Multi-view Polarization HRRP Target Recognition Based on Convolutional Neural Network

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Abstract. This paper proposes a multi-view polarization high-resolution range profile (HRRP) target recognition method based on convolutional neural network (CNN-based MVPHRRP), which combines high-resolution technology with polarization technology to extract radar signal features. Using the feature layer fusion method, the intensity of scattering centers, the ratios of odd and even scattering extracted by Pauli decomposition constitute a three-dimensional feature tensor. On the basis of retaining the time-domain distribution characteristics, the multi-polarization characteristics and the target's structural composition are fitted. Then we build a CNN for radar target recognition. The simulation results show that the use of CNN-based MVPHRRP for radar target recognition has a good effect, and the classification accuracy is less affected by the signal-to-noise ratio (SNR). Increasing the number of multi-views plays a positive role in improving the recognition performance, and the introduction of multi-view multi-polarization information can effectively increase the average recognition probability of target recognition.

Keywords: Polarization radar · Target recognition · Convolutional neural network · High-resolution range profile · Scattering center

1 Introduction

Smart cars need the capabilities of perception, decision-making and control. Millimeter-wave radar is one of the core sensors for intelligent driving. It has a measurement distance farther than that of lidar or camera, and can work normally in bad weather. The mobility of objects is related to the type of target. Therefore, it is necessary to obtain information such as the type, size and weight of the measured object. Robust target recognition technology has a positive significance for ensuring the safety of autonomous vehicles.

The feature extraction of wideband radar echoes has been a hot topic in radar target recognition over the world. The large bandwidth provides a higher target resolution. When the range resolution of the radar is much smaller than the target size, the scattering centers of the target are separated in the radial direction, occupying several distance units to form an HRRP, as shown in Fig. 1. The broadband polarization

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sensitive array has high resolution both in distance and angle, which can obtain multi-view HRRP in an angular range.

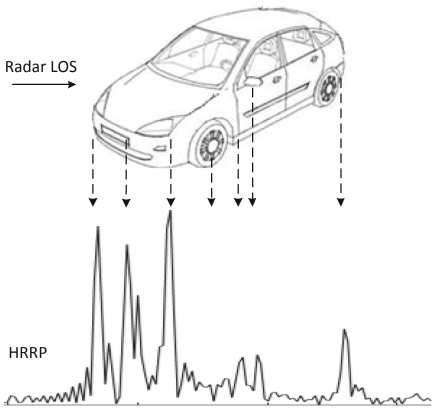

Fig. 1. HRRP formed by a radar.

CNN is widely used in image recognition. The multi-level structure and convolution calculation method can obtain a classifier with better performance. In recent years, deep learning has also been introduced in the field of radar target recognition to extract higher-level features of radar data [1]. The acquisition method of radar HRRP is simple. The one-dimensional geometrical theory of diffraction (GTD) model can be used to extract the scattering centers of the target's fully polarized echo, and obtain the corresponding polarization scattering matrix. The polarization decomposition technology can be used to analyze the characteristics of the scattering centers. Combining polarization technology with high-resolution technology is an idea to improve target recognition performance, and has broad application prospects. Existing technologies for HRRP identification only consider the HRRP amplitude [2], phase, and shift sensitivity. Most of them eliminate the adverse effects caused by the sensitivity and do not use complementary information among related angular domains [3]. In addition, the use of polarization HRRP mostly ignores the relative position relationship of the scattering centers, and the features of different polarization decomposition may be redundant.

In view of above problems, to make full use of the advantages of deep learning in adaptive feature extraction, the multi-view polarization HRRP target recognition based on CNN (CNN-based MVPHRRP) is proposed in this paper. First, we use high resolution technology to obtain more accurate HRRP in the angular range. Then we combine the one-dimensional GTD model and Pauli decomposition to extract the target parameters and form the feature tensor of the target. Finally, CNN is used to train the classification network to obtain a classifier with higher accuracy.

The remainder of the paper is organized as follows. Section 2 introduces the feature extraction of multi-view HRRP and polarization decomposition based on the scattering center model, and then proposes the CNN-based MVPHRRP. Section 3 uses the civilian vehicle (CV) data domes provided by the Air Force Research Laboratory (AFRL) for experimental analysis. Simulation results are given under different multi-view angles and signal-to-noise ratio (SNR). Section 4 concludes this paper.

