Radar HRRP Group-Target Recognition Based on Combined methods in the Backgroud of Sea Clutter

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***Abstract*—In recent years, radar target recognition based on High-resolution range profile (HRRP) has received intensive attention. However, relevant researches mainly focus on HRRP single target recognition. In this paper, we study the problem of radar HRRP group-target recognition, especially when overlap and occlusion occur among the multiple targets in the group. The group-target recognition is designed as a two-stage process. The first is to classify the specific group-target or single target based on principal component analysis (PCA) dimension reduction method, back propagation (BP) neural network and support vector machine (SVM), the second is to recognize the specific targets contained in the group based on maximum correlation coefficient (MCC) method with sliding window. In the numerical simulation with both the Gaussian white noise and sea clutter background, we present maximum correlation coefficient result and the statistical recognition rate of specific targets in the group with respect to rotation angle.**

Keywords—High resolution range profiles (HRRP); group-target recognition; rotation angle; feature extraction

I. INTRODUCTION

Radar automatic target recognition (RATR) is a very difficult task since the radar cross-section (RCS) is highly dependent on operating frequency and aspect angle. To solve these problems, many features are considered, such as range profiles, synthetic aperture radar images (SAR), nature frequencies.

High-resolution range profiles (HRRP) contain much important structure information of targets and are the most easily obtainable feature vectors. Therefore, radar target recognition based on HRRP has received intensive attention. Li et al. use maximum correlation coefficient method to recognize aerospace objects based on HRRP, but the computation is much complex [1]. Some using the super-resolution range profiles and higher order spectra are respectively proposed in [2] and [3], which guarantee the translational invariance. In order to find more feature information, neural networks on radar target recognition are attaching more and more attention [4-6]. Some other methods, such as K-SVD algorithm and complex HRRP are introduced in [7-8]. Recently, many researchers suggest that non-linear, deep networks can achieve superior performance in many different tasks [9-11].

However, above studies on HRRP mainly focus on the single target, which fail to provide the effective classification on multiple targets. Due to the difficulty of the modeling of multi-target on detection, resolution and identification, there are few reports in this field. Most of the literatures are still in the process of model establishment and exploration. Some related researches on RCS from echoes of multi-target show that RCS fluctuation characteristics are difficult to apply to the multi-target recognition [12]. Some valuable research is made on multi-target resolution. In [13], multi-target is simplified as an indistinguishable target. Wang. et al. have studied the synthesis model from multi-target echoes in a single cell [14]. In terms of recognition on multi-target, the B-distribution and Viterbi algorithm are combined to extract the micro-Doppler features [15]. But in this way, they can only achieve the number of the multi-targets, but not identify the specific target among them. In this paper, the multi-target recognition based on HRRP is studied, including both the existence and specific target types in the group target.

The outline of this paper is as follows. In Section II, the multiple independent scattering centers model of HRRP target is introduced and the corresponding HRRP simulation results are given. In Section III, the recognition algorithms and processes, including group target recognition and specific target recognition in the group are studied. In Section IV, the recognition results for group targets are given and discussed. Finally, conclusions are made in Section V.

II. HRRP MODEL AND SIMULATION

For the radar operating in the optical region, its echoes can be approximately regarded as the vector sums of the echoes from multiple independent scattering centers within a range cell [16]. The type of this model is called scattering center model, which can better simulate the HRRP target echoes and speed the process for the large size target. Under the assumption of that, the radar high-resolution range profiles provide the distribution of the target scattering points along the radar line of sight.

A. Formulation

According to the scattering center model, the *mth* ($m = 1,2,\ldots,M$) echo of the radar can be expressed as [16]:

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$$x(m) = [x_1(m), x_2(m), ..., x_d(m)]^T \quad (1)$$

$[\cdot]^T$ represents the transposition. And the echo in the *nth (n = 1,2,…,d)* range cell is as follows:

$$x_n(m) = \sum_{l=1}^{V_n} \sigma_{nl} \exp\left\{-j[\frac{4\pi}{\lambda}\Delta r_{nl}(m) - \psi_{nl0}]\right\}$$
$$= \sum_{l=1}^{V_n} \sigma_{nl} \exp[-j\phi_{nl}(m)] \quad (2)$$

$$\phi_{nl}(m) = \frac{4\pi}{\lambda}\Delta r_{nl}(m) - \psi_{nl0} \quad (3)$$

Where λ represents the wavelength of the signal, V_n is the number of the scattering points in the nth range cell, j is the imaginary unit, $\Delta r_{nl}(m)$ is the radial distance from the *lth* scattering point to the center of the target, σ_{nl} and ψ_{nl0} represent the amplitude and initial phase of the echo respectively. In this model, the secondary scattered waves are ignored and the value of σ_{nl} is based on empirical model.

