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Radar group target recognition based on HRRPs and weighted mean shift clustering

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Abstract: When range high-resolution radar is applied to target recognition, it is quite possible for the high-resolution range profiles (HRRPs) of group targets in a beam to overlap, which reduces the target recognition performance of the radar. In this paper, we propose a group target recognition method based on a weighted mean shift (weighted-MS) clustering method. During the training phase, subtarget features are extracted based on the template database, which is established through simulation or data acquisition, and the features are fed to the support vector machine (SVM) classifier to obtain the classifier parameters. In the test phase, the weighted-MS algorithm is exploited to extract the HRRP of each subtarget. Then, the features of the subtarget HRRP are extracted and used as input in the SVM classifier to be recognized. Compared to the traditional group target recognition method, the proposed method has the advantages of requiring only a small amount of computation, setting parameters automatically, and having no requirement for target motion. The experimental results based on the measured data show that the method proposed in this paper has better recognition performance and is more robust against noise than other recognition methods.

Keywords: clustering, group target recognition, high resolution range profile (HRRP), mean shift (MS).

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1. Introduction

In recent years, radar target classification and recognition has become an important research direction in the military field. The high-resolution range profile (HRRP) of radar targets contains a wealth of target information, such as structure, strength, shape and so on [1−4]. Compared with two-dimensional image, such as synthetic aperture radar (SAR) or inverse synthetic aperture radar (ISAR), HRRPs are easier to obtain and require less computation. Therefore, radar automatic target recognition (RATR) based on HRRPs has attracted attention of many researchers [5,6].

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To enable a convenient description, we define multiple targets moving in a beam as group targets and the individual targets among them as subtargets. In the group target environment, HRRPs of the subtargets will be close to or even overlap with each other due to their close radial distances. In this case, the overlapping HRRPs from different subtargets will be misjudged as coming from a single target, resulting in a lower recognition rate. Hence, it is necessary to study radar group target recognition based on HRRP in real applications.

The main idea of group target recognition is to separate the subtarget echoes first and then recognize each subtarget echo separately. The key is the subtarget segmentation algorithm, which can be classified into four categories.

The first method uses ISAR for target echo segmentation [7–9]. In [7], a well-focused ISAR image of the group targets was obtained and extracted via the modified CLEAN technique, and then each subtarget could be segmented and extracted based on the clustering number estimation and K-means clustering algorithm. However, this method is restricted by ISAR imaging condition, which is not sufficient in many applications. The second method is for group target echo segmentation by exploiting the fact that subtargets with different velocities have different time-frequency curves [10]. This method does not apply to the situation in which the subtargets have approximately equal speeds. The third method exploits the statistical model [11–16] to estimate parameters of each subtarget. For example, Blair et al. estimated angles of subtargets using the instantaneous matching moment method [11], and Wang et al. estimated angles of subtargets using the maximum likelihood estimation model [12,13]. In [14] and [15], the angle information of two subtargets was estimated by using the super-resolution algorithms based on the four-channel monopulse radar. In [16], the parameters of up to five targets, including distance azimuth angle and elevation angle, were estimated simultaneously by using the minimum description length criterion and the maximum likelihood estimation. These methods can extract the angle and position information of each subtarget, but cannot obtain HRRP of each subtarget which will be used for target recognition. The fourth method uses independent component analysis (ICA) to segment group target echoes in the time domain [17]. This method is suitable for the situation in which the echoes of group targets are separated. When group target echoes overlap, the performance will deteriorate greatly.

There are two main ideas in the current research: one is to use ISAR images to distinguish group targets, whose application is limited by imaging conditions; the other is to use the parameter estimation method, which is no longer effective when targets overlap in azimuth. In this paper, we propose a group target recognition method based on the weighted mean shift (weighted-MS) clustering algorithm. The main principle of this paper is as follows: the subtarget HRRPs are separated by weighted-MS clustering in the range-azimuth distance plane, and then each subtarget is recognized based on HRRP.

The method first utilizes the monopulse angular measurement results of the strong range cells (SRCs) and then uses the weighted-MS clustering algorithm to segment the HRRP on the radial distance-azimuth distance plane of the SRCs. Finally, the features of each subtarget HRRP are extracted and used for target recognition.

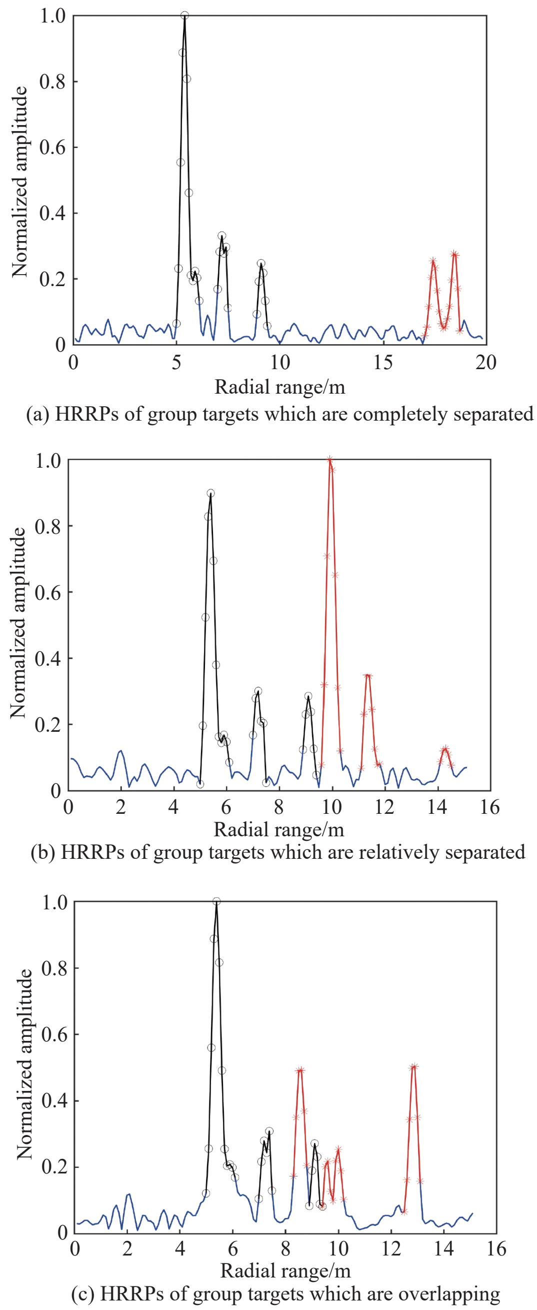
The proposed method has three main advantages: first, the weighted-MS clustering algorithm is proposed to solve the problem of group target resolution for the first time, and the algorithm only needs to set a parameter of bandwidth. Second, since the amplitude of the target echo is larger than the noise echo and cluster samples are weighted by their amplitude, the proposed method is more robust to noise. Finally, the initial value of the cluster is designed according to the maximum amplitude criterion, which improves the iterative efficiency and reduces the amount of calculation required.

The paper is organized as follows. Section 2 analyzes the range-azimuth angle plane of the group target HRRP. Section 3 introduces the group target recognition method based on the weighted-MS clustering algorithm in detail. Section 4 presents the experimental results and Section 5 presents the conclusions.

2. Analysis of the range-azimuth angle distribution of the SRCs

In this section, taking the measured data of two targets as an example, we analyze the property of group target HRRP.

There are three typical positional relationships of the group target HRRPs. In the first case, the HRRP of each subtarget is completely separated, as shown in Fig. 1(a), so clustering in the distance dimension can be used to segment the subtarget HRRP. Traditional HRRP targets are usually based on this assumption. In the second case, multi-target HRRPs are close to each other, as shown in Fig. 1(b). The HRRPs are judged to contain group targets using the estimated target size information, but it is difficult to extract each subtarget HRRP, which increases the difficulty of target recognition. The third case is that the subtarget HRRPs partially or completely overlap, as shown in Fig. 1(c).



(a) HRRPs of group targets which are completely separated

(b) HRRPs of group targets which are relatively separated

(c) HRRPs of group targets which are overlapping

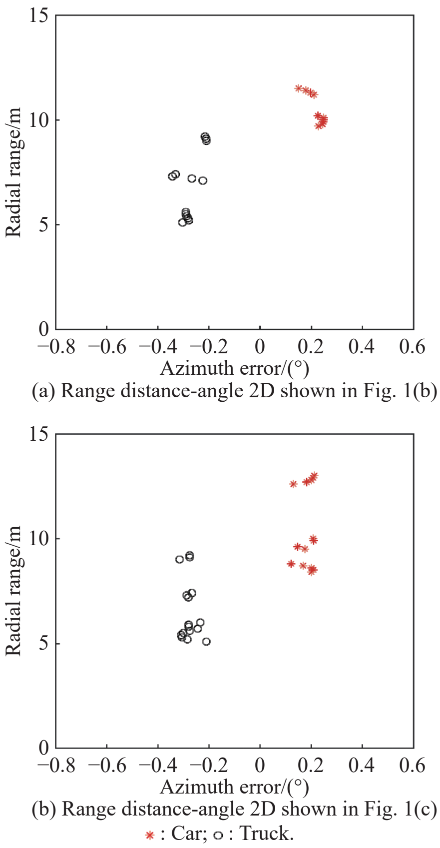
: Noise; : Car; : Truck.

Fig. 1 Three typical position relationships of group target HRRPs

When the coincidence degree of the group targets is high, it is impossible to judge from the target size estimated by the distance dimension whether the size results from a single target or a group of targets.

The range distance and angle information of SRCs are used for HRRP extraction and target recognition in this paper. Although the range distance of group targets in a radar beam may be small or even coincident, leading to overlapping HRRPs in the time domain, their space angles may be different relative to the radar, which is useful to segment the HRRPs of group targets. For air-to-ground airborne radar, the pitch angles of group targets are very small, so we use the radial distances and azimuth angles to achieve subtarget HRRPs segmentation in this paper.

The two-dimensional plane of the "radial distance-azimuth error" of the SRCs extracted from the group target HRRP is shown in Fig. 2, in which the categories of the subtarget HRRP are marked manually as follows. First, the HRRP of the truck is collected at the designated position. Then, the car is driven into the test scene, and the group target's HRRP is collected. Because the HRRP of the truck is acquired in advance, the part in the group target's HRRP corresponding to it is easy to determine, and the other SRCs are denoted as "car".



(a) Range distance-angle 2D shown in Fig. 1(b)

(b) Range distance-angle 2D shown in Fig. 1(c)
*: Car; o: Truck.

Fig. 2 Radial range and azimuth angle of the SRCs of group target HRRPs

It is clear from Fig. 2 that most of the SRCs from the same subtarget are gathered together, so it is possible to separate the SRCs of group targets along the range or azimuth angle dimension.

Based on the range distance-angle 2D information, the method proposed in this paper adopts a new clustering algorithm to separate the SRCs of each subtarget. In this way, the features of each subtarget HRRP are extracted and used for target recognition.

3. Group target recognition method based on the weighted-MS clustering algorithm

The proposed method is divided into two steps: training and classification, as shown in Fig. 3. In the training phase, each subtarget echo library is first established through simulation or data acquisition. Second, subtarget features consisting of moment, distance from the maximum peak to edge, the size, the power ratio of the maximum peak to the secondary peak are extracted based on the template database. Third, the features are fed to the support vector machine (SVM) classifier to obtain the penalty factor and the support vectors of the SVM classifier.

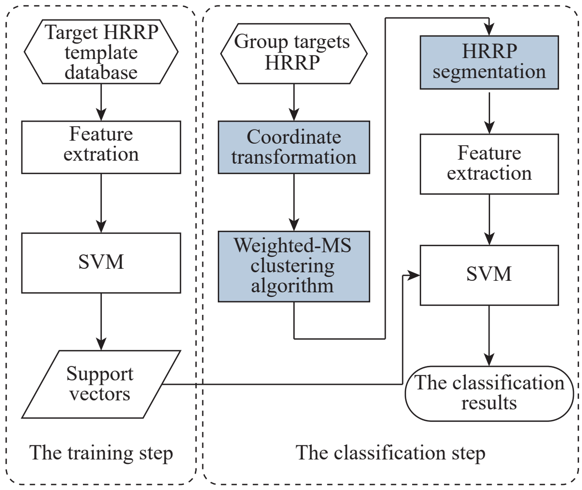


Fig. 3 Flowchart of the proposed group target recognition method

In the classification phase, the amplitudes and the corresponding azimuth angles of the HRRP are first obtained by the monopulse radar. Second, the radial distance-azimuth distance plane of the SRCs can be obtained by threshold detection and coordinate transformation. Then, the weighted-MS algorithm is exploited to cluster the SRCs from each subtarget in the radial distance-azimuth distance plane. Next, the HRRP of each subtarget is extracted based on the results of the last step. Finally, the features are extracted from the HRRP and classified by using the SVM classifier.

The basic principle of the mean shift (MS) clustering algorithm is to search the region with the densest sample points in the feature space through repeated iteration, and these regions represent clusters [18,19]. On the basis of MS, weighted-MS takes the scattering point amplitude as the weight of the sample point, and clustering in the range-azimuth distance plane. Each cluster represents a subtarget, and group targets segmentation is completed.

3.1 Traditional MS algorithm

Let $\{\boldsymbol{x}_i\}_{i=1,2,\cdots,n}$ be an arbitrary set of n points in d-dimensional Euclidean space $\mathbf{R}^d$. The multivariate kernel density estimate obtained with kernel $K(\boldsymbol{x})$ and bandwidth h, computed at point $\boldsymbol{x}$, is given by the following well-known expression:

$$\hat{f}(\boldsymbol{x}) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right). \tag{1}$$

We are interested only in a special class of radically symmetric kernels satisfying

$$K(\boldsymbol{x}) = c_k k(\|\boldsymbol{x}\|^2), \tag{2}$$

in which it suffices to define the function $k(\boldsymbol{x})$, called the profile of the kernel, only for $\boldsymbol{x} \geqslant 0$. The normalized constant c_k that makes $K(\boldsymbol{x})$ integrate to one, is assumed to be strictly positive; $\|\boldsymbol{x}\|$ is the norm of $\boldsymbol{x}$.

Employing the profile notation, (1) can be rewritten as

$$\hat{f}(\boldsymbol{x}) = \frac{c_k}{nh}\sum_{i=1}^{n} k\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right). \tag{3}$$

The density gradient estimator is obtained as the gradient of the density estimators and can be calculated as

$$\hat{\nabla} f(\boldsymbol{x}) = \nabla \hat{f}(\boldsymbol{x}) = \frac{2c_k}{nh}\sum_{i=1}^{n} (\boldsymbol{x}-\boldsymbol{x}_i)k'\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right). \tag{4}$$

Define the function $g(\boldsymbol{x}) = -k'(\boldsymbol{x})$. Then (4) can be rewritten as

$$\begin{aligned}\hat{\nabla} f(\boldsymbol{x}) &= \frac{2c_k}{nh}\sum_{i=1}^{n}(\boldsymbol{x}_i-\boldsymbol{x})g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right) = \frac{2c_k}{nh}\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)\left[\frac{\sum_{i=1}^{n}(\boldsymbol{x}_i-\boldsymbol{x})g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}\right] = \\ &\frac{2c_k}{nh}\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)\left[\frac{\sum_{i=1}^{n}\boldsymbol{x}_i g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right) - \sum_{i=1}^{n}\boldsymbol{x} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}\right] = \\ &\frac{2c_k}{nh}\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)\left[\frac{\sum_{i=1}^{n}\boldsymbol{x}_i g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right) - \boldsymbol{x}\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}\right] = \frac{2c_k}{nh}\left[\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)\right]\left[\frac{\sum_{i=1}^{n}\boldsymbol{x}_i g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)} - \boldsymbol{x}\right].\end{aligned} \tag{5}$$

The second bracket in (5) is the MS, and the sample mean at x is defined as

$$m(\boldsymbol{x}) = \frac{\sum_{i=1}^{n}\boldsymbol{x}_i g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right\|^2\right)}. \tag{6}$$

3.2 Weighted-MS clustering algorithm

The distance and angle information of each scattering point can be directly measured by the radar. However, the radial distance and azimuth angle have different scales, which will substantially affect the result of clustering. Therefore, when the target is far from the radar, the azimuth angle can be converted to the azimuth distance by using

$$R_{\text{crossrange}} \approx R\cdot\theta\cdot\pi/180 \tag{7}$$

where R is the radial distance relative to the radar, and θ is the azimuth angle of the SRCs measured by the radar.

Define a set $\boldsymbol{W}:\{\boldsymbol{A}_i,\boldsymbol{R}_i,\boldsymbol{C}_i\}$ ($i=1,2,\cdots,m$), where m is the number of SRCs of the group target HRRP, and $\boldsymbol{A}_i$, $\boldsymbol{R}_i$ and $\boldsymbol{C}_i$ represent the amplitude, radial distance, and azimuth distance of the ith SRC, respectively. The sample in the azimuth distance-radial distance plane is denoted as $\boldsymbol{x}_i^1 = (\boldsymbol{R}_i,\boldsymbol{C}_i)$ $(i=1,2,\cdots,m)$.

When a nonnegative weight $w(\boldsymbol{x}_i^1)$ is associated with each sample $\boldsymbol{x}_i^1$, the MS is still convergent [15]. The sample mean at $\boldsymbol{x}^1$ can be rewritten as

$$m(x^1) = \frac{\sum_{i=1}^{n} w(\boldsymbol{x}_i^1) g\left(\left\|\frac{\boldsymbol{x}^1-\boldsymbol{x}_i^1}{h}\right\|^2\right)\boldsymbol{x}_i^1}{\sum_{i=1}^{n} w(\boldsymbol{x}_i^1) g\left(\left\|\frac{\boldsymbol{x}^1-\boldsymbol{x}_i^1}{h}\right\|^2\right)}. \tag{8}$$

When a flat kernel function is adopted, the sample mean can be calculated as

$$m(\boldsymbol{x}^1)=\frac{\sum_{i=1}^{n} w(\boldsymbol{x}_i^1)\boldsymbol{x}_i^1}{\sum_{i=1}^{n} w(\boldsymbol{x}_i^1)}. \tag{9}$$

The weights $w(\boldsymbol{x}_i^1)$ can be normalized so that $\sum_{i=1}^{n} w(\boldsymbol{x}_i^1)=1$. The new sample mean can be calculated as

$$m(\boldsymbol{x}^1)=\sum_{i=1}^{n} w(\boldsymbol{x}_i^1)\boldsymbol{x}_i^1. \tag{10}$$

In this paper, the MS algorithm is improved in two ways.

First, the traditional MS algorithm randomly selects a sample point as the initial value, which causes low iteration efficiency. This paper proposes a new initial value selection method: the sample point corresponding to the maximum SRC is selected as the initial value in every iteration. The initial value is defined as $\boldsymbol{u}_0$, and the calculation method is given by

$$\boldsymbol{u}_0=\boldsymbol{x}_{\hat{i}}^1,\ \hat{i}=\arg\max_{i\in\{1,2,\cdots,n\}}(\boldsymbol{A}_i). \tag{11}$$

Second, in order to improve the anti-noise performance of the algorithm, a new weight design method is proposed in this paper that takes the amplitude of the SRCs as the weight of samples. The weight of samples can be calculated as

$$w(\boldsymbol{x}_i^1)=\frac{\boldsymbol{A}_i}{\sum_{j\in\{1,2,\cdots,n\}}\boldsymbol{A}_j}. \tag{12}$$

The amplitude of the target echo is generally larger than the noise echo. If the amplitude is taken as the sample weight in the MS clustering algorithm, the MS clustering algorithm will iterate to the target sample direction, which reduces the influence of noise on the clustering result.

According to (10) and (12), the new sample mean can be calculated as

$$m(\boldsymbol{x}^1)=\frac{\sum_{i\in\{1,2,\cdots,n\}}\boldsymbol{A}_i\boldsymbol{x}_i^1}{\sum_{j\in\{1,2,\cdots,n\}}\boldsymbol{A}_j}. \tag{13}$$

The weighted-MS clustering algorithm based on the amplitudes of the SRCs can be summarized as Algorithm 1.

Algorithm 1 Weighted-MS clustering algorithm based on SRC amplitude

Input Amplitude, radial distance, and azimuth angle of SRCs of group targets; bandwidth h; convergence threshold σ.

(i) Transform the azimuth error into the azimuth distance using (7), and obtain the SRC parameter set $\boldsymbol{W}$ containing the amplitude, radial distance, and azimuth distance.

(ii) Initialize the cluster number $k=1$.

(iii) **While** $\boldsymbol{W}\neq\varnothing$

Calculate the initial value $\boldsymbol{u}_0$ with $\boldsymbol{x}_i^1\in\boldsymbol{W}$ by using (11);

$j=0$;

Repeat

A circle is formed with centre $\boldsymbol{u}_j$ and a radius of h. Here, $\boldsymbol{u}_j$, h and the samples in the circle are defined as the set $\boldsymbol{Q}$;

Update the sample mean $m(\boldsymbol{x}^1)$ with $\boldsymbol{x}_i^1\in(\boldsymbol{W}\cap\boldsymbol{Q})$ using (13);

$\boldsymbol{u}_j=m(\boldsymbol{x}^1)$;

$j=j+1$;

Until the change of sample mean is less than σ.

$\boldsymbol{t}_k=\boldsymbol{Q}$;

Use $\boldsymbol{W}=\boldsymbol{W}\cap(\text{not }\boldsymbol{c}_k)$ to upgrade the set $\boldsymbol{W}$;

$k=k+1$;

End while

Output Number of clusters k, clustering results $\boldsymbol{t}_1,\boldsymbol{t}_2,\cdots,\boldsymbol{t}_k$.

3.3 Summary of the group target recognition steps

The group target recognition method based on the weighted-MS algorithm can be summarized as follows:

Step 1 According to Algorithm 1, the clustering results are obtained.

Step 2 The HRRP of each subtarget is extracted according to the clustering results.

Step 3 The features corresponding to size, moment, distance between the maximum peak and the target edge, and the amplitude ratio of the peak with the maximum amplitude to the peak with the second largest amplitude are extracted from the HRRP of each subtarget.

Step 4 The target features are classified using the SVM classifier generated in the training stage.

4. Experimental results

We validate the proposed group target recognition method using the real group target HRRP data, which are collected from two targets, i.e., the truck and the car. The characteristics of the two targets are shown in Table 1. The transmitted signal is in the range of Ku band, and the distance between the radar and the stationary truck is 600 m. The radar transmitted signal form is the chirp waveform with a signal bandwidth of 1 GHz and the time width is 1 μs. The training samples of the two targets are collected under high signal-to-noise ratio (SNR) conditions, and the azimuth angle is traversed from 0° to 360°. The test data of group targets are obtained from the scenario shown in Fig. 4, where the truck target is stationary. In the azimuth dimension, the azimuth distance of the two targets is approximately 10 m, which is 1/4 of the beam width. In the radial distance dimension, the car moves slowly in a straight line until it stops 5 m behind the truck. The SNR of the truck is 32.06 dB, and the SNR of the car is 25.76 dB.

Table 1 Information on training data and test data

Target type		Sample size	Length/m	Width/m
Training data	Truck	4500	6.8	2.7
	Car	4500	4.8	1.9
Test data	Truck+Car	520	—	—

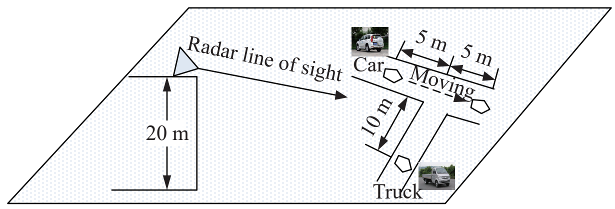


Fig. 4 Top view of radar-target geometry

First, we provide the comparison of clustering results as shown in Fig. 5 by using the weighted-MS clustering algorithm and the MS clustering algorithm. It can be seen that the weighted-MS clustering algorithm can effectively cluster the SRCs of group targets and extract the HRRP of each target. In this paper, all objects outside the library (including noise) are labeled as noise.

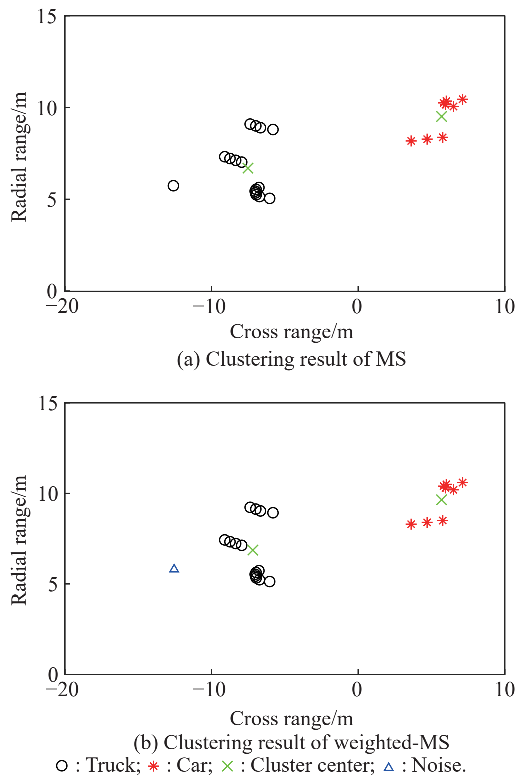


Fig. 5 Comparison of clustering results of test data

Second, to quantitatively evaluate the performance of the proposed algorithm, we compare the proposed method with several state-of-the-art group target recognition algorithms. All the five methods (weighted-MS, MS, density peaks (DP) [20,21], density-based spatial clustering of applications with noise (DBSCAN) [22,23] and K-means) perform group target segmentation on the radial distance-azimuth distance dimension using clustering algorithms. The five methods all adopt the cell average constant false alarm rate (CA-CFAR) detection algorithm as preprocessing, with protection unit of 50, reference unit of 100 and threshold multiplier of 3. In the weighted-MS method, we take the bandwidth to be 5. In the traditional MS method, we set the kernel function to be a uniform kernel and take the bandwidth to be 5. The DBSCAN algorithm involves two parameters, bandwidth and minimum number of adjacent samples, which are learned from the training data [24]. In the K-means method, we set the number of clusters to 2 and use the K-means++ algorithm to optimize the initial value selection [25]. All of the compared group target recognition algorithms use the same feature extraction method based on the HRRP and employ the SVM [26,27] classifier to complete the classification.

The recognition performances of the proposed method and the competing methods are presented in Fig. 6 under various SNRs. By means of further contamination with independent additive white Gaussian noise, the SNR value of the group target's HRRP varies in 1 dB decrements. It is apparent that the proposed method outperforms the other three group target recognition methods. With the decrease in SNR, the recognition rate decreases more slowly than that of the other four methods. At an SNR of 15 dB, the method proposed in this paper still has a recognition rate up to 95%, while that of the other methods involved in the comparison are less than 90.84%. The main reason is that the method proposed in this paper takes the SRC amplitude as the weight, and the SRC amplitude of the target is much larger than that of the noise scattering point. Therefore, the proposed method has better noise robustness.

However, this method has a constraint that the azimuth distance of group targets should be smaller than the product of target distance and monopulse angular measurement accuracy.

Thirdly, we further verify the performance of the proposed algorithm by using the measured data with a group target number of 4. All the four targets are in the forward direction of the radar and in the same beam. The recognition performances of the proposed method and the competing methods under various SNRs are presented in Fig. 7. When SNR is greater than 18 dB, there is little difference in the average recognition rate of these methods because of the small echo overlap of four targets. With the decrease of SNR, the proposed method shows better performance.

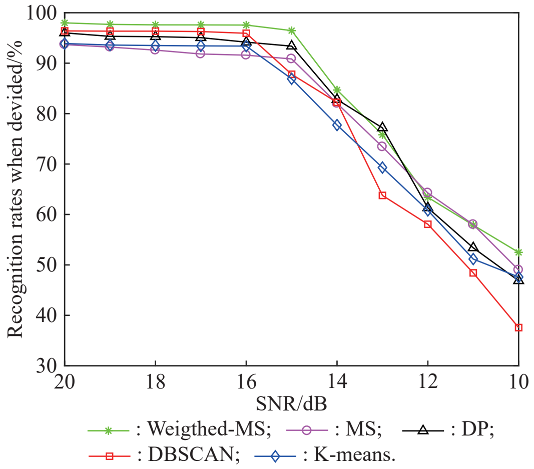


Fig. 6 Average recognition rate of the measured data with a group target number of 2 at different SNRs

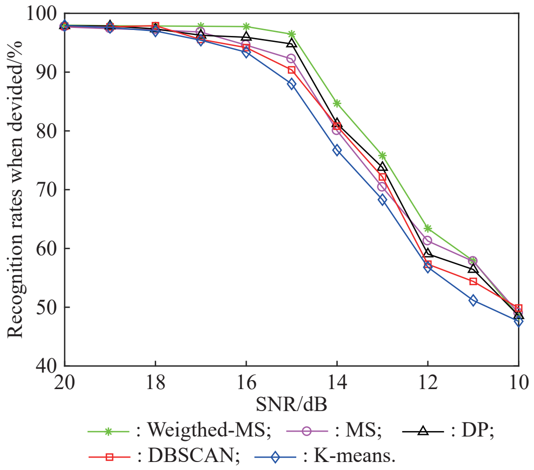


Fig. 7 Average recognition rate of the measured data with a group target number of 4 at different SNRs

Finally, we evaluate the computational complexity of several group target recognition methods. The DBSCAN method needs to calculate the distance between the SRC and all the other SRCs, and the computational complexity is $o(n^2)$. The computational complexity of the MS, DBSCAN, and K-means methods are $o(n)$. For the MS and K-means methods, the initial value is selected randomly, while the method in this paper selects the initial value based on the maximum amplitude criterion, so the proposed method has a higher iteration efficiency and a smaller amount of calculation. Table 2 shows the operation time of different methods in the test phase.

Table 2 Comparison of operation times of different methods ms

Method	Operation time
Weighted-MS	0.793
MS	0.936
DP	1.160
DBSCAN	1.200
K-means	0.850

5. Conclusions

In this paper, we propose a group target recognition method based on the weighted-MS clustering algorithm. The proposed method is not restricted to the target motion; in addition, it sets the target number automatically and has a small computational cost. The experimental results of real measured data show that the recognition rate of the proposed method is higher than that of the traditional method and that the proposed method is more robust to noise than other recognition methods.

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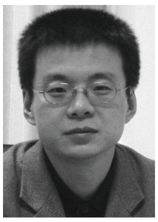

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