3D millimeter-Wave Multi-Target Sensing

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***Abstract*—This paper addresses the challenge of achieving precise 3D localization of multiple objects in indoor environments using millimeter-wave (mmWave) sensing. mmWave positioning systems have recently emerged as a promising technology offering cm-level accuracy and robustness; however, the radar-like nature of mmWave technology presents challenges in multi-target positioning, particularly in complex environments where distinguishing between multiple objects becomes difficult. To address this, we explore clustering as a solution to analyze data from mmWave sensors and group similar data points, facilitating the identification of distinct targets. This paper aims to leverage the potential of mmWave radar technology to achieve precise ranging and angling measurements in multi-target environments, presenting a comprehensive methodology for evaluating the performance of mmWave sensors for achieving 3D positioning accuracy using four clustering approaches: K-Means, DBSCAN, Affinity Propagation, and BIRCH. The experimental results highlight the potential and challenges of each approach in terms of accuracy, robustness and execution time.**

***Index Terms*—3D, Indoor Positioning, millimeter-wave sensing, clustering, multi-target**

I. Introduction

Accurate three-dimensional (3D) localization of multiple objects in indoor environments remains a significant challenge across various domains, including robotics, human–computer interaction, and security. Achieving high precision in these conditions is essential for autonomous navigation, crowd-control, and surveillance systems. However, existing localization methods often struggle to maintain the required accuracy and reliability when multiple targets must be tracked.

Over the past couple of decades, research was focused on solving the localization problem in satellite-denied environments, using various radio and non-radio technologies; however, solutions have been limited to estimating positions in 2D (xy), often overlooking the vertical (z) dimension. This omission can lead to challenges in accurately determining the position of objects, such as UAVs, in a 3D space, where precision is critical to avoid obstacles, often requiring accuracy at sub-meter levels. In our previous work [1], we provided a thorough review of the available technologies for 3D positioning. Another challenge lies in the difficulty of identifying multiple targets that are not radio-capable, like in a typical crowd control application. Radar-based millimetre-wave (mmWave) positioning systems have been identified as a promising solution to address this need. mmWave technology is already utilized in Wi-Fi (e.g. IEEE802.11ad), and it is expected to play a significant role in 5G (and beyond) communications due to its flexibility to use wider bandwidths at frequencies between 26-300 GHz. This enables exact timing (thus, ranging) resolution to non-radio-enabled targets based on sensing. Sensing is typically implemented using range estimation from moving targets, which generate Doppler shifts and constitute a crucial key-enabling technology in the 6G era. Moreover, using large-scale phase array antennas facilitates accurate phase estimation, which enables angle determination. Combined, these capabilities empower mmWave systems to achieve centimeter-level 3D positioning accuracy or better [2].

The utilization of mmWave technology in various applications has undeniably demonstrated its potential for high precision and accuracy. However, unlike technologies that use receiver-transmitter setups such as Ultra-Wideband (UWB) [3], a notable challenge associated with mmWave lies in its radar-like nature, particularly when identifying multiple objects in 3D space. A mmWave sensor emits high-frequency electromagnetic waves that bounce off surrounding objects and return as echoes. These echoes can merge in complicated environments, making it difficult to differentiate specific objects. This becomes particularly more challenging when using multiple sensors and is critical in applications such as indoor crowd control or autonomous vehicle navigation, where the ability to discern and track multiple objects is paramount.

When addressing the complexities associated with multi-target positioning using mmWave sensing, clustering emerges as a promising solution. It involves analyzing the mmWave data and grouping it based on its proximity, allowing for the identification of distinct clusters representing individual targets. Several solutions are proposed in literature that utilize various clustering techniques for multi-target positioning; however, most of them focus on 2D, while only a few of them focus on mmWave, and most of the proposed solutions have not been tested in real-time. Our work addresses this gap by investigating the use of 3D mmWave technology for multi-target positioning while evaluating various state-of-the-art clustering approaches.

This paper addresses the challenges mentioned above by exploring novel strategies for precise 3D localization of mul-

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tiple objects using mmWave sensing. Specifically, we investigate techniques that enhance target discrimination and tracking capabilities in cluttered indoor environments, thereby unlocking the full potential of mmWave-based positioning for multi-object scenarios. By identifying the limitations of current systems and proposing effective solutions, this work lays the foundation for more reliable and accurate localization in advanced indoor multi-target applications.

The remainder of this paper is organized as follows: Section II provides the recent related works in multi-object clustering for 3D localization using mmWave, while Section III describes the methodology and setup used for the experimentation as well as an analysis of the precision of the sensors used and the clustering techniques. Section IV presents the experimentation results, including the accuracy achieved using four clustering approaches. Sections V and VI, provide a critical discussion and conclusion.

II. Related Work

Various partition-based, hierarchical, and density-based clustering algorithms, such as K-Means or DBSCAN (Density-Based Spatial Clustering of Applications with Noise), can be tailored to the specific requirements of the positioning system and are among the most frequently mentioned in the literature. The authors in [4] provide a review of the multi-object tracking techniques and algorithms as well as their challenges and limitations. This review encompasses the integration of mmWave sensors with other technologies, such as cameras, and the exploration of Micro-Doppler effects for human detection, including the analysis of heartbeat and breathing patterns, as well as the application of machine learning. Similarly, the authors of [5] provide a systematic review of clustering and multi-target tracking techniques for LiDAR point clouds in autonomous driving applications. LiDAR is a radar system that emits laser beams to detect targets, which have similar radar-like qualities to mmWave. This paper provides a detailed overview of current challenges, research gaps, and advancements in clustering and Multi-Target Tracking (MTT) techniques for LiDAR point clouds, thus contributing to the field of autonomous driving. It discusses various clustering techniques, however, it is not mmWave-focused. The mmWave-focused works include [6], which discusses the use of a DBSCAN-clustering algorithm for mmWave multi-target detection. It emphasizes that with DBSCAN, it is difficult to distinguish points effectively due to multipath noise, but this difficulty is reduced when combined with multi-frame joint processing. [7] extends the reliability of a mm-wave-radar tracking by combining it with camera data. It takes into consideration the error bounds of the two different coordinate systems from the heterogeneous sensors and uses a new fusion-extended Kalman Filter to fuse the heterogeneous data, demonstrating a range accuracy of $0.29m$ with an angular accuracy of $0.013rad$ in real-time. A hybrid method of combining K-Means and DBSCAN (Kmeans-DBSCAN) for image segmentation is proposed in [8]; however, the focus is only on 2D. Due to the high computational complexity of DBSCAN and the large size of image datasets, K-Means is applied to reduce the size of image datasets in the proposed approach. The most similar work to ours is the one reported in [9] that uses two IWR1642BOOST mmWave radar sensors for accurate object detection and tracking. The Unscented Kalman Filter tracking algorithm with data association tracks multiple objects simultaneously in terms of accuracy and timing. DBSCAN is used to group all the clustered points to combine data from the two sensors. The authors mention that they have tried to implement a modified version of DBSCAN, VDBSCAN, but have shown no significant improvement in accuracy. K-Means is then implemented to distinguish the clustered points and convert them to centroids, demonstrating an average 2D positioning accuracy of $0.57m$.

III. Methodology

This section presents the methodological framework used and it describes the experimental setup and equipment used while considering the particular challenges that the clustering techniques and mmWave sensors impose in achieving high 3D positioning accuracy. A precision analysis was performed for the mmWave sensor used to verify its measurement precision and single-target 3D positioning accuracy.

A. Equipment

The mmWave radar sensor used for the experimentation was the Texas Instruments (TI) IWR1843BOOST. It is equipped with 4 receiving and 3 transmitting antennas operating at frequencies between 76-81 GHz with a 120-degree field of view and ranging capabilities of up to 72 meters. The sensor possesses a Frequency Modulated Continuous Wave (FMCW) transceiver, which enables the measurement of range, azimuth, and elevation angles to the target. We used 5 sensors, connected to a Raspberry Pi that parses the collected data and sends it to a central PC. The experimental setup involved utilizing a set of basketballs with a $24.0cm$ diameter.

B. Sensor Precision Analysis

An experiment was conducted to evaluate the sensing quality of the IWR1843BOOST mmWave sensor in terms of range, azimuth and elevation measurement precision. Our previous work reported in [10], [11] provides full details about this precision analysis. In a nutshell, a basketball hanging from the ceiling was used to emulate a flying target, paying particular attention to the importance of the dynamic motion of that target, which is required to generate the needed Doppler shift that triggers the detection and thereafter the range/angle estimation. To mimic a moving drone behavior, a pivot was pinned around the axis of the rope from which it was hanging. Measurements were collected at varying distances up to $6.5m$ and at various azimuth and elevation angles ranging between 0-60^o and 0-45^o respectively. In summary, the range-precision analysis has shown that at 0^o, the average distance error stands at $0.17m$, gradually rising to approximately $0.32m$ at 60^o. The azimuth precision analysis indicates that errors ranged between 0.5 and 3.5^o, which increased due to reduced target size, facilitating more accurate detection. A consistent pattern was observed for elevation errors, where errors increased with both the azimuth angle and distance. The sensor was most accurate at measuring elevation at bore-sight (at 0^o azimuth), with errors between 1-2^o up to 30^o of elevation.

C. Experimental Setup

Both the precision analysis and the 3D positioning accuracy experimentation using the IWR1843BOOST mmWave sensors were carried out in an $8.93{\times}6.55m$ laboratory, the top-view of which is shown in Figure 1a. The setup includes 5 IWR1843BOOST sensors, each positioned and oriented differently while targeting the center of the room (indicated with different capital letters in Figure 1a). These sensors collect numerous data points around a target, including some random outliers. This data includes range and angle (azimuth, elevation) estimations of the targets. Each sensor determines the location of the targets it "sees" relative to its own body coordinate system, which is subsequently converted to the local coordinate system of the room using standard conversions (see [10]). Due to the data collected from multiple sensors, clusters are formed around the targets, which must be distinguished.

Using this methodology, multi-target positioning experiments were conducted employing various clustering techniques to investigate their detection accuracy. The setup involved a set of balls, each representing the size of a typical drone, suspended at various locations at different heights within the room. Their ground truth position was measured using a laser rangefinder (KALEAS LDM500-60). These balls, were set into motion by spinning to mimic the dynamic behaviour of moving objects. This complex setup aimed to replicate real-world conditions where multiple objects might operate simultaneously in close proximity. Two different experimental use cases were used to evaluate the performance of the clustering techniques. In the first scenario (see Figure 1b), 5 objects were strategically placed far apart from each other within the lab, creating five easily distinguishable targets. This setup facilitated the clustering algorithms' task of segregating and pinpointing distinct centroids. The second scenario (see Figure 1c) introduced an additional target, bringing the total to 6, and featured two pairs of clusters (P1-P2 and P3-P4) positioned relatively close to each other (around one meter). This arrangement was designed to test the clustering techniques' ability to discern and separate the two closely situated clusters, presenting a more complex challenge. The mmWave sensors were tasked with gathering numerous data points, which were predominantly dispersed around each object within the room. This collection of data points, embodying the spatial distribution of objects, was subsequently input into the clustering algorithms to assess their performance in terms of accuracy, robustness, and execution time.

D. Clustering Techniques

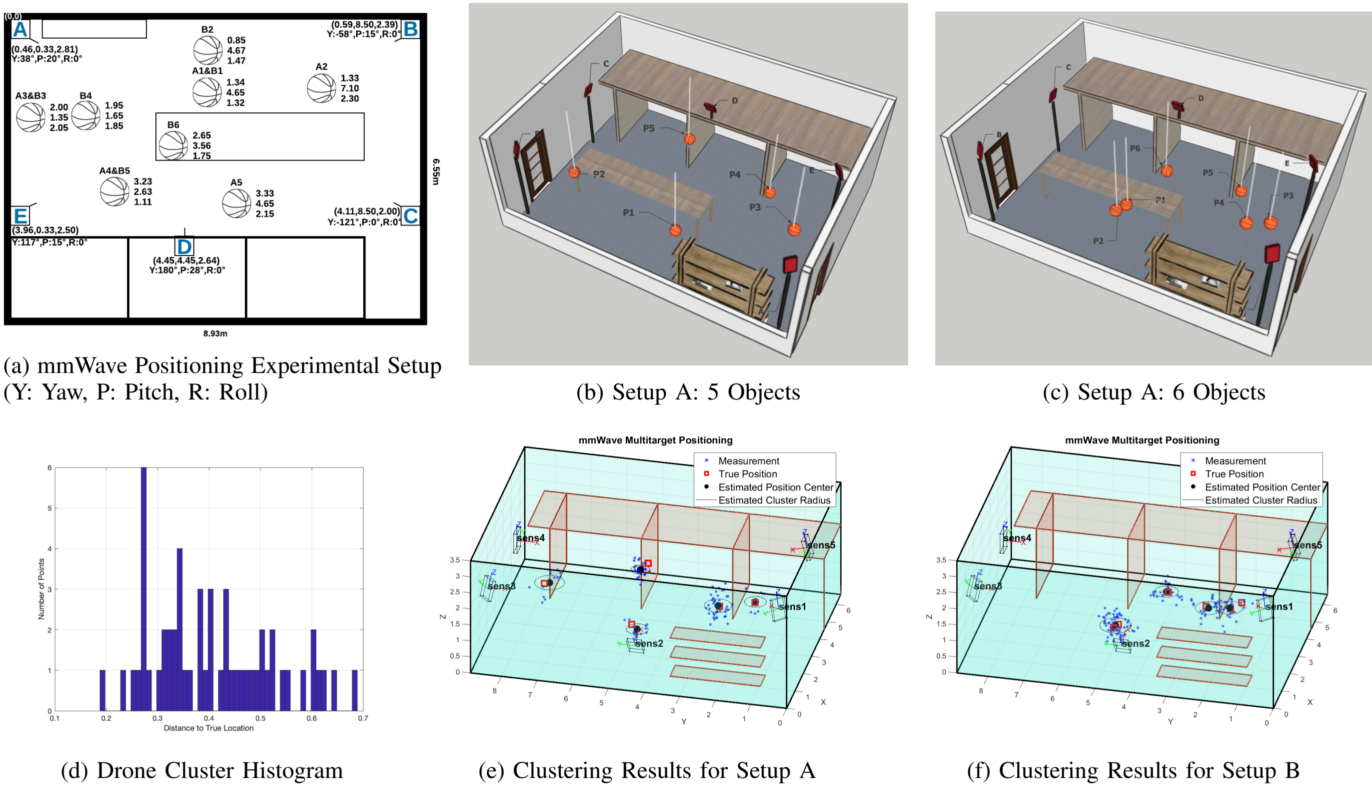
In data analysis, clustering algorithms play a pivotal role in interpreting complex datasets. The experimentation's core revolved around applying four distinct clustering approaches: K-Means, DBSCAN, Affinity Propagation, and BIRCH. Each algorithm offers a unique clustering approach, ranging from centroid-based to density-based and hierarchical techniques.

1) K-Means Clustering: K-Means is a centroid-based clustering algorithm that partitions the data into K distinct, non-overlapping clusters. The algorithm iteratively adjusts the centroids to reduce the total variance within each cluster [12]–[14]. It requires the number of clusters (K) to be specified in advance, which is a key parameter that directly influences the clustering outcome, as it determines the granularity of the clustering. A value that is too low may merge distinct groups into a single cluster, while a value that is too high may lead to overfitting, identifying clusters within what is essentially noise, splitting cohesive clusters into multiple, smaller ones.

2) DBSCAN Clustering: DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based clustering algorithm. It groups up points that are closely packed together, marking as outliers any points that lie alone in low-density regions. This method is effective for data with clusters of similar density [15], [16] and its algorithm effectiveness relies heavily on two parameters: epsilon (ε) and minimum cluster size ($MinPts$). ε sets the neighborhood radius around each centroid, dictating what is considered close enough to form a cluster, while $MinPts$ defines the minimum number of points a cluster needs, distinguishing core points (points in dense areas) from noise (points in sparse areas). Balancing ε and $MinPts$ is essential to ensure the correctness of the clustering result. For our experiments, to accurately determine these parameters, a drone was stationary and hovered at random points in the lab at different heights, and several data captures were performed, which formed a cluster of points around it. The collected data points within the cluster were then counted to determine the $MinPts$ value, and distances to the true locations of each point were averaged to calculate the ε value. As can be seen by the histogram shown in Figure 1d, the majority of the clustered points were within $0.3 - 0.5m$ distance averaging at around $0.35m$ from the true location, and $MinPts$ was averaged to around 30 points.

3) Affinity Propagation Clustering: Affinity Propagation distinguishes itself by not necessitating a predefined number of clusters, instead creating clusters through messages exchanged between data points. It includes two parameters: preference ($preference$) and damping factor ($damping$). $preference$ is key in deciding the likelihood of data points becoming exemplars, thus influencing the number of clusters. Adjusting preference directly impacts the clustering detail; higher values increase cluster numbers by permitting more points to act as centers, while too high a preference can lead to over-fragmentation, and too low may overlook dataset diversity [17], [18]. $damping$ modulates the availability of message updates to avert numerical oscillations during iterations. Generally set between 0.5 and 1, with 0.5 being a typical default, tuning the damping factor is crucial for balancing convergence, speed and stability, particularly in complex datasets.

4) BIRCH Clustering: The BIRCH algorithm (Balanced Iterative Reducing and Clustering using Hierarchies) is de-



(a) mmWave Positioning Experimental Setup (Y: Yaw, P: Pitch, R: Roll)

(b) Setup A: 5 Objects

(c) Setup A: 6 Objects

(d) Drone Cluster Histogram

(e) Clustering Results for Setup A

(f) Clustering Results for Setup B

Fig. 1: Setup and Results

signed to efficiently cluster large datasets through a CF-Tree structure, which summarizes the data, followed by a clustering algorithm applied to the tree's leaf nodes [19]. Its efficiency hinges on three parameters: i) the $threshold$, ii) the $branchingfactor$, and iii) optionally, the desired number of clusters. The $threshold$ parameter dictates the maximum diameter of subclusters in the leaf nodes, influencing the clusters' compactness and detail. A lower $threshold$ leads to smaller clusters, while a higher threshold may merge clusters, reducing detail but possibly increasing noise sensitivity. The $branchingfactor$ limits the number of child nodes a tree node can have, affecting the CF Tree's size and complexity. This factor is crucial for managing memory usage and can impact the algorithm's speed and clustering accuracy.

IV. Results

This section describes the results of the 3D positioning experiment using the two setups described in Section III. In each experimental case, every clustering algorithm was executed using consistent parameters to ensure a fair comparison of their performance. For the K-Means algorithm: Setup A utilized $K = 5$, while Setup B used $K = 6$. DBSCAN parameters were uniformly set with an ε value of 0.35 and a $MinPts$ threshold of 30. Affinity Propagation was configured with a $damping$ factor of 0.5, and it internally optimized the $preference$ value to identify the most suitable number of clusters automatically. The proposed process begins with an initial estimation of clusters using Mean Shift clustering to understand the data distribution. The $preference$ value is then varied across a range derived from the data variance, indicating the spread of data and suggesting how closely points should be grouped. For each $preference$ value, the Affinity Propagation model is fitted, and the clustering quality is evaluated using the silhouette score, which assesses the compactness and separation of the clusters. The preference leading to the highest silhouette score, indicating optimal clustering, is selected. This optimized preference is used in the final model fitting to produce coherent and well-separated clusters. Similarly, BIRCH was allowed to optimize its parameters within specified ranges: the $threshold$ for clustering was tested across a spectrum from 0.1 to 1 (in increments of 0.1), and the branching factor varied from 20 to 100 (in increments of 10), facilitating the exploration of different hierarchical clustering structures.

Experiments in both cases were performed over a period of 30 seconds while capturing measurements every second. The results were averaged and are tabulated in Tables I and II, indicating the mean and standard deviation of the XYZ and 3D errors across all targets in each use case. No additional noise was introduced to account for environment variability, assuming static conditions around the targets. Table III showcases the comparison summary between all the clustering approaches for both setups: average 3D accuracy, clusters detected and execution times on a MacBook Pro deployed with a 2.3 GHz Quad-Core Intel Core i7 and 16GB of memory.

As indicated in Table I, for Setup A, the DBSCAN and K-Means methods demonstrated the most promising results, aver-

TABLE I: Multi-Object Clustering 3D Positioning (Setup A) - (* - no clusters were found)

Point	K-Means				DBSCAN				Affinity Propagation				BIRCH			
	XYZ Error(m)			3D Error(m)	XYZ Error(m)			3D Error(m)	XYZ Error(m)			3D Error(m)	XYZ Error(m)			3D Error(m)
	x	y	z		x	y	z		x	y	z		x	y	z	
A1	0.08	0.15	0.12	0.21	0.06	0.13	0.05	0.16	0.20	0.17	0.08	0.27	*	*	*	*
A2	0.12	0.20	0.10	0.26	0.12	0.14	0.14	0.23	0.18	0.06	0.15	0.24	0.10	0.20	0.09	0.24
A3	0.12	0.14	0.22	0.29	0.14	0.07	0.17	0.23	0.11	0.07	0.24	0.27	0.22	0.39	0.12	0.53
A4	0.15	0.03	0.17	0.22	0.19	0.01	0.22	0.29	0.27	0.02	0.27	0.39	*	*	*	*
A5	0.11	0.12	0.04	0.17	0.09	0.14	0.01	0.17	0.17	0.15	0.14	0.27	0.22	0.03	0.25	0.34
Average	***0.12***	***0.13***	***0.13***	***0.23***	***0.12***	***0.10***	***0.12***	***0.22***	***0.19***	***0.09***	***0.18***	***0.29***	***0.18***	***0.20***	***0.15***	***0.35***
St Dev	***0.02***	***0.06***	***0.07***	***0.04***	***0.05***	***0.06***	***0.08***	***0.05***	***0.06***	***0.06***	***0.08***	***0.06***	***0.07***	***0.18***	***0.09***	***0.11***

TABLE II: Multi-Object Clustering 3D Positioning (Setup B) - (* - no clusters were found)

Point	K-Means				DBSCAN				Affinity Propagation				BIRCH			
	XYZ Error(m)			3D Error(m)	XYZ Error(m)			3D Error(m)	XYZ Error(m)			3D Error(m)	XYZ Error(m)			3D Error(m)
	x	y	z		x	y	z		x	y	z		x	y	z	
B1	0.13	0.22	0.16	0.30	0.20	0.23	0.09	0.31	0.15	0.22	0.11	0.29	*	*	*	*
B2	0.25	0.19	0.12	0.34	*	*	*	*	0.22	0.18	0.08	0.30	0.29	0.21	0.14	0.38
B3	0.15	0.14	0.06	0.21	0.11	0.21	0.11	0.26	0.15	0.27	0.13	0.34	0.11	0.15	0.07	0.20
B4	0.15	0.12	0.08	0.21	*	*	*	*	0.25	0.14	0.09	0.30	*	*	*	*
B5	0.17	0.18	0.15	0.29	0.17	0.15	0.19	0.30	0.22	0.13	0.17	0.30	*	*	*	*
B6	0.06	0.03	0.18	0.20	0.14	0.11	0.14	0.23	0.19	0.17	0.03	0.26	0.20	0.30	0.11	0.38
Average	***0.15***	***0.15***	***0.13***	***0.25***	***0.15***	***0.17***	***0.13***	***0.27***	***0.20***	***0.19***	***0.10***	***0.29***	***0.20***	***0.22***	***0.11***	***0.32***
St Dev	***0.06***	***0.07***	***0.05***	***0.06***	***0.04***	***0.05***	***0.05***	***0.04***	***0.04***	***0.05***	***0.05***	***0.03***	***0.09***	***0.08***	***0.04***	***0.11***

TABLE III: Setup A and B Experimental Results Comparison

Clustering Approach	Setup A			Setup B		
	3D Accuracy (m)	Clusters Found	Execution Time (s)	3D Accuracy (m)	Clusters Found	Execution Time (s)
K-Means	0.23	5/5	0.0017	0.25	6/6	0.0022
DBSCAN	0.22	5/5	0.0018	0.27	4/6	0.0022
Affinity Propagation	0.29	7/5	1.25	0.29	8/6	2.35
BIRCH	0.35	3/5	1.04	0.32	3/6	1.59

aging $0.22m$ and $0.23m$ 3D positioning accuracy, respectively while both approaches managed to find the exact number of clusters with an impressive execution time of around $0.0018s$ compared to others. Affinity Propagation has achieved around $0.29m$ accuracy; however, for most of the performed tests, the algorithm identified more clusters than their actual value. Often it would output two clusters within one and had the slowest execution time of around $1.25s$. BIRCH had the poorest performance, identifying only 3 out of 5 clusters with an accuracy of $0.35m$ and a slow execution time of $1.04s$.

Results got slightly worse in Setup B (see Table II). The K-Means achieved a 3D positioning accuracy of around $0.25m$ while detecting all clusters. On the other hand, DBSCAN has failed to separate the two pairs of closely positioned targets, only identifying 4 clusters with an accuracy of around $0.27m$. This is also indicated in Figures 1e and 1f which show the detected clusters versus the actual (ground truth) object positions for the two setups using DBSCAN. The execution time for both K-Means and DBSCAN was still found to be as low as $0.0022s$. The Affinity Propagation approach has achieved a 3D accuracy of around $0.29m$; however, similarly to the Setup A experiment, it has failed to distinguish the exact number of clusters and, in most cases, has outputted on average eight instead of six clusters as well as doubled its execution time to around $2.35s$. BIRCH, similarly to Setup A, has only identified 3 clusters out of 6 with an average accuracy of around $0.32m$ and an execution time of around $1.59s$.

V. Discussion

Our experimental results underscore the suitability of various clustering techniques for precise 3D multi-target positioning using mmWave sensing. Among the evaluated methodologies, K-Means and DBSCAN clustering have emerged as notably promising solutions, although for different reasons. K-Means has consistently delivered the most compelling outcomes across the two experimental setups, successfully identifying all intended clusters. This achievement aligns with expectations, given the algorithmic design of K-Means, which necessitates a predefined input for the number of clusters (K). However, despite its overall success, K-Means exhibited limitations in certain instances, failing to distinguish all clusters accurately. While correctly predicting the number of clusters, it sometimes amalgamated two clusters into one or erroneously identified an outlier as a separate cluster. Nonetheless, K-Means demonstrated significant promise, achieving a 3D positioning accuracy of $0.23m$ in Setup A with 5 clusters and $0.25m$ in Setup B with 6 clusters. DBSCAN showcased commendable performance, particularly in Setup A, which identified all 5 clusters with a $0.22m$ accuracy. However, its performance faltered in Setup B, where it struggled to differentiate between 2 proximate targets, often merging them into a single cluster. This limitation is anticipated due to DBSCAN's inherent design, highlighting its ability to cluster without a predefined number of clusters, juxtaposed with its difficulty in separating closely situated clusters. Nevertheless, DBSCAN managed to identify 4 out of 6 clusters with a $0.27m$ accuracy in Setup B. Affinity Propagation presented as an intriguing alternative, identifying all clusters in both setups with a $0.29m$ accuracy. However, it overestimated the number of necessary clusters, which could pose complications in real-time operations. Additionally, its execution time, ranging between 1 and 2.5 seconds, is considered significant, marking a substantial drawback for real-time performance. BIRCH did not perform satisfactorily in either setup, failing to recognize all clusters and only identifying 3 clusters in both setups. It exhibited the lowest accuracy among the tested clustering approaches, with $0.35m$ in Setup A and $0.32m$ in Setup B while its execution time was also as high as 1-1.5 seconds, indicating its unsuitability for real-time applications.

Although prior studies (e.g., [7]) show that fusing mmWave and camera data can boost localization accuracy and prevent closely spaced targets from being merged into a single detection, privacy-sensitive scenarios may demand relying exclusively on mmWave sensing. Compared to the work reported in [9] that fuses only two FMCW radars and assesses a single density-based clusterer plus UKF in 2-D people-tracking scenarios—yielding $XY - RMSE \approx 0.25m$—our work deploys five IWR1843 radars positioned around the scene, captures laser-surveyed ground truth in full 3D, and systematically evaluates four distinct clustering families (K-Means, DBSCAN, Affinity Propagation, BIRCH) on both well-separated and 1 m-spaced targets. This denser sensor geometry and broader algorithmic sweep cuts end-to-end processing to $\approx 2\ ms$ while sustaining similar accuracy (0.22–0.25m).

VI. Conclusion and Future Work

In our study, we evaluated the use of mmWave radar technology for accurate 3D localization of multiple targets. We evaluated four clustering algorithms across different experimental setups to determine their effectiveness in real-world scenarios. Our findings indicate that K-Means and DBSCAN stand out for their accuracy and robustness in 3D positioning, with K-Means achieving cluster identification accuracies around $0.23m$ and $0.25m$ in different setups. DBSCAN showed similar accuracy in one setup but struggled with closely placed objects in another, revealing its limitations. Affinity Propagation and BIRCH, despite certain benefits, face challenges that may limit their applicability for real-time 3D positioning tasks. The comparative analysis performed highlighted the critical need for tailored clustering approaches that can adapt to the specific requirements of various positioning applications.

This research confirms the viability of mmWave radar for precise 3D indoor mutli-target localization and emphasizes the crucial role of appropriate clustering techniques to enhance positioning accuracy. It opens avenues for future work to improve these methods and investigate new algorithms by varying the number and size of objects, the number of sensors used, the range of cluster environments, etc. The experimental setup involves suspended objects in a controlled laboratory environment, which may not fully capture the complexity of real-world indoor scenarios, where obstacles, occlusions, and clutter can significantly impact sensor performance and clustering accuracy. Future work will incorporate more realistic targets—such as moving people or flying drones—and introduce dynamic environmental conditions to better reflect dynamic environmental changes.

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