The power of $x_n(m)$ can be given by equation (2):

$$|x_n(m)|^2 = \sum_{l=1}^{V_n} \sigma_{nl}^2 + 2\sum_{l=2}^{V_n}\sum_{k=1}^{l-1} \sigma_{nl}\sigma_{nk} \cos[\phi_{nlk}(m)] \quad (4)$$

Where $\phi_{nlk}(m)$ represents the phase difference between the *lth* and *kth* scattering point echoes in the *nth* range cell. From Eq. (4), we can see that the power of each range cell depends on both the echo intensity of each dominant scattering point and the cross coupling between these scattering points. The cross coupling is sensitive to the relative phase difference $\phi_{nlk}(m)$ and will lead to the fluctuation of $|x_n(m)|^2$, especially when migration through resolution cell (MTRC) happens. Group target can be considered as a composite type, so the scattering point model is also applied.

B. Simulation Parameters For Models

Three single models (A, B, C) and two group types are simulated. Detailed simulation parameters are showed in Table I.

TABLE I
SIMULATION PARAMETERS FOR AIRCRAFTS AND RADAR

Radar parameters	**Wave length**		0.012m
	Bandwidth		300MHz
Aircraft	**Length (m)**	**Width (m)**	**Height (m)**
A	16.1	10.7	4.4
B	17.6	24.6	5.6
C	11.6	18.9	3.1
Group1	Composed of two type A, horizontal distance: 40 meters, vertical distance: 50 meters		
Group2	Composed of two type A and one type B, horizontal distance: 50 meters, vertical distance: 30 meters		

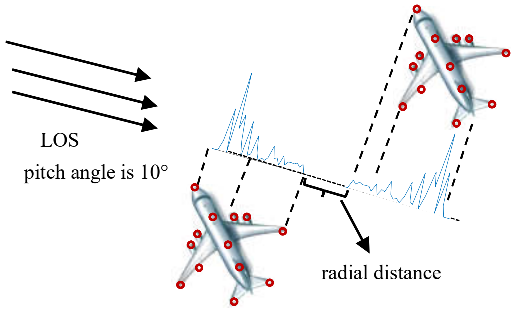


Fig. 1. The relative position of the Group I

Fig. 1 shows the relative position of the Group I. The pitch angle of the radar is 10 degrees. When the radial distance between the two targets is close to zero, the occlusion will occur between the scattering points. Also, the HRRP will overlap.

C. HRRP Simulation Result

When establishing the model, some factors are also taken into account as follows:

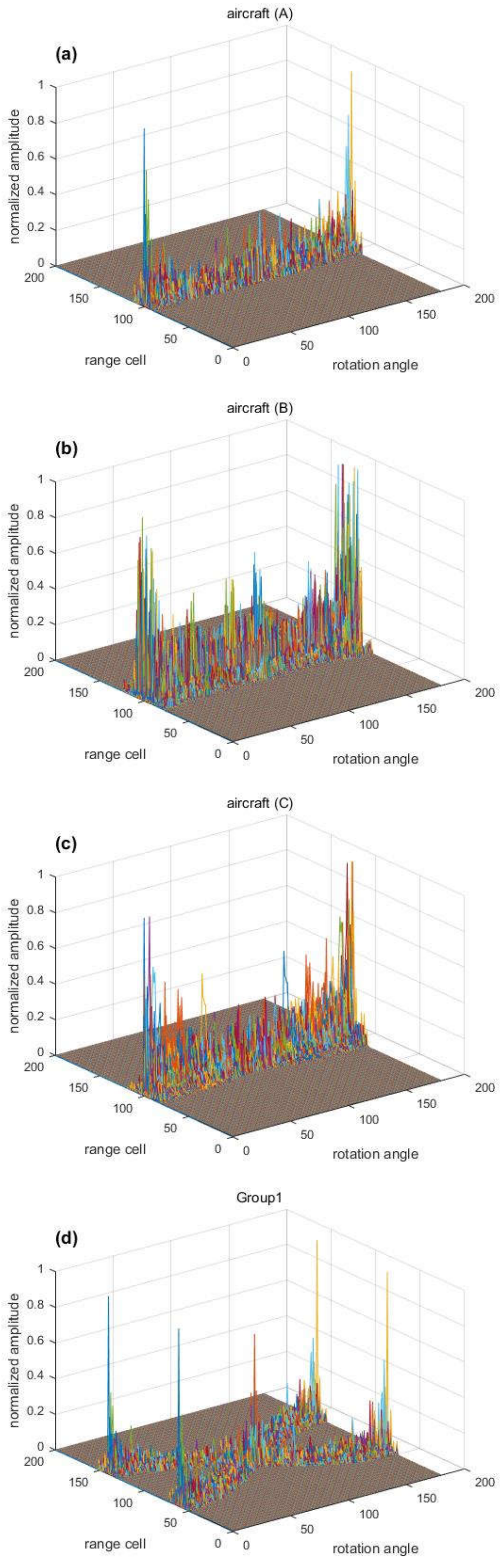
- Due to the characteristics of targets, the RCS values of the scattering points at a specific angle are processed.
- At different angles, the spatial occlusion relations between the scattering points are considered.

Assume that $P_1(x_1, y_1, h_1)$ and $P_2(x_2, y_2, h_2)$ are the two scattering points of the targets. When they satisfy the following relation, we consider P_1 is obscured by P_2.

$$\begin{cases} \tan\left|\dfrac{h_2 - h_1}{x_2 - x_1}\right| < \theta_0 \\ \tan\left|\dfrac{y_2 - y_1}{x_2 - x_1}\right| < k_0 \end{cases} \quad (5)$$

Where θ_0 represents the pitch angle, k_0 is a constant.

Fig. 2 shows the simulated HRRP of target A, B, C, Group1 and Group2 with respect to the range cell and rotation angle. The rotation angle ranges from 0 to 180 degrees and the radar line of sight is parallel to the fuselage at 0 degree. In Fig. 2, there is a great difference among the HRRPs of aircraft A, B, C and other two group targets because they have different structures. A is a stealth fighter; B is an AWACS (Airborne Warning and Control System); C is an UCAV (Unmanned Combat Air Vehicle); Group1 is composed of two type A; and Group2 is composed of one type B and one type A.



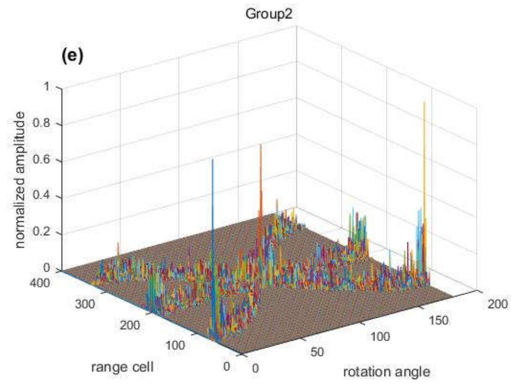


Fig. 2. (a), (b) and (c) are the simulated HRRP of three single models A, B and C respectively; (d) is the simulated HRRP of Group1; (e) is the simulated HRRP of Group2. The size of range cell depends on the actual length of the target on the LOS of radar. The radar resolution is 0.5m. Rotation angle ranges from 0 to 180 degrees. All of their amplitudes are normalized.

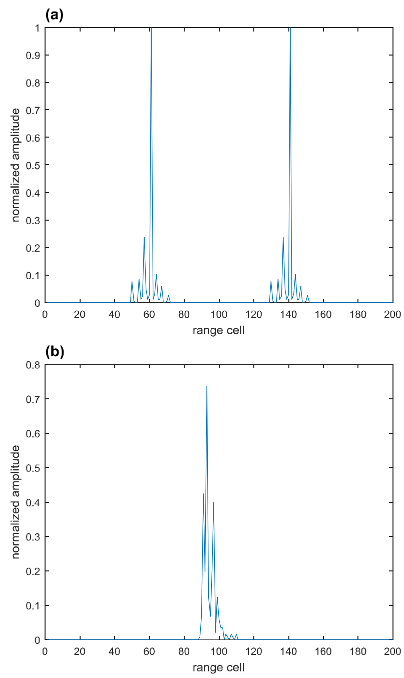


Fig. 3. (a), (b) are the simulated HRRP of Group1 with specific rotation angles; (a) is at 0 degree and (b) is at 90 degrees.

