Decimetre-Level Single- and Multi-Target 3D mmWave Sensing Using Mechanical Sensor Steering and Kalman Filtering

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***Abstract*—Millimeter-wave (mmWave) sensing has emerged as a promising solution for accurate indoor positioning due to its ability to provide range, azimuth, and elevation measurements. While prior work has demonstrated decimetre-level accuracy for single-target localization using fixed sensor deployments, performance degrades in dynamic and multi-target scenarios due to limited sensing coverage and challenges in measurement association. This paper presents a unified framework for single- and multi-target 3D positioning based on adaptive sensor steering, robust measurement association, and Kalman filtering. The proposed approach dynamically orients sensors towards predicted target locations, improving measurement geometry and visibility. For multi-target tracking, a prediction-guided gating and association strategy is introduced, enabling reliable separation of closely spaced targets without relying solely on clustering techniques. The proposed framework is evaluated in a realistic simulation environment that incorporates experimentally derived mmWave error models. Results demonstrate that sensor steering provides measurable improvements in accuracy, while the integration of Kalman filtering significantly enhances robustness. Overall, the proposed method achieves consistent decimetre-level accuracy, with approximately 25% reduction in RMSE compared to fixed sensor configurations, and improved resilience in dense multi-target scenarios.**

***Index Terms*—mmWave sensing, indoor positioning, multi-target tracking, sensor steering, Kalman filter**

I. Introduction

Millimeter-wave (mmWave) sensing has emerged as a promising technology for indoor positioning due to its ability to provide high-resolution measurements in range, azimuth, and elevation. These capabilities enable direct three-dimensional (3D) localization, which is essential for applications such as drone navigation, robotics, and advanced location-based services [1].

Existing mmWave-based positioning systems have demonstrated decimetre-level accuracy in single-target scenarios using multiple sensors and appropriate coordinate transformations [2], [3]. However, extending such systems to multi-target environments introduces significant challenges. In particular, mmWave sensors inherently produce unlabeled reflections, making it difficult to distinguish between multiple targets without additional processing.

Previous approaches have addressed multi-target sensing using clustering techniques to group measurements corresponding to different targets [4]. While effective under certain conditions, these methods struggle in dense environments where targets are closely spaced, leading to cluster ambiguity and degraded positioning accuracy.

In addition, most existing systems rely on fixed sensor orientations, which, in conjunction with the limited field of view of these sensors, may result in suboptimal measurement geometry as targets move within the environment. This limitation, combined with the lack of temporal tracking mechanisms, restricts the achievable performance in dynamic scenarios.

This paper proposes a unified framework for single-target and multi-target mmWave sensing that integrates mechanical sensor steering and Kalman filter-based tracking. By dynamically adjusting sensor orientation and incorporating temporal prediction, the proposed approach improves measurement quality, enhances robustness, and enables reliable tracking of multiple closely spaced targets.

The main contributions of this work are: (1) A dynamic sensor steering framework that improves measurement geometry and target visibility. (2) A Kalman filter-based tracking approach for enhanced temporal consistency. (3) A prediction-guided association method for resolving ambiguities in multi-target scenarios and (4) A comprehensive simulation framework for evaluating fixed and adaptive sensing configurations. The remainder of this paper is organized as follows. Section II reviews related work on mmWave-based indoor positioning and multi-target tracking. Section III introduces the system model and measurement formulation. Section IV presents the proposed single-target tracking framework with adaptive sensor steering, while Section V extends the approach to multi-target tracking and association. Section VI evaluates the proposed methods through simulation. Finally, Section VII and Section VIII discuss the results and conclude the paper, identifying potential future research directions and improvements.

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II. Related Work

The increasing demand for accurate three-dimensional (3D) indoor positioning has driven significant research efforts toward the development of advanced localization technologies. A comprehensive overview of 3D indoor positioning techniques is presented in [1], highlighting the growing interest in mmWave sensing due to its ability to provide high-resolution range and angular measurements.