2 CNN-Based MVPHRRP

2.1 Multi-view HRRP

Array radar can separate the multiple scattering centers of the target in distance and direction with high resolution. The distribution of scatters and target size is included in HRRP. Wideband multi-polarization radar can obtain HRRP under four kinds of polarization configurations (HH, HV, VH and VV) [4]. As shown in Fig. 2, HRRP under different polarization configurations has a certain correlation, and the combination of polarization information and multi-view HRRP can improve target recognition performance. Meanwhile, HRRP between adjacent angles is similar, and two dimensional imaging result of the target contains more information.

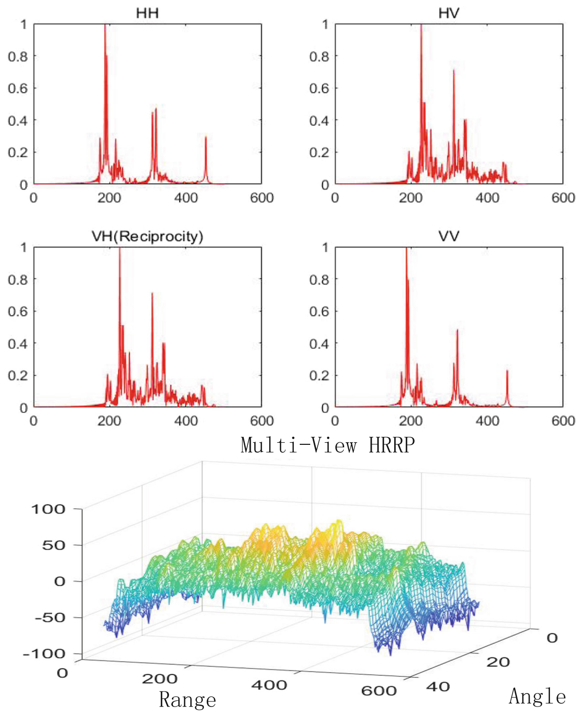

Fig. 2. Multi-polarization and multi-view HRRP.

In this paper, the multi-view full polarization information in the fixed azimuth domain is obtained at first. Secondly, the multi-view HRRP is solved, the target area is detected, and the position of scattering centers is calculated. Then the GTD model is used to calculate the scattering matrix, and the multi-view polarization distance matrix feature tensor is constructed. Finally, CNN is used to train the classifier.

2.2 Feature Tensor Construction

The CP-GTD is used to calculate the scattering matrix, it is expressed as [5]:

$$z_{pq}(n) = \sum\nolimits_{m=1}^{d} s_{m,pq}\left(j\frac{f_n}{f_c}\right)^{a_m} e^{-j\frac{4\pi r_m}{c}f_n} + u_{pq}(n), n = 1, 2, \ldots, N \tag{1}$$

Where, c is the speed of electromagnetic wave propagation, N is the number of step frequency points, f_n is the frequency of the nth frequency point, d is the number of scattering centers, p and q represent the type of polarization channel, r_m is the position of the mth scattering center, $s_{m,pq}$ is the polarization scattering matrix element of the mth scattering center, $p, q \in \{H, V\}$, u represents noise, a_m is the frequency-dependent factor, and f_c is the center frequency.

The matrix of the GTD model is expressed as:

$$\boldsymbol{z} = \boldsymbol{AS} + \boldsymbol{u} \tag{2}$$

Single-station polarization radar usually satisfies reciprocity, $\mathrm{S_{HV}} = \mathrm{S_{VH}}$. Under the condition of reciprocity, $\boldsymbol{z}$ is the $N \times 3$ dimensional echo matrix. $\boldsymbol{S}$ is the polarization scattering matrix. $\boldsymbol{A}$ is the $N \times d$ dimensional steering vector matrix, $a(\alpha_m, r_m)$ represents the steering vector corresponding to the mth scattering center and $\boldsymbol{u}$ is an $N \times 3$ dimensional measurement noise matrix. Specifically expressed as:

$$\boldsymbol{z} = [X_{HH}X_{HV}X_{VV}] \tag{3}$$

$$\boldsymbol{A} = [a(\alpha_1, r_1)a(\alpha_2, r_2)a(\alpha_d, r_d)] \tag{4}$$

$$\boldsymbol{S} = [S_{HH}S_{HV}S_{VV}] \tag{5}$$

$$\boldsymbol{u} = [u_{HH}u_{HV}u_{VV}] \tag{6}$$

The polarization scattering matrix is a complex matrix, which is related to the electromagnetic wave frequency, incident attitude, polarization mode and target structure. When two types of linearly polarized waves are sent and received, the data of the four channels obtained by the polarized radar sensor can be represented by the Sinclair scattering matrix S [6]:

$$S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \tag{7}$$

Where, H and V represent horizontal and vertical polarization respectively. S completely describes the polarization characteristics, amplitude and phase characteristics of object scattering. Without considering noise, the scattering matrix is solved by the least square method as:

$$\boldsymbol{S} = \left(\boldsymbol{A}^{\boldsymbol{H}}\boldsymbol{A}\right)^{-1}\boldsymbol{A}^{\boldsymbol{H}}\boldsymbol{z} \tag{8}$$