Group1 is taken as an example to show some characteristics of HRRP. In Fig. 3, (a) is at 0 degree, which means the LOS of radar is perpendicular to the fuselage; (b) is in parallel position. When the rotation angle equals 90 degrees, the HRRP of Group1 is completely overlapped. In this case, it is hard to recognize the single target in the group. According to Table I, the size of the target can be also obtained from the HRRP.

III. Recognition Algorithm For Group Targets

In this section, we study the problem of group-target recognition, especially when the overlap and occlusion of multiple targets occur in the group. Our group-target recognition algorithm is designed as a two-stage process. The first is to classify the group target, and the second is to recognize the single target contained in the group. Several methods are well combined to apply to this problem, such as PCA [20], BP [17], SVM [18], MCC [19] etc.. Detailed recognition processes are showed in Fig. 4.

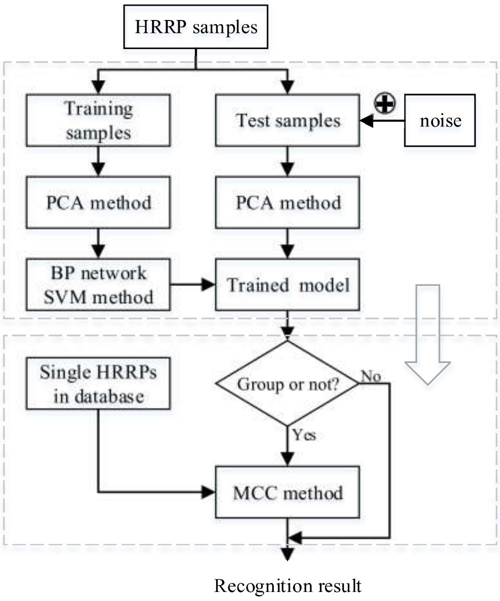


Fig. 4. The overall flowchart for group targets recognition

A. Group target recognition

In this stage, all the simulated HRRP samples of our models (including target A, B, C, Group1, Group2) are divided into two types – training samples and test samples, which are all normalized. Detailed operations are as follows:

1) First, the principal component analysis (PCA) method [20] is used to reduce the dimension of all the samples, because it can not only reduce the amount of computation but also show a good performance on linear structure information [21].

2) Then, the training samples are trained to acquire a satisfied model by using the BP or SVM method respectively.

3) At last, the test samples are put into the well-trained model for identification.

B. Specific target recognition in the group

For group target, the specific single target contained in the group is expected to be identified. In this stage, the maximum correlation coefficient method based on sliding window is applied. Also, the statistical recognition result is given on our model.

The steps of this algorithm are as follows:

1) To add a window for all samples in our databases which are nonzero (remove the small values at both ends).

$$data = data(i:j)\ ,\ len = j - i + 1 \tag{6}$$

For $data(1:i-1) \approx 0$, $data(j+1:n) \approx 0$, $1 \le i < j \le n$

2) To calculate the maximum value of the correlation coefficients for all linear shifts between the sample data in the database and the test data. For our model, the sample data include target A, B and C. Group1 is regarded as the test data. Assume $a(i), i = 1, 2, ..., l_1$ represents a sequence of test data; $b_{3n}(i), i = 1, 2, ..., l_2$ represents sequences of our samples and it has $3n$ sequences, $l_1 > l_2$.

$$c_j = \max\{\frac{\sum_{i=1}^{l_2} a(k+i)\cdot b(i)}{(|\,a(k+i)\,|\cdot|\,b(i)\,|)}\}, k = 1, ..., l_1 - l_2 \tag{7}$$

$$r = \{j \mid c_j = \max(c_j), j = 1, 2, ..., 3n\} \tag{8}$$

Where $a(k+i)$ represents k translation of $a(i)$.

3) From step 2, we can determine the type of the testing target from value r . Since the samples are arranged in order, the recognition result is as follows.

$$type = \begin{cases} A, & r \in [1, n] \\ B, & r \in [n+1, 2n] \\ C, & r \in [2n+1, 3n] \end{cases} \tag{9}$$

IV. SIMULATION AND DISCUSSIONS

The HRRP data of five targets, including A, B, C, Group1 and Group2, are simulated according to the introduced scattering center model in Section II. In the first recognition stage, target A, Group1 and Group2 are selected. The interval of azimuth rotation angle is 0.05 degrees. So each target has 3601 samples and we randomly select 2/3 of them as training samples, the rest as test samples. There are a total of 7200 training samples and 3603 samples. These data are already normalized and the PCA method is used to reduce the dimension of them from 200 to 30. Experiment shows that dimension of 30 can not only remain the principal components of our target models, but also greatly reduce the computation complexity. In BP neural network simulation, a model of 30-25-3 layers are adopted and the learning rate is set to 0.2. For SVM, RBF is used as kernel functions. Two types of noise are also considered respectively – Gaussian noise and sea clutter. The real data of sea radar is derived from the lab of anti-jamming of radar, gathered from the sea radar on mobile platform. The detection system is pseudo-random modulated CW radar, and the Sea state grade was III level. Fig. 5 and Fig. 6 show the change of recognition rate with SNR based on BP algorithm and SVM method respectively.

From the above simulation results, we can see that both algorithms have outstanding recognition capability of Group1 and Group2 when the SNR is high. Fig. 5 shows the group recognition rate under Gaussian noise is better than that under sea clutter. In Fig. 6, when the SNR is greater than 10dB, group recognition rates under the two type noises are relatively close. But with the decrease of SNR, recognition rates show much differences because of their different structures. In general, for group target recognition, we propose to preferentially select SVM because their recognition rate is higher on average, especially under small SNR (0dB to 10dB).

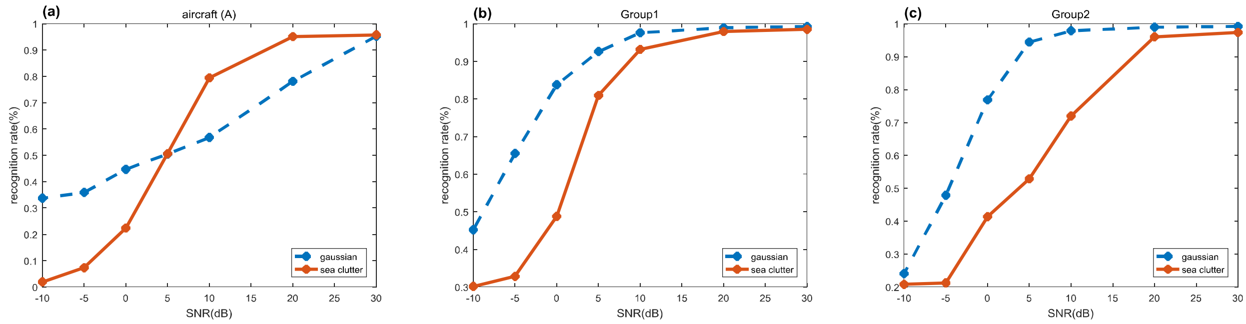


Fig. 5. Recognition rate using BP algorithm based on Gaussian and sea clutter; (a) aircraft A; (b) Group1; (c) Group2

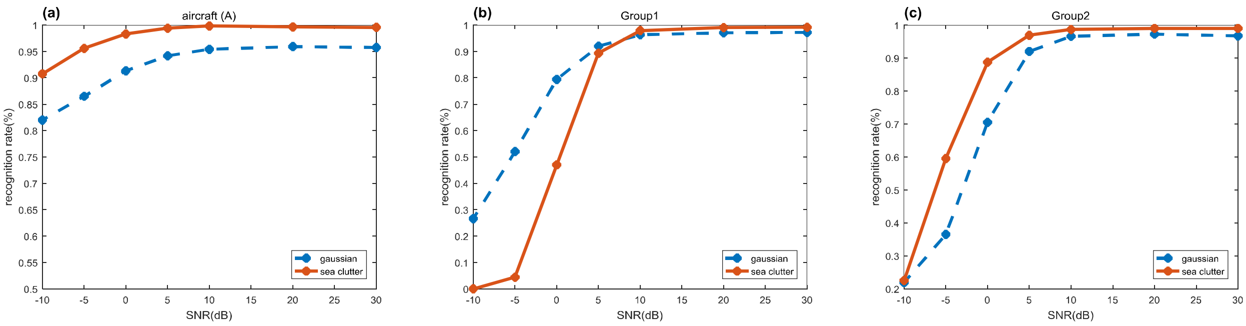


Fig. 6. Recognition rate using SVM algorithm based on Gaussian and sea clutter; (a) aircraft A; (b) Group1; (c) Group2

In the second recognition stage, the maximum correlation coefficient method based on sliding window is used to identify the specific single target in the Group1. We take Group1 as an example. Group1 is composed of two aircraft A. The horizontal and vertical distance between them are 40 and 50 meters respectively. In this stage, the sample database includes model A, B, C and Group1 is regarded as testing objective.

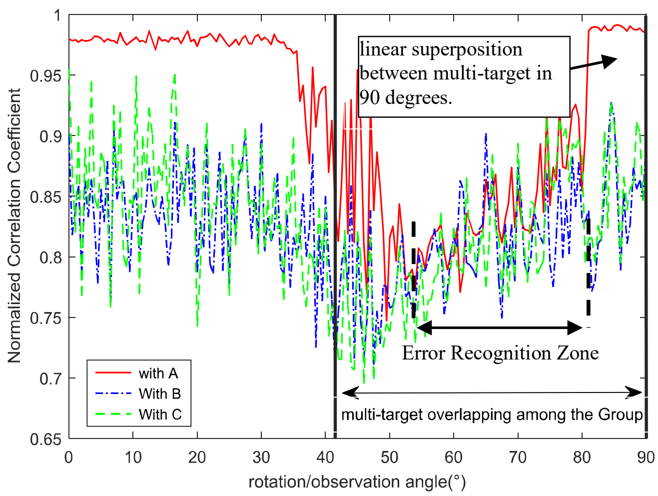


Fig. 7. Result of maximum correlation coefficient between the sample data (A, B, C) and the testing target – Group1

Fig. 7 shows the result of maximum correlation coefficient between the sample data (A, B, C) in the database and the testing target – Group1. The SNR of Group1 is 10dB. When rotation angle is less than 50°, the maximum correlation coefficient from A is obviously bigger than the other two. When the rotation angle is between 53° and 80°, the results from the three types are relatively close, and they fail to recognize the targets. When the rotation angle equals 90°, we can also acquire a right result. Because the single targets in Group1 has the same HRRP, and they all completely overlap – the amplitude of HRRP just increase in proportion.

In Fig. 8, several special angles are selected to gather the statistical recognition rate, such as 0, 40, 50, 55 degrees, under different SNR (Signal-to-noise Ratio of Power). When the rotation angle is 0 or 40 degrees, the two targets in the Group1 do not overlap. So, the recognition performance is good even the SNR is less than 5dB. But when the angle equals 55 degrees, the recognition result is greatly affected by the overlap and the Gaussian noise.

From the simulation, we can deduce that, for the Group1 recognition, time accumulation of single radar detection or multi-static radar system are expected to eliminate the influence of spatial and electrometric overlap and improve the recognition rate of group target based on HRRP. For Group2, we have also made the relevant simulation and a similar conclusion is obtained.

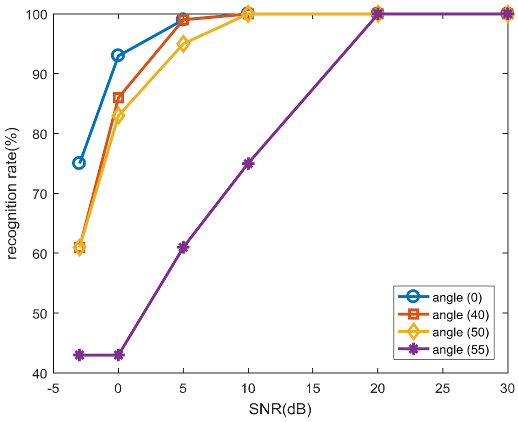


Fig. 8. Statistical recognition rate for specific single target contained in Group1 at some special angles with respect to SNR

V. CONCLUSION

In this paper, BP neural network, SVM, and MCC methods are well combined to recognize the group target. Our recognition process is designed as a two-stage process. The first is to classify the specific group-target or single target, and the second is to recognize the specific targets contained in the group. We study the problem of radar HRRP group-target recognition, especially when overlap and occlusion occur among the multiple targets in the group. The statistical recognition rate of specific targets in the group with respect to rotation angle is discussed. However, the HRRPs of the targets are greatly affected by the noise, so how to extract the anti-performance of the eigenvectors of HRRP are expected to be studied. For group-target recognition, due to the existence of overlapping phenomena, there are some problems worth exploring, such as how to reduce the impact of overlapping on the recognition rate and how to find other effective methods to recognize the group target.

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