

Evaluation of Elevation Angle Representation Methods for Clustered Detections in Multi-Beam Radar

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Abstract— In radar data processing systems, determining the representative value of a detection cluster is a crucial step following the clustering process. Most existing systems employ the centroid-based method to compute the cluster representative. However, field evaluations on operational multi-beam air-defence surveillance radars have revealed several limitations of this approach, particularly in estimating the elevation angle of clustered detections. This paper presents a comprehensive analysis and evaluation of multiple alternative solutions for determining the representative elevation angle of clusters in multi-beam radar systems. A three-step clustering-based framework is introduced, encompassing hit-level, plot-level, and group-level processing to improve the stability and accuracy of elevation estimation. A total of 32 method configurations are systematically examined using real-world data collected from a 3D air-defence surveillance radar. Experimental results demonstrate that the proposed method achieves up to 47% improvement in Root Mean Square Error (RMSE) and 45% enhancement in trajectory smoothness (Roughness) compared with the conventional centroid-based approach. The findings provide practical insights and an effective framework for enhancing elevation-angle representation in multi-beam radar data processing, thereby contributing to more accurate and reliable 3D target tracking.

Keywords— multi-beam radar, elevation angle estimation, cluster representation, radar signal processing, target detection, centroid method, air-defence surveillance radar

I. INTRODUCTION

Multi-beam radar (MBR) systems have become essential instruments in a wide range of applications, including air-surveillance, navigation, and meteorological monitoring, owing to their capability to detect and track targets across large volumes and under various weather conditions with high accuracy. MBR systems generate multiple beams in transmission to simultaneously scan different segments, which enhances the radar's overall coverage and detection probability [1-3].

In air-defence surveillance applications, one of the most critical tasks in the multi-beam radar data processing is the accurate estimation of the elevation angle of detected targets. Precise elevation determination is vital for reliable three-dimensional localization, target classification, and track

initiation [4]. However, environmental effects such as multipath propagation, side-lobe interference, and overlapping beam patterns often cause multiple detections to originate from the same physical target, producing what are commonly referred to as clustered detections in the elevation domain.

For reliable object detection and tracking, the first step after target detection is to identify and group measurement points that belong to the same physical object before performing higher-level association or tracking. Clustering algorithms therefore play a crucial role in enhancing the radar's ability to accurately determine target position and motion [5, 6]. Studying and applying clustering techniques in radar systems is particularly important under challenging conditions such as rain or cloud clutter, where object discrimination becomes more difficult. Popular clustering algorithms, including K-means, Mean Shift, OPTICS, Spectral Clustering, DBSCAN, and Gaussian Mixture Models, have been extensively investigated and applied in various radar and remote sensing systems [7-12].

A common characteristic among most existing clustering algorithms is the use of a centroid-based approach to determine a representative value for each cluster [13-15]. Although simple and computationally efficient, this approach often fails to yield optimal results when applied to multi-beam radar data. Field observations from operational multi-beam air-surveillance radars have shown several drawbacks, such as irregular elevation-angle fluctuations over time, inverted elevation trends compared to reference trajectories, and systematic overestimation of elevation angles. These effects can significantly degrade the accuracy of three-dimensional target representation and tracking performance.

To address these limitations, this paper presents a detailed analysis and evaluation of multiple solutions for determining the representative elevation angle of clustered detections in multi-beam radar systems. Using real-world data collected from a 3D air-defence surveillance radar, the proposed methods are evaluated against reference data and compared with the conventional centroid-based approach.

The main novelty and contributions of this paper are summarized as follows:

1. A three-step clustering-based framework is proposed for determining the representative elevation angle of detections in multi-beam radar systems, addressing the limitations of traditional centroid-based approaches.
2. Multiple selection and computation strategies are systematically combined, forming 32 possible configurations to comprehensively assess their impact on estimation performance.
3. Extensive experiments on real data collected from an operational 3D air-defence radar demonstrate that the proposed method significantly improves both accuracy and stability, achieving up to 47% RMSE reduction and 45% Roughness enhancement compared with the centroid-based method.

II. RADAR DATA AND CLUSTERING PROCESS

A. System overview

The data used in this study were collected from an air defence surveillance radar equipped with a multi-beam antenna array operating in the S-band. The input data to the clustering module consist of hits (detection points) obtained after the signal processing stage, which provides the reflected power and Doppler information at each resolution cell. Each hit contains information such as position (range, azimuth, elevation), timestamp, Doppler, received power, and beam index. Because the beam responses partially overlap, multiple detections can be generated for a single target, forming what is referred to as a cluster in the elevation domain.

B. Cluster formation

Cluster formation aims to group detections that originate from the same physical target. A cluster $C_k = \{h_1, h_2, \dots, h_m\}$ is defined as a set of m hits (detections) corresponding to one physical target observed in multiple beams. Each hit h_i is represented as $(r_i, \theta_i, \phi_i, t_i, F_{di}, P_i, B_i)$, where r_i is range, θ_i azimuth, ϕ_i elevation, t_i timestamp, F_{di} Doppler velocity, P_i received power, B_i beam index. The goal of the subsequent processing step is to determine a single representative elevation angle for each cluster.

Because individual hits are prone to false alarms and noise, spatial and temporal correlation techniques are applied to aggregate adjacent detections into a plot, which serves as an estimated target position within one radar scan. The group stage clusters plots that are spatially and temporally consistent, forming potential target hypotheses and improving reliability under cluttered or multi-target scenarios. Finally, the track stage associates a sequence of plots or groups across successive scans to establish a continuous target trajectory (Figure 1).

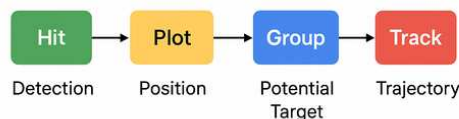


Figure 1. Overall processing flow in the clustering module

III. CLUSTER REPRESENTATION APPROACH

A clustering-based approach is proposed to determine the representative elevation angle for each Group (cluster) in the multi-beam radar data. The procedure consists of three main steps, as described below.

Step 1 – Determining the Representative Elevation of a Plot from Hits

In the first step, each Plot is generated from multiple Hits. Two alternative methods are considered for computing the representative elevation angle of a Plot:

- A₁: The elevation angle is taken from the Hit with the maximum received power.
- A₂: The elevation angle is computed as the average of the elevation angles of all Hits belonging to the Plot.

Step 2 – Selecting the “Good” Plot Set within a Group

From all Plots within a Group, a subset of “good” Plots is selected for further processing. Eight different selection strategies are proposed:

- B₁: Cluster the Plots according to their Doppler values, then select the cluster with the largest number of Plots.
- B₂: Select the beam that contains the Plot with the maximum power.
- B₃: Cluster the Plots according to their Doppler values, then select the cluster containing the Plot with the maximum power.
- B₄: Select the beam that contains the largest number of Plots.
- B₅: Select the beam that appears consistently across the N most recent radar scans.
- B₆: Select the beam with the highest total Plot power.
- B₇: Cluster the Plots according to their Doppler values, then select the cluster with the highest total Plot power.
- B₈: Select all Plots in the Group.

Step 3 – Determining the Representative Elevation of the Group

Finally, the representative elevation angle for the Group is computed using the selected “good” Plot set. Three computation methods are proposed:

- C₁: Use the elevation angle of the Plot with the maximum power.
- C₂: Compute a power-weighted centroid of elevation angles, where the representative value is obtained as the sum of (power × elevation) divided by the total power of all selected Plots.

By combining the alternative methods proposed for each step, a total of 32 configurations for computing the representative elevation angle are formed (as summarized in Table 1).

TABLE 1. METHODS FOR COMPUTING THE REPRESENTATIVE ELEVATION ANGLE

No.	Method	No.	Method	No.	Method
1	A ₁ B ₁ C ₁	12	A ₁ B ₆ C ₁	23	A ₂ B ₄ C ₁
2	A ₁ B ₁ C ₂	13	A ₁ B ₇ C ₁	24	A ₂ B ₄ C ₂
3	A ₁ B ₂ C ₁	14	A ₁ B ₇ C ₂	25	A ₂ B ₅ C ₁
4	A ₁ B ₂ C ₂	15	A ₁ B ₈ C ₁	26	A ₂ B ₅ C ₂
5	A ₁ B ₃ C ₁	16	A ₁ B ₈ C ₂	27	A ₂ B ₆ C ₁
6	A ₁ B ₃ C ₂	17	A ₂ B ₁ C ₁	28	A ₂ B ₆ C ₂
7	A ₁ B ₄ C ₁	18	A ₂ B ₁ C ₂	29	A ₂ B ₇ C ₁
8	A ₁ B ₄ C ₂	19	A ₂ B ₂ C ₁	30	A ₂ B ₇ C ₂
9	A ₁ B ₅ C ₁	20	A ₂ B ₂ C ₂	31	A ₂ B ₈ C ₁
10	A ₁ B ₅ C ₂	21	A ₂ B ₃ C ₁	32	A ₂ B ₈ C ₂
11	A ₁ B ₆ C ₁	22	A ₂ B ₃ C ₂		

To compare and evaluate the effectiveness of the proposed solutions, two performance metrics are employed.

The first metric is the Roughness measure, which quantifies the stability of the estimated elevation trajectory. A good trajectory is expected to be smooth and free from abrupt directional changes. Therefore, a smaller Roughness value indicates a more stable trajectory. The Roughness is computed as:

$$Roughness = \frac{1}{N} \sum_{i=1}^{N-1} (d_i - \bar{d})^2 \quad (1)$$

where d_i represents the deviation of the elevation value between consecutive points, defined as the difference between the following and preceding points.

$$d_i = |X_n - X_{n-1}| \quad (n = 2, \dots, N; i = 1, \dots, N)$$

$$\bar{d} = \text{mean}(d_i)$$

The second evaluation metric is the Root Mean Square Error (RMSE). After calculating the representative elevation angle of each cluster (Group) for every radar scan, the RMSE is computed using reference data (ground-truth) to quantify the estimation accuracy. The method that yields the smallest RMSE is considered the most accurate in determining the representative elevation angle. The RMSE is calculated as:

$$RMSE = \sqrt{\sum_{i=1}^N \frac{(\hat{x}_i - x_i)^2}{N}} \quad (2)$$

where $\hat{x}_i$ denotes the estimated representative elevation angle (i.e., the estimated target elevation at scan i), and x_i is the true elevation angle of the target.

IV. RESULT AND DISCUSSION

Civil aviation flight trajectories collected from the 3D air-defence surveillance radar are utilized to evaluate the effectiveness of the proposed methods. These real-world radar tracks provide reliable reference data for assessing the performance of different representative elevation estimation strategies under realistic operating conditions.

Each method described in Section III is applied to the same dataset, and the resulting elevation trajectories are analyzed using the two evaluation metrics introduced in Section IV—Roughness and Root Mean Square Error (RMSE). The comparison allows a quantitative assessment of trajectory stability and estimation accuracy across all 32 solution configurations and the traditional centroid method.

Figure 2 provides an overview of the representative elevation angle values obtained across radar scans for three different target trajectories when applying the proposed solution configurations. The best-performing configuration is determined based on the smallest values of both RMSE and Roughness values. Table 2 summarizes the corresponding Roughness and RMSE values for the best, worst, and traditional centroid-based methods.

The best solution, labeled as $A_2B_7C_2$, follows the sequence: The elevation angle is computed as the average of the elevation angles of all Hits belonging to the Plot; cluster the Plots according to their Doppler values, then select the cluster with the largest number of Plots; finally, compute a power-weighted centroid of elevation angles, where the representative value is obtained as the sum of (power $\times$ elevation) divided by the total power of all selected Plots. In contrast, the worst solution, labeled as $A_1B_4C_2$, performs the following steps: The elevation angle is taken from the Hit with the maximum received power; select the beam that contains the largest number of Plots; compute a power-weighted centroid of elevation angles using the same formulation as above.

TABLE 2. METHODS FOR COMPUTING THE REPRESENTATIVE ELEVATION ANGLE

Method		Best method (A ₂ B ₇ C ₂)	Centroid method	Worst method (A ₁ B ₄ C ₂)
RMSE (deg)	ID 1001	0.9	1.2	2.2
	ID 1002	1.1	1.3	1.8
	ID 1003	0.7	1.1	1.6
	Mean	0.9	1.2	1.9
Roughness	ID 1001	1	1.5	2.2
	ID 1002	1.25	1.4	1.75
	ID 1003	0.75	1.1	1.6
	Mean	1	1.3	1.8

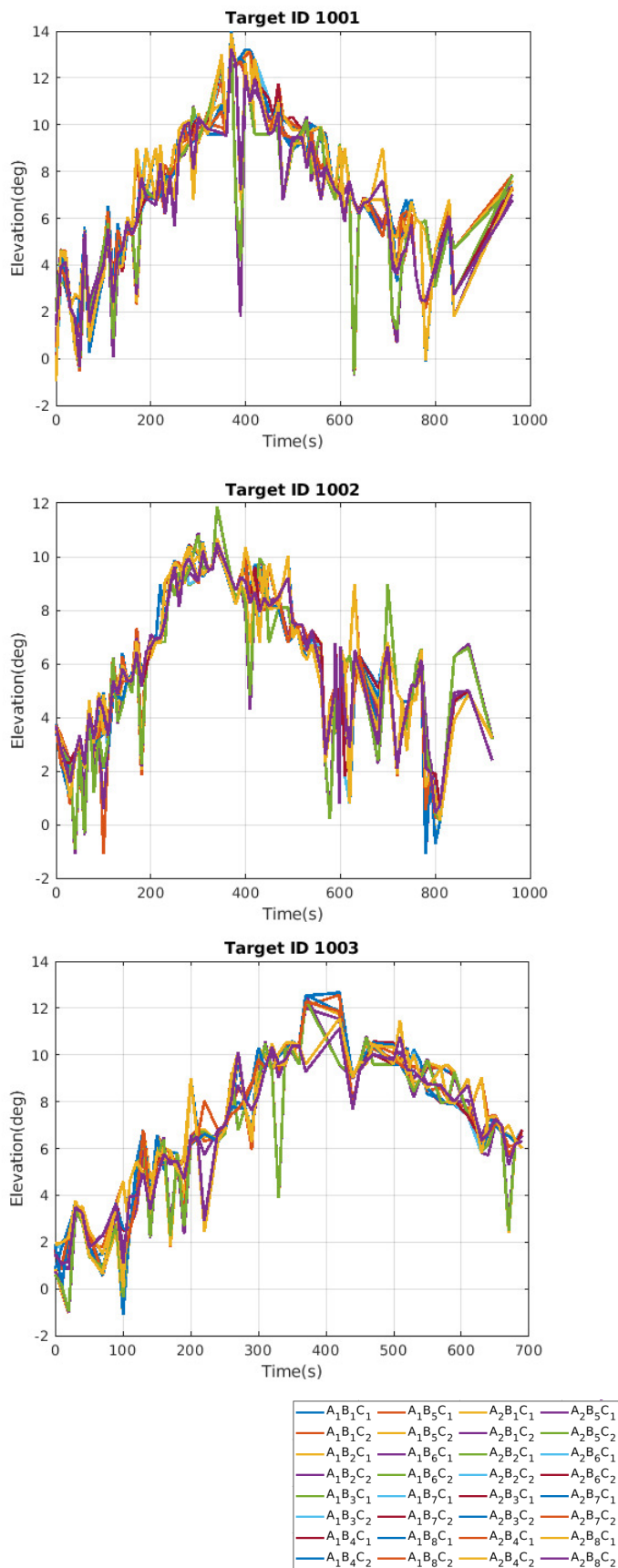


Figure 2. Representative elevation angles obtained by all evaluated methods

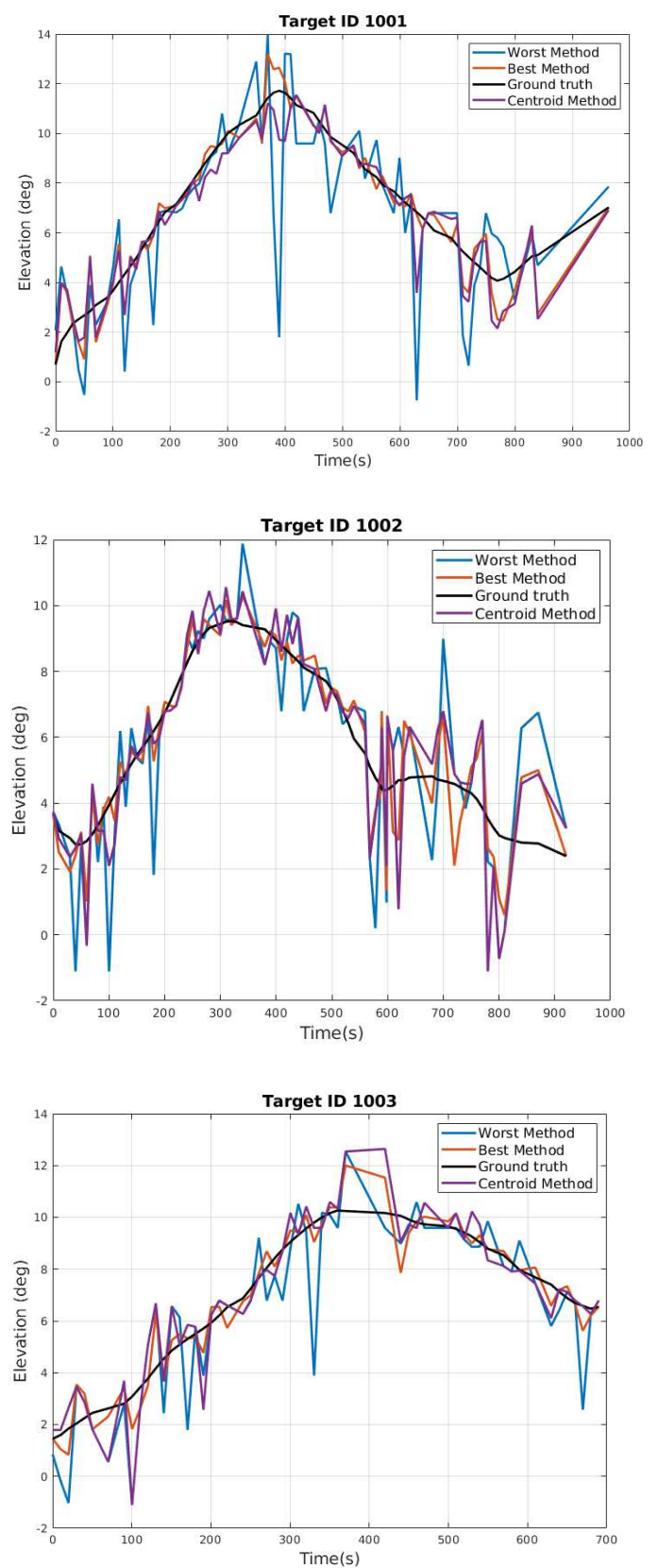


Figure 3. Comparison of Elevation representation for best, worst and centroid methods

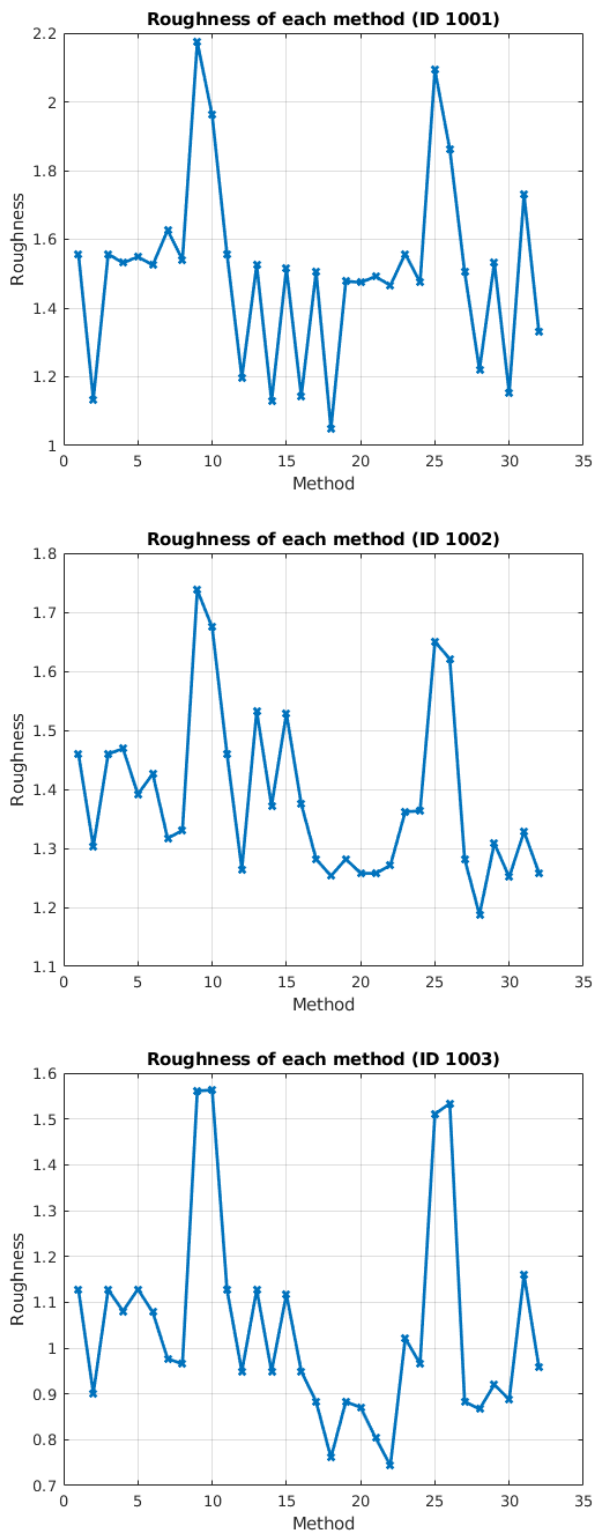


Figure 4. Roughness values of all evaluated methods

Figure 3 illustrates the representative elevation angle trajectories obtained using the best, worst, and centroid-based methods, compared with the reference data. As observed, the best configuration produces elevation estimates that closely match the true target elevation, while the worst configuration

exhibits large deviations and unstable fluctuations over time. Figure 4 illustrates the Roughness values obtained from all evaluated methods. It can be observed that most configurations exhibit significant differences in trajectory smoothness, reflecting the influence of how representative elevation angles are computed.

Table 2 presents the quantitative comparison of RMSE and Roughness values among the three configurations. The proposed best method achieves an RMSE improvement of approximately 47% compared with the worst configuration and 27% improvement over the traditional centroid method. Similarly, the Roughness metric of the best configuration shows an enhancement of about 45% relative to the worst case and 28% compared with the centroid-based approach. These results confirm that the proposed method significantly improves both the accuracy and stability of the estimated elevation angle.

V. CONCLUSION

This paper presented a systematic analysis and evaluation of multiple clustering-based approaches for determining the representative elevation angle of target detections in multi-beam radar systems. A novel three-step framework was proposed, consisting of (1) hit-to-plot elevation computation, (2) selection of reliable plots within each group, and (3) final estimation of the group-level representative elevation. By combining multiple alternatives at each stage, 32 method configurations were generated and evaluated using real-world data collected from an operational 3D air-defence radar. Two objective performance metrics—Root Mean Square Error (RMSE) and Roughness—were employed to assess both estimation accuracy and trajectory stability. Experimental results demonstrated that the best-performing configuration (A2B1C2) significantly outperformed the conventional centroid-based method, achieving up to 47% improvement in RMSE and 45% enhancement in trajectory smoothness. These findings confirm that careful selection of representative parameters at both the hit and plot levels can substantially enhance the reliability of elevation estimation in clustered detections.

The proposed framework not only improves target representation accuracy in existing multi-beam radar systems but also provides a foundation for further research on adaptive and learning-based cluster representation methods. Future work will focus on integrating machine learning techniques to dynamically select optimal configurations based on environmental and target characteristics, thereby enhancing system robustness under complex operational conditions.

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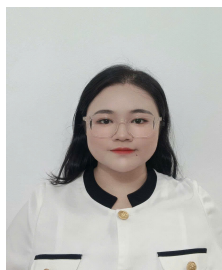
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