Early mmWave positioning studies primarily focused on single-target scenarios. Several works have demonstrated the feasibility of achieving sub-meter accuracy using a single mmWave sensor by exploiting line-of-sight (LoS) and multipath components. For example, [5] combines Angle of Arrival (AoA), Time of Arrival (ToA), and motion information within a Kalman filtering framework, achieving positioning accuracy on the order of 60 cm. Similarly, [6] leverages multipath propagation using MIMO and OFDM techniques, achieving sub-meter accuracy in controlled environments. Multipath-assisted localization is further explored in [7], where reflected signals are exploited for positioning even in challenging scenarios. Previous work by the authors' group investigated single-target mmWave-based positioning using multiple sensors and experimentally derived error models [2], [4]. These studies demonstrated that decimetre-level 3D accuracy can be achieved through appropriate sensor deployment. The results also highlighted the strong dependency of positioning accuracy on sensor geometry and orientation, motivating the need for adaptive sensing strategies. In another work [8], the same group also critically compared mmWave with the well-established UWB technology in terms of 3D positioning accuracy. Radar point cloud-based approaches have also been investigated, where target positions are estimated from clustered measurement points. For instance, [9] estimates the target position as the centroid of a processed point cloud, achieving positioning accuracy of approximately 30–40 cm. Hybrid techniques combining different measurement modalities, such as received signal strength and AoA, have also been proposed [10], while emerging technologies such as Reconfigurable Intelligent Surfaces (RIS) have demonstrated the potential for centimeter-level positioning accuracy under favorable conditions [11], [12]. This cloud-based approach is what we deploy in our works.

More recently, research has shifted towards multi-target sensing, in which multiple objects are present in the environment simultaneously. In such scenarios, clustering techniques are commonly employed to group radar point clouds into distinct targets. Partition-based, hierarchical, and density-based clustering algorithms, including K-Means and DBSCAN, are among the most widely used methods. Reviews such as [13] provide a comprehensive overview of multi-object tracking techniques, including sensor-fusion approaches and machine-learning-based methods. Similarly, [14] surveys clustering and multi-target tracking techniques for LiDAR point clouds, highlighting common challenges such as data association and scalability, which are also relevant to mmWave sensing. Several works have specifically addressed mmWave-based multi-target detection. For example, [15] applies DBSCAN clustering to mmWave data and highlights the challenges of distinguishing targets in the presence of multipath noise. The authors show that performance can be improved through multi-frame processing, albeit at the cost of increased system complexity. Sensor fusion approaches have also been explored, such as in [16], where mmWave radar is combined with camera data and processed using an Extended Kalman Filter to improve tracking accuracy. Hybrid clustering approaches have also been proposed, such as combining K-Means and DBSCAN in [17], aiming to reduce computational complexity while maintaining clustering performance. Prior work on multi-target mmWave sensing employed clustering techniques to separate measurements corresponding to different targets [4]. Although effective in well-separated scenarios, these methods exhibited limitations in dense environments due to ambiguity in cluster assignments and a lack of temporal tracking. A closely related work is presented in [18], where multiple mmWave sensors are used for object detection and tracking. In this approach, DBSCAN is first applied to group measurements, followed by K-Means to extract cluster centroids. An Unscented Kalman Filter is then used for tracking multiple targets. While this approach demonstrates improved performance, achieving an average positioning accuracy of approximately 0.57 m, it remains limited by clustering ambiguities and the reliance on frame-based association.

Despite these advances, several challenges remain in mmWave multi-target sensing. Clustering-based approaches are inherently sensitive to noise and measurement uncertainty, particularly in scenarios where targets are closely spaced. In such cases, clusters may overlap or merge, leading to incorrect target identification. Furthermore, many existing approaches rely on frame-by-frame processing and do not fully exploit temporal continuity for robust tracking. Additionally, most systems assume fixed sensor configurations, without considering the impact of sensor orientation and field of view on measurement quality.

These limitations highlight the need for integrated frameworks that combine spatial clustering, temporal tracking, and adaptive sensing strategies. In particular, the joint use of prediction-based tracking and dynamic sensor control has the potential to significantly improve robustness and accuracy in complex multi-target environments.

III. System Model and Measurement Framework

In this section, we describe the methodological framework for simulating and collecting measurements for our work.

A. Simulation Framework Overview

To enable a systematic evaluation of mmWave-based positioning under controlled and repeatable conditions, a simulation framework has been developed in MATLAB. The simulator is designed to model the behavior of mmWave sensing systems, incorporating realistic measurement characteristics derived from experimental data. It extends previous

implementations [2], [3] by supporting both single-target and multi-target scenarios, as well as dynamic sensor steering and temporal tracking using a Kalman filter. The simulation environment represents a 3D indoor space with predefined geometry, including walls, obstacles, and sensor placements. Multiple mmWave sensors are deployed at fixed locations within the environment, each characterized by its position and orientation. The simulator supports both static and dynamically adjustable sensor orientations, enabling the evaluation of adaptive sensing strategies. Target motion is defined through smooth trajectories within the indoor environment, emulating realistic drone-like movements without abrupt changes in direction. For multi-target scenarios, multiple independent trajectories are generated to ensure controlled variations in target proximity and interaction.

B. Measurement Generation Model

The measurement generation process is based on experimentally derived error models obtained from real mmWave radar measurements as reported in [2], [4]. Specifically, measurement uncertainty in range, azimuth, and elevation is modeled using interpolated error matrices, capturing the dependency of measurement accuracy on distance and angular position. At each time step, the true target position is used to generate a set of scattered points that represent radar measurements. These points are distributed around the ground truth position using a Gaussian model, simulating the spatial spread of mmWave reflections. The scattered points are then transformed into the coordinate frame of each sensor, where range, azimuth, and elevation measurements are computed. Measurement errors are introduced by perturbing these quantities using the interpolated error model. The corrupted measurements are subsequently transformed back into the global coordinate system, resulting in a point cloud representation of the detected target(s). The output of this process is a set of reconstructed 3D points for each sensor, which are combined to form a global measurement cloud. This enables the simulator to realistically capture key characteristics of mmWave sensing, including angular-dependent errors, range uncertainty, and measurement dispersion.

C. Single-Target Position Estimation

In the single-target case, all measurements generated by the sensors correspond to a single object. The reconstructed point clouds from all sensors are combined, and the target position is estimated by computing the centroid of the aggregated measurements. Two sensing configurations are considered:

1) Fixed Sensor Configuration: In the fixed configuration, sensor orientations remain constant throughout the simulation. Measurements are collected independently at each time step, and the target position is estimated directly from the aggregated point cloud.

2) Dynamic Sensor Steering: In the dynamic configuration, sensor orientations are updated at each time step to align with the estimated target position. Specifically, after each position estimate is obtained, the yaw and pitch angles of each sensor are adjusted to point towards the estimated target location. This ensures that the target remains within the optimal field of view of the sensors, improving measurement quality and geometric diversity.

To enhance temporal consistency and reduce estimation noise, a Kalman filter is optionally applied. The filter models the target motion using a constant-velocity model and incorporates both prediction and measurement update steps. The predicted state is used to refine the position estimate and to guide sensor steering in the dynamic configuration.

D. Multi-Target Position Estimation

In the multi-target case, the measurement cloud contains points originating from multiple targets, which are not explicitly labeled. This introduces the challenge of separating measurements corresponding to different targets.

1) Clustering-Based Segmentation: To address this, a two-stage clustering approach is employed. First, density-based clustering (DBSCAN) is used to remove outliers and identify dense regions in the measurement cloud. Subsequently, K-Means clustering is applied to partition the remaining points into a predefined number of clusters corresponding to the expected number of targets. The centroids of these clusters provide initial position estimates for each target.

2) Prediction-Guided Association: To ensure consistent target identification over time, a prediction-guided association mechanism is introduced. Each target is associated with a Kalman filter that predicts its position at the next time step. These predictions are used to gate the clustering results, assigning each cluster to the most likely target based on spatial proximity and consistency with the predicted state. This approach mitigates cluster ambiguity, particularly in scenarios where targets are closely spaced or when clusters overlap.

3) Sensor Steering for Multi-Target Tracking: In the multi-target scenario, sensor steering is performed based on the predicted positions of all targets. The steering strategy aims to maximize overall measurement quality by directing sensors towards regions of interest, taking into account field of view constraints and target distribution. This adaptive sensing mechanism improves the reliability of measurements and enhances the separability of target clusters.

IV. Single-Target Tracking with Sensor Steering

In the single-target case, all reconstructed measurements correspond to a single object, and the target position is estimated directly from the aggregated point cloud. Let $\mathcal{Z}_k = \{\mathbf{z}_{k,j}\}_{j=1}^{M_k}$ denote the set of reconstructed points at time step k. The measurement is obtained as the centroid:

$$\mathbf{z}_k = \frac{1}{M_k} \sum_{j=1}^{M_k} \mathbf{z}_{k,j} \tag{1}$$

To exploit temporal continuity, a Kalman filter with a constant-velocity model is employed. The state is defined as $\mathbf{x}_k = [\mathbf{p}_k^T \ \mathbf{v}_k^T]^T$, with prediction:

$$\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k + \mathbf{w}_k, \quad \mathbf{F} = \begin{bmatrix} \mathbf{I} & \Delta t\, \mathbf{I} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \tag{2}$$

and measurement model $\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k$, where $\mathbf{H} = [\mathbf{I}\ \mathbf{0}]$.

The standard Kalman prediction and update steps are applied, yielding the estimated position $\hat{\mathbf{p}}_k$.

To improve sensing quality, sensor orientations are dynamically adjusted based on the estimated target position. For each sensor located at $\mathbf{s}_i$, the steering direction is $\mathbf{d}_i(k) = \hat{\mathbf{p}}_k - \mathbf{s}_i$, with yaw and pitch computed as $\psi_i = \tan^{-1}(d_y/d_x)$ and $\theta_i = \tan^{-1}(d_z/\sqrt{d_x^2 + d_y^2})$.

V. Multi-Target Tracking and Association

In the multi-target case, the measurement set $\mathcal{Z}_k = \{\mathbf{z}_{k,j}\}_{j=1}^{M_k}$ contains reflections from multiple targets without explicit labeling. The objective is to estimate and track N_t targets while maintaining consistent associations over time.

To separate measurements, a two-stage clustering approach is employed. First, DBSCAN is applied to remove outliers, yielding a filtered set $\mathcal{Z}_k^{\text{filtered}}$. K-Means is then used to partition the remaining points into N_t clusters, with centroids $\{\mathbf{c}_k^{(j)}\}_{j=1}^{N_t}$ providing candidate measurements.

To resolve clustering ambiguities, a prediction-guided association mechanism is introduced. Each target is tracked using a Kalman filter (Section IV), providing a predicted position $\hat{\mathbf{p}}_{k|k-1}^{(m)}$. A gating constraint $\|\mathbf{c}_k^{(j)} - \hat{\mathbf{p}}_{k|k-1}^{(m)}\| \leq \gamma$ is applied to reject unlikely associations.

Data association is performed using a nearest-neighbor rule:

$$j^* = \arg\min_j \|\mathbf{c}_k^{(j)} - \hat{\mathbf{p}}_{k|k-1}^{(m)}\| \tag{3}$$

and the assigned centroid $\mathbf{z}_k^{(m)} = \mathbf{c}_k^{(j^*)}$ is used for the Kalman update. If no centroid satisfies the gating condition, prediction-only is applied.

Sensor steering is extended to the multi-target case by directing each sensor towards the most relevant target. In this work, each sensor selects the closest predicted target $m^* = \arg\min_m \|\hat{\mathbf{p}}_{k|k-1}^{(m)} - \mathbf{s}_i\|$, and updates its orientation as in Section IV.

VI. Simulation Framework and Results

A. Simulation Setup

The proposed framework is evaluated using a custom MATLAB-based simulator that models a realistic indoor mmWave sensing scenario. The simulator incorporates experimentally derived error models to reproduce measurement uncertainty as a function of range and angular position.

Five mmWave sensors are deployed at fixed locations in a 3D indoor environment, each with a field of view of 90° (azimuth), 50° (elevation), and a maximum range of $7\,\text{m}$. The framework supports both fixed and dynamically steered sensor configurations. Target motion is defined using smooth parametric trajectories, and measurements are generated as noisy point clouds at each time step.

Unless otherwise stated, all simulations use identical sensor configurations, trajectory sampling (220 time steps), and random seeds to ensure fair comparison.

B. Single-Target Evaluation Results

A single target following a smooth spiral trajectory is considered. Three configurations are evaluated: fixed sensors, steering sensors, and steering sensors with Kalman filtering.

Fig. 1 shows that fixed sensors lead to degraded estimates when the target moves outside optimal sensing regions. Steering improves alignment and reduces geometric degradation, producing smoother trajectories. The addition of Kalman filtering further stabilizes the estimate by reducing noise and enforcing temporal consistency.

Fig. 3 confirms these observations. Steering reduces the mean error from $0.1653\,\text{m}$ to $0.1335\,\text{m}$ and the RMSE from $0.1932\,\text{m}$ to $0.1585\,\text{m}$. The addition of Kalman filtering further improves performance to a mean error of $0.1169\,\text{m}$ and an RMSE of $0.1333\,\text{m}$, while significantly reducing the maximum error from $0.8132\,\text{m}$ to $0.3462\,\text{m}$.

TABLE I: Single-target 3D positioning performance

Method	Mean [m]	RMSE [m]	Max [m]
Fixed	0.1653	0.1932	0.9008
Steering	0.1335	0.1585	0.8132
Steering + KF	**0.1169**	**0.1333**	**0.3462**

C. Multiple-Target Evaluation Results

Five targets are simultaneously tracked using diverse trajectory patterns (spiral, elliptical, Lissajous, and perturbed circular), ensuring both well-separated and closely spaced configurations. Each target generates up to 35 scattered points per time step with Gaussian noise ($\sigma = 0.25\,\text{m}$), while measurement uncertainty follows the radar error model.

For steering, sensor motion is constrained to 10° (yaw) and 8° (pitch) per step. Association is performed using gating thresholds of 12° (azimuth), 10° (elevation), and $1.2\,\text{m}$ (range), with adaptive gating and robust fusion requiring at least four detections.

Fig. 2 shows that fixed sensors result in reduced coverage and increased noise, while steering improves spatial alignment and trajectory consistency. The best performance is achieved when steering is combined with Kalman filtering, producing smoother and more accurate estimates. Fig. 4 shows a consistent reduction in error across all targets when steering is applied, with further improvement using Kalman filtering.

Table II summarizes the results. Steering alone yields a modest reduction in RMSE from $0.15\,\text{m}$ to $0.14\,\text{m}$ and lowers the maximum error from $0.66\,\text{m}$ to $0.54\,\text{m}$ (18%). When combined with Kalman filtering, the improvements become substantial: the mean error drops from $0.12\,\text{m}$ to $0.10\,\text{m}$ (17%), the RMSE from $0.15\,\text{m}$ to $0.11\,\text{m}$ (27%), and the maximum error from $0.66\,\text{m}$ to $0.51\,\text{m}$ (23%).

VII. Discussion

The results presented demonstrate that both adaptive sensor steering and temporal filtering with a Kalman Filter play a critical role in improving mmWave-based 3D positioning, particularly in multi-target scenarios. While fixed sensor

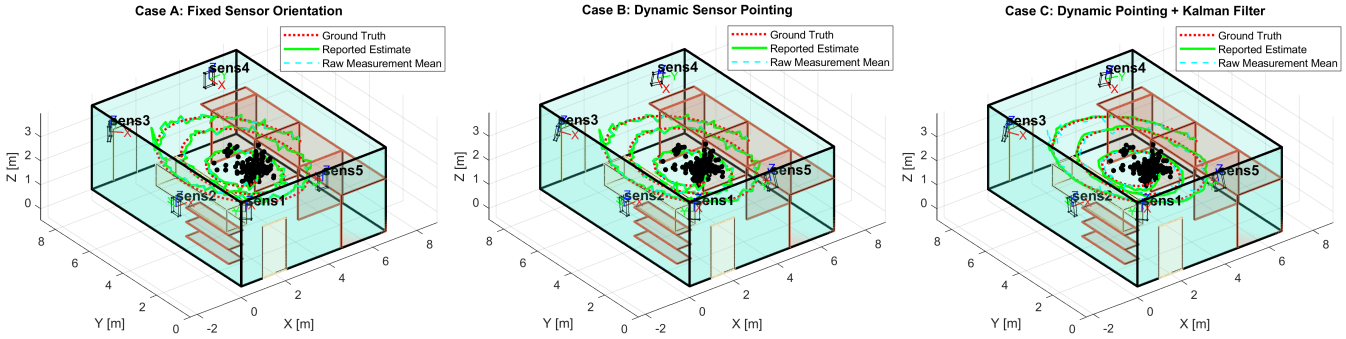


Fig. 1: Single-target trajectory estimation under (left) fixed sensors, (middle) steering, and (right) steering with Kalman filtering.

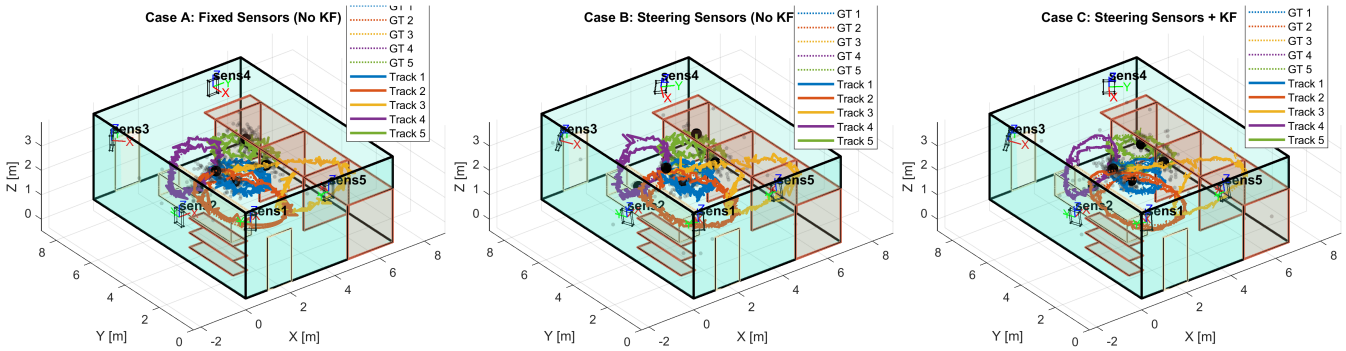


Fig. 2: Multi-target trajectory estimation under (left) fixed sensors, (middle) steering, and (right) steering with Kalman filtering.

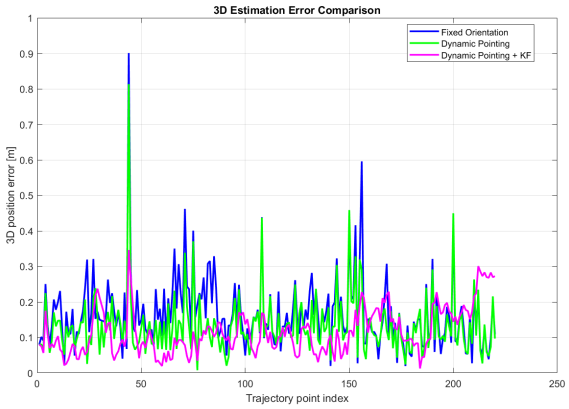


Fig. 3: 3D positioning error for the single-target case.

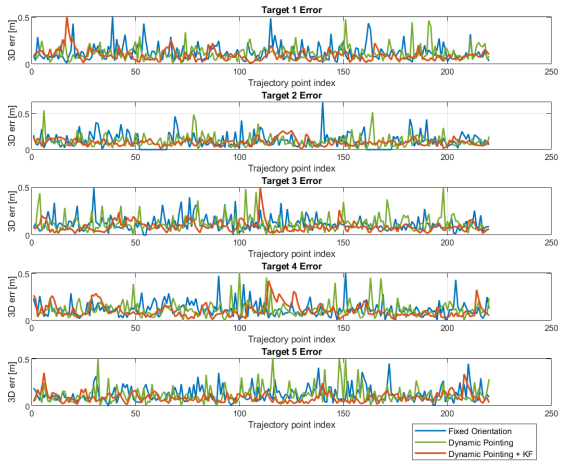


Fig. 4: Per-target 3D error for the multi-target case.

configurations provide acceptable baseline performance, their limitations become evident when targets move outside optimal sensing regions, leading to degraded geometry and increased estimation error. Sensor steering improves spatial coverage by dynamically aligning the sensors with predicted target positions, resulting in more informative measurements and reduced geometric dilution of precision. However, steering alone provides only modest gains in mean and RMSE error, indicating that measurement noise and association uncertainty remain limiting factors. The integration of Kalman filtering yields the most significant improvement, reducing both average and worst-case errors. This highlights the importance of exploiting temporal correlation in target motion, particularly in the presence of noisy and partially degraded measurements. Notably, the reduction in maximum error indicates improved robustness against outliers and temporary loss of visibility.

In the multi-target case, the proposed gating and association strategy effectively separates closely spaced targets, addressing a key limitation of clustering-based approaches such as DBSCAN, which are known to struggle in dense environments [15]. Compared with prior work that relies heavily on clustering or sensor fusion [16], [18], the proposed

TABLE II: Multi-target tracking performance (m)

Case	Metric	T1	T2	T3	T4	T5	Overall
Fixed	Mean	0.12	0.12	0.12	0.12	0.12	**0.12**
	RMSE	0.15	0.16	0.14	0.14	0.15	**0.15**
	Max	0.51	0.66	0.49	0.50	0.45	**0.66**
Steering	Mean	0.12	0.12	0.12	0.12	0.12	**0.12**
	RMSE	0.14	0.14	0.15	0.14	0.15	**0.14**
	Max	0.48	0.54	0.50	0.51	0.51	**0.54**
Steer + KF	Mean	**0.09**	**0.10**	**0.09**	**0.10**	**0.09**	**0.10**
	RMSE	**0.11**	**0.11**	**0.10**	**0.12**	**0.10**	**0.11**
	Max	**0.51**	**0.26**	**0.50**	**0.42**	**0.35**	**0.51**

approach achieves competitive decimetre-level accuracy while maintaining a relatively simple and flexible framework.

Furthermore, unlike approaches based on multipath exploitation [5], [7] or RIS-assisted localization [11], [12], the proposed method does not require complex environment modeling or additional infrastructure. While some of these methods report comparable or slightly higher accuracy under controlled conditions, they often entail greater system complexity or rely on assumptions that are difficult to verify in practice.

Overall, the results suggest that combining adaptive sensing with probabilistic tracking provides a robust and scalable solution for indoor multi-target positioning, particularly in scenarios where targets are dynamic and intermittently observable.

VIII. Conclusion

This paper presented a unified framework for single- and multi-target 3D indoor positioning using mmWave sensing, combining adaptive sensor steering, robust measurement association, and Kalman filtering. The proposed approach was evaluated using a realistic simulation environment incorporating experimentally derived error models.

Compared to existing approaches, the proposed method offers a favorable trade-off between accuracy, complexity, and flexibility, without requiring additional infrastructure such as RIS or multi-modal sensing systems.

Potential applications of this work include indoor drone localization, human tracking, smart environment monitoring, and industrial automation, where reliable multi-target positioning is essential.

Future work will focus on the experimental validation of the proposed framework in real-world environments using physical mmWave radar platforms. Additional directions include integrating learning-based association methods, extending to fully distributed sensor coordination, and investigating cooperative multi-sensor fusion strategies to further enhance accuracy and scalability.

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