The formula for calculating the intensity of the scattering centers is:

$$span\left(\widehat{S}_m\right) = \left|\widehat{S}_{m,HH}\right|^2 + \left|\widehat{S}_{m,HV}\right|^2 + \left|\widehat{S}_{m,VH}\right|^2 + \left|\widehat{S}_{m,VV}\right|^2 \tag{9}$$

Under the condition of satisfying the reciprocity theorem, Pauli decomposition is simplified as:

$$\boldsymbol{S} = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} = a \cdot S_a + \beta \cdot S_b + \gamma \cdot S_c \tag{10}$$

The Pauli vector is solved as [6]:

$$\vec{k} = \begin{bmatrix} \alpha \\ \beta \\ \gamma \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{bmatrix} \tag{11}$$

α, β and γ respectively represent the components of odd-bounce scattering, even-bounce scattering, and the components of a diplane oriented at 45°. Choosing α and β to be the characteristic parameters.

Combined with the GTD model and Pauli polarization decomposition [7], the feature tensor of radar target is formed as $T \in R^{I_1 \times I_2 \times I_3}$, as shown in Fig. 3. Where, I_1 is the unit length of HRRP, I_2 is the number of multi-views, and I_3 is the feature number. In this paper, $I_3 = 3$, which is composed of the intensity of scattering centers, α and β of Pauli decomposition.

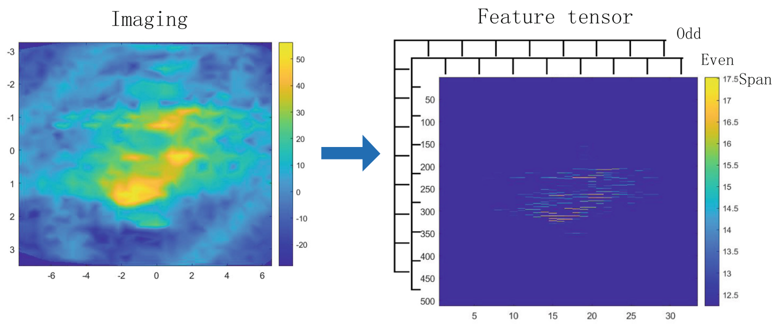

Fig. 3. Feature tensor of a target.

2.3 CNN-Based MVPHRRP Model

At the stage of constructing the data set, the multi-view polarization echoes of the target at the 360° azimuth were captured at a fixed pitch angle. The data of N small azimuth positions near θ is obtained, and the obtained azimuth domain is as follows: $\theta - \left[\frac{N}{2}\right] \times \Delta\theta, \theta - \left[\frac{N}{2} - 1\right] \times \Delta\theta, \ldots\ldots, \theta + \left[\frac{N}{2}\right] \times \Delta\theta$, where $\Delta\theta$ indicates the interval between adjacent angles. The echo data in this angular domain is called multi-view polarization echo. The multi-view polarization echo is processed to obtain the characteristic tensor T mentioned before, and then the T is divided into 70% train samples and 30% test samples for training and recognition probability statistics.

Classical CNN usually consists of convolutional layer, pooling layer, fully connected layer and classifier. We use the feature tensor extracted from the targets as the input of CNN to train our CNN-based MVPHRRP model. As shown in Fig. 4, we build a CNN model consisting of 2 convolutional layers, 2 maximum pooling layers, 1 fully connected layer and 1 classifier layer. The convolutional layer is used to obtain a new feature map. Then we select the largest pooling layer to reduce the dimension of the feature map to avoid over-fitting. The Adam algorithm is used to optimize and update the weights. The initial learning rate is 0.001, the mini-batch is 16, and the number of iterations is 50. On the basis of the classical CNN model, rectified linear units (ReLU) activation function, L2 regularization and dropout technology are added to suppress over-fitting. Finally, the fully polarized radar echo feature tensor of vehicles is trained to obtain a target classifier.

The target feature tensor dimension of the input is $33 \times 512 \times 3$, representing 33×512 features of three channels. The first convolