &= \arg \max_{\mathbf{x}, \tau} \mathcal{L}_\cap(\mathbf{x}, \tau) \\ &= \arg \max_{\mathbf{x}, \tau} \{ \mathcal{L}_T(\mathbf{x}, \tau) + \mathcal{L}_\angle(\mathbf{x}) \}. \end{aligned} \quad (5)$$

IV. ROBUST INITIALIZATION ROUTINE

Since we rely on gradient-based optimization to maximize the LL functions with affordable complexity, a proper initial search point is necessary to allow convergence to the global maximum. Additionally, the performance of the algorithms can be optimized by rejecting - or weighting less - outlier measurements, and by giving higher confidence to the ones that are deemed more reliable. Towards this end, we introduce a robust initialization routine to maximize the potential of probabilistic positioning. Our routine comprises a novel IRLS TDoA algorithm, which is the main contribution of this paper and will be described extensively in what follows. To complement the TDoA part, we utilize a prior-art IRLS AoA algorithm based on similar principles [16]. These two techniques can be employed separately to initialize the optimization of the ToA and AoA ML functions of (2) and (4), respectively. We then show in Subsection IV-C how we combine their outputs for the initialization of the joint ToA/AoA positioning of (5).

A. IRLS TDoA Algorithm

Selecting arbitrary locator r as the reference, $K - 1$ distance difference (or TDoA, terms to be used interchangeably hereinafter) measurements are constructed as

$$\hat{d}_{k,r} = \hat{d}_k - \hat{d}_r, \quad k \in \mathcal{K} \setminus \{r\}. \quad (6)$$

In order to solve the positioning problem based on these TDoA measurements, various prior-art techniques exist in literature. As done e. g., in [8], an estimate of the UE's position \mathbf{x} can be computed by solving the linear equation system

$$\mathbf{A}_r \boldsymbol{\Theta}_r = \mathbf{b}_r + \mathbf{n}, \quad (7)$$

with

$$\mathbf{A}_r = \begin{bmatrix} (\mathbf{p}_1 - \mathbf{p}_r)^T & \hat{d}_{1,r} \\ \vdots & \vdots \\ (\mathbf{p}_{r-1} - \mathbf{p}_r)^T & \hat{d}_{r-1,r} \\ (\mathbf{p}_{r+1} - \mathbf{p}_r)^T & \hat{d}_{r+1,r} \\ \vdots & \vdots \\ (\mathbf{p}_K - \mathbf{p}_r)^T & \hat{d}_{K,r} \end{bmatrix}, \quad (8)$$

$$\boldsymbol{\Theta}_r = [x - x_r \quad y - y_r \quad z - z_r \quad d_r]^T, \quad (9)$$

and

$$\mathbf{b}_r = \frac{1}{2} \begin{bmatrix} \|\mathbf{p}_1 - \mathbf{p}_r\|^2 - \hat{d}_{1,r}^2 \\ \vdots \\ \|\mathbf{p}_{r-1} - \mathbf{p}_r\|^2 - \hat{d}_{r-1,r}^2 \\ \|\mathbf{p}_{r+1} - \mathbf{p}_r\|^2 - \hat{d}_{r+1,r}^2 \\ \vdots \\ \|\mathbf{p}_K - \mathbf{p}_r\|^2 - \hat{d}_{K,r}^2 \end{bmatrix} \quad (10)$$

where $d_r = \|\mathbf{x} - \mathbf{p}_r\|$, and \mathbf{n} is the noise vector. The closed-form approximate weighted least squares (WLS) solution of (7) is obtained as

$$\hat{\boldsymbol{\Theta}}_r = (\mathbf{A}_r^T \mathbf{W}_r \mathbf{A}_r)^{-1} \mathbf{A}_r^T \mathbf{W}_r \mathbf{b}_r \quad (11)$$

with $\mathbf{W}_r = \text{diag}\{w_{T,1}, \dots, w_{T,r-1}, w_{T,r+1}, \dots, w_{T,K}\}$ being the diagonal weighting matrix. The position estimate is then

$$\hat{\mathbf{x}}_r = \mathbf{p}_r + \hat{\boldsymbol{\Theta}}_{r,1:3} \quad (12)$$

where $\hat{\boldsymbol{\Theta}}_{r,1:3}$ is a vector of the first three elements of $\hat{\boldsymbol{\Theta}}_r$. The major drawback of the estimator in (12) is that it requires the definition of a unique reference locator. If the distance estimate at this locator is an outlier, the position estimate $\hat{\mathbf{x}}_r$ will be severely impacted. We therefore propose an iterative solution that circumvents the need for a single reference locator. Instead of determining a unique reference locator to compute $\hat{\mathbf{x}}_r$, we use every locator as the reference once to obtain a matrix with K distinct position estimates $\hat{\mathbf{X}} = [\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_K]$ utilizing (7) - (12). Then, a weighted average position estimate can be computed as

$$\hat{\mathbf{x}}_{\text{WA}} = \sum_{k \in \mathcal{K}} \bar{w}_{T,k} \cdot \hat{\mathbf{x}}_k \quad (13)$$

where $\bar{w}_{T,k}$ represents the normalized k -th locator weight. In every iteration, the weights $w_{T,k}$ are normalized by dividing them by their total sum

$$\bar{w}_{T,k} = \frac{w_{T,k}}{\sum_{k \in \mathcal{K}} w_{T,k}}, \quad k \in \mathcal{K}. \quad (14)$$

For the first iteration, equal weights per locator are used, i.e., $\bar{w}_{T,k} = 1/K, k \in \mathcal{K}$. To detect locators with erroneous measurements, a measure of reliability is required for each of the K position estimates. We therefore define the residual error of each locator's estimate as

$$e_r = \frac{1}{K-1} \sum_{k \in \mathcal{K} \setminus \{r\}} |\hat{d}_{k,r} - (\|\hat{\mathbf{x}}_{\text{WA}} - \mathbf{p}_k\| - \|\hat{\mathbf{x}}_{\text{WA}} - \mathbf{p}_r\|)| \quad (15)$$

representing the averaged deviation between the *measured* TDoAs of the $K - 1$ locators and the reference locator r , and the *currently predicted* TDoAs (i. e., w. r. t. the current estimate $\hat{\mathbf{x}}_{\text{WA}}$) of the $K - 1$ locators and the reference locator. With this formulation, the residual error may be interpreted as a measure of how much the estimated distance differences agree with the current position estimate $\hat{\mathbf{x}}_{\text{WA}}$. After computing all residuals, the weights for the next iteration are obtained using Andrews' sine function [17]

$$w_{T,k} = f_e(e_k) = \begin{cases} \frac{e_{\max}}{e_k \pi} \cdot \sin\left(\frac{e_k \pi}{e_{\max}}\right) & \text{if } e_k \leq e_{\max} \\ 0 & \text{else} \end{cases} \quad (16)$$

with e_{\max} being the maximum value of the residual error above which the weights are set to 0. In this case, the corresponding locator is discarded. After each iteration, a convergence check is performed by comparing

$$\Delta = \|\hat{\mathbf{x}}_{\text{WA}}^i - \hat{\mathbf{x}}_{\text{WA}}^{i-1}\| \quad (17)$$

to a pre-defined threshold ϵ . In case $\Delta > \epsilon$, we repeat the procedure from the beginning or until a maximum number of iterations N_{it} is reached. Algorithm 1 summarizes the entire

Algorithm 1: IRLS TDoA Positioning

Input: estimated distances $\hat{\mathbf{d}} = (\hat{d}_1, \hat{d}_2, \dots, \hat{d}_K)$,
locator positions $\mathbf{P} = (\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_K)$,
number of iterations N_{it} , stopping criterion ϵ ,
maximum residual error e_{max}

Output: IRLS TDoA position estimate $\hat{\mathbf{x}}_{T,IRLS}$,
locator weights \mathbf{w}_T

- 1: $i \leftarrow 0$
 - 2: get position estimates $\hat{\mathbf{X}}$ with (7) - (12)
 - 3: estimate initial position $\hat{\mathbf{x}}_{WA}^0$ using (13)
 - 4: **while** $i \leq N_{it}$ and $\Delta > \epsilon$ **do**
 - 5: $i \leftarrow i + 1$
 - 6: get residual errors \mathbf{e} from (15)
 - 7: update \mathbf{w}_T using (16)
 - 8: get normalized weights $\bar{\mathbf{w}}_T$ using (14)
 - 9: get new estimate $\hat{\mathbf{x}}_{WA}^i$ according to (13)
 - 10: re-compute position estimates $\hat{\mathbf{X}}$ with (7) - (12)
 - 11: compute Δ with (17)
 - 12: **end while**
 - 13: $\hat{\mathbf{x}}_{T,IRLS} \leftarrow \hat{\mathbf{x}}_{WA}^i$
 - 14: **return** $\hat{\mathbf{x}}_{T,IRLS}$, \mathbf{w}_T
-

IRLS procedure.

As outputs, an initial TDoA position estimate $\hat{\mathbf{x}}_{T,IRLS}$ and locator weights \mathbf{w}_T are provided. Note that, while Algorithm 1 describes a TDoA approach, the TDoA measurements obtained with (6) clearly directly depend on the measured ToAs. We can therefore use $\hat{\mathbf{x}}_{T,IRLS}$ and \mathbf{w}_T as initial search point and weights, respectively, for the optimization of the ToA ML function in (2) and (5).

Moreover, note that the complexity is quadratic w.r.t. the number of measurements, which is reasonable, since typically only few locators are available in a given area. Otherwise, one can choose only a subset of K' , $K' \ll K$ locators. The selection should be made based on an a-priori assessment of the reliability of the locators, e.g., by choosing the K' ones with the lowest distance or highest received signal strength (RSS) measurements.

B. IRLS AoA Algorithm

The IRLS AoA algorithm from [16] is also based on an iterative routine and provides an initial AoA-based position estimate $\hat{\mathbf{x}}_{\angle,IRLS}$ and angular weights $\mathbf{w}_{\angle} = (w_{\angle,1}, w_{\angle,2}, \dots, w_{\angle,K})$ for the K locators. Analogous to the outputs of the TDoA algorithm, $\hat{\mathbf{x}}_{\angle,IRLS}$ and \mathbf{w}_{\angle} are utilized for the optimization of the AoA ML function in (4) and (5). Note that both IRLS algorithms can also be employed as standalone positioning solutions, but in this work we only use them to improve the ML techniques introduced in Section III by avoiding local maxima caused by outliers.

C. Joint Positioning Initialization Routine

For initializing the gradient-based optimization of the joint ToA/AoA ML function given in (5), we combine the initial



Fig. 1: Experimental setup with six locators in the industrial research campus ARENA2036. The area under investigation spans roughly 20 x 10 meters and the locators are mounted at a height of about 7 meters.

points $\hat{\mathbf{x}}_{T,IRLS}$ and $\hat{\mathbf{x}}_{\angle,IRLS}$. We assume the two position estimates to be independent measurements with additive Gaussian noise and diagonal covariance matrices. Therefore, the initial joint location estimate, to be used as the initial search point, can be estimated according to ML estimation theory [18] as

$$\hat{\mathbf{x}}_{\cap}^0 = \frac{\hat{\sigma}_T^{-2} \cdot \hat{\mathbf{x}}_{T,IRLS} + \hat{\sigma}_{\angle}^{-2} \cdot \hat{\mathbf{x}}_{\angle,IRLS}}{\hat{\sigma}_T^{-2} + \hat{\sigma}_{\angle}^{-2}} \quad (18)$$

where $\hat{\sigma}_T^2$ and $\hat{\sigma}_{\angle}^2$ are the estimated variances at the respective TDoA and AoA IRLS position estimates. The variances are obtained from the inverse of the Hessian of the LL functions (1) and (3), evaluated at $\hat{\mathbf{x}}_{T,IRLS}$ and $\hat{\mathbf{x}}_{\angle,IRLS}$, respectively. Notice that more elaborate techniques exist to fuse the two position estimates, e.g., covariance intersection, which does not make the independence assumption [19]. However, those algorithms typically come with added complexity, and we found (18) to be sufficient to obtain a good performance.

We make further use of the variances by discarding the ToA or AoA part of (5) if the corresponding variance at the initial position estimates $\hat{\mathbf{x}}_{T,IRLS}$ and $\hat{\mathbf{x}}_{\angle,IRLS}$ exceeds a pre-defined threshold σ_{max}^2 . For joint ToA/AoA positioning, we now use the final sets of locator weights \mathbf{w}_T and \mathbf{w}_{\angle} for time and angle, respectively.

V. EXPERIMENTAL SETUP

The performance of our positioning algorithms is evaluated with an experimental lab setup installed at the industrial research campus ARENA2036¹. The testbed (Fig. 1) comprises six tightly synchronized (sub-nanosecond accuracy) locators that are mounted at a height of roughly 7 m and capable of sniffing 5G signals. Each locator is equipped with a planar antenna array, enabling the estimation of azimuth and elevation AoAs. The estimated channel state information (CSI) provided from each locator is centrally processed by a server that handles the estimation of the three parameters of interest, as well as the computation of the position estimates, according to the schematic in Fig. 2. The UE to be localized transmits a 5G

¹<https://www.arena2036.de/en/>

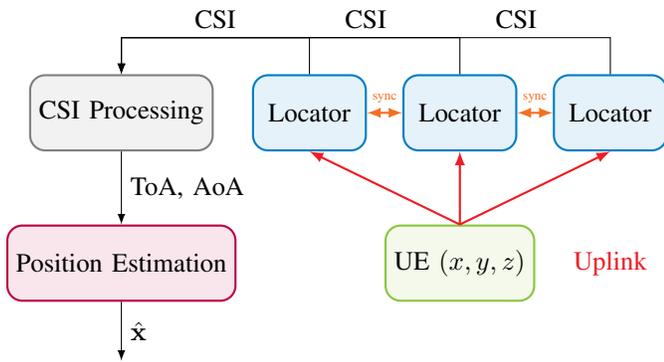


Fig. 2: Block diagram of our 5G positioning setup.

orthogonal frequency-division multiplexing (OFDM) signal at carrier frequency $f_c = 3.75$ GHz with a bandwidth B of roughly 100 MHz. The accuracy of our algorithms is evaluated by computing the 2D positioning errors w.r.t. the 28 ground truth points depicted in Fig. 3.



Fig. 3: Top-down view of the area under investigation including the six locators. The positioning accuracy is evaluated at the 28 ground truth points (small green squares).

VI. RESULTS

In this section, we compare the investigated algorithms' 2D positioning accuracy using our previously described experimental setup. Table I lists the parameters used for our initialization routine. Our proposed robust initialization in conjunction with ML positioning is compared to two baselines using the same probabilistic positioning algorithms, but no initialization. In both cases, the available measurements from all locators are always used and equally contribute to the respective LL-functions (i. e., they have unit weights). The first

TABLE I: Algorithm Parameters.

Maximum iterations of IRLS TDoA algorithm N_{it}	10
Maximum residual error e_{max}	2.5 m
Stopping criterion ϵ	10^{-5} m
Maximum variance of position estimate σ_{max}^2	10 m ²
Maximum concentration parameter κ_{max}	10

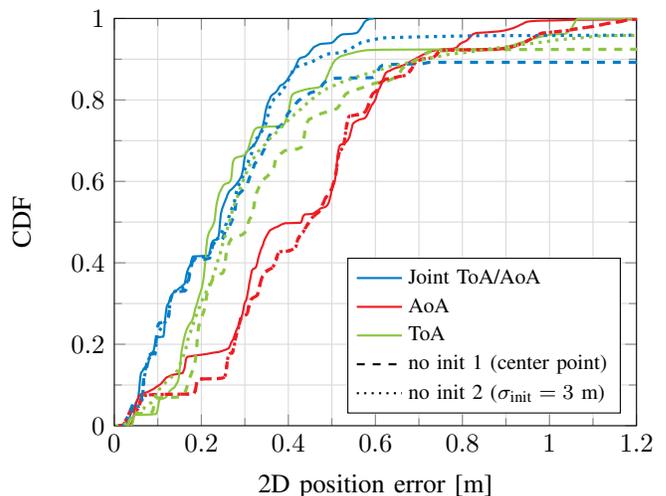


Fig. 4: CDF of the 2D position error for the three algorithms (ToA, AoA, and joint ToA/AoA). The proposed robust ML initialization routine (represented by the solid lines) exhibits no heavy tail. By contrast, the lack of a robust initialization leads to large outliers (dashed and dotted lines).

baseline “no init 1” uses the center point of the investigation area as an initial guess, while the second baseline “no init 2” assumes knowledge about the UE’s rough position. Such information could e. g., be obtained via tracking techniques. For “no init 2”, we model the 2D uncertainty of the initial point with a standard deviation $\sigma_{init} = 3$ m, corresponding to the root-mean-square deviation of non-initialized ToA position estimates.

Analyzing the cumulative distribution function (CDF) curves in Fig. 4, one can observe that joint ToA/AoA ML is the most robust technique, clearly outperforming ML positioning relying only on ToA or AoA measurements. Moreover, the benefits of our initialization routine become clear, as the baselines without initialization generally perform slightly worse and, more importantly, exhibit heavy tails. On the other hand, our proposed initialization routine allows to achieve a 2D positioning error below 0.6 m in all cases. Similar observations can be made by comparing ToA-only and AoA-only positioning with and without initialization. Also here, initialization slightly improves the overall performance and shows the capability to limit outliers.

Table II compares the position error of our proposal and “no init 2” w.r.t. their mean and at different percentiles. Analyzing these values, one can see that the initialization routine has only a small impact on the performance under good conditions, as the median error only slightly improves. However, analyzing higher percentiles, the benefits of proper initialization become clear. While “no init 2” exhibits position estimates that can deviate very far from the true position (e. g., up to over 10 m for ToA-only), we are able to keep the 2D position error below 1.06 m in 99% of all measurements for all three algorithms when our initialization routine is applied.

TABLE II: 2D position error summary.

	Joint ToA/AoA		ToA		AoA	
	init	no init 2	init	no init 2	init	no init 2
Mean [m]	0.24	0.49	0.31	0.68	0.42	0.45
Median [m]	0.24	0.26	0.23	0.26	0.43	0.45
95th %ile [m]	0.51	0.60	0.96	1.05	0.81	0.96
99th %ile [m]	0.57	6.35	1.06	10.24	0.94	1.15

This further highlights the importance of rejecting outliers, as they can cause the position estimate to diverge far from the ground truth, even with a-priori knowledge about the rough position. Remarkably, joint ToA/AoA positioning achieves errors of 0.51 m and 0.57 m at the 95th %ile and 99th %ile, respectively. The performance at high percentiles is crucial, since the deployment of indoor positioning demands extreme reliability due to requirements for people safety.

Lastly, Fig. 5 depicts the distribution of the estimated positions obtained with joint ToA/AoA positioning w. r. t. the 28 ground truth points. Analyzing the distribution of the blue crosses, one can infer that our system - even at points where the error is higher - provides stable position estimates without large fluctuations. Moreover, it is clearly visible that the errors at the outer points of the investigation area tend to be higher. This is due to the fact that locators can lie outside of the coverage area at some ground truth points. In these cases, the signal at those locators can be weak and/or arrive at unfavorable (i. e., large) AoAs. Limiting our analysis only to the six ground truth points of the central area (see orange box in Fig. 5), we are able to achieve a mean and maximum error of 0.12 m and 0.23 m, respectively.

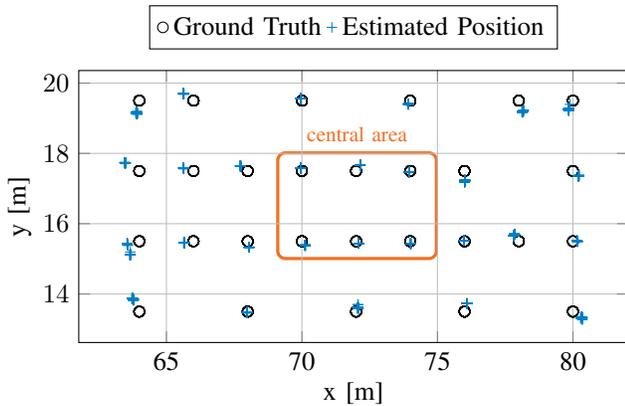


Fig. 5: Ground truth (black circles) and estimated (blue crosses) positions using joint ToA/AoA positioning with initialization.

VII. CONCLUSION

In this work, we presented a robust initialization routine that is applied in an experimental 5G positioning system. The results show that our technique can enhance the performance

of probabilistic positioning algorithms by detecting and rejecting outliers and by assigning weights to the measurements based on the confidence in them. For the particular case of joint ToA/AoA ML positioning, we are able to avoid large errors at high percentiles, achieving a positioning error of not more than roughly 0.5 m for 95% of the measurements. Moreover, we showed that joint probabilistic positioning with initialization accomplishes precise localization under good conditions, exhibiting a mean error of 0.12 m for the points located in the central area.

While our findings underline the potential of 5G indoor positioning, there are still open questions to be addressed. Those include the relationship between locator deployment density and position error, and the system performance in harsh radio environments with more severe multipath propagation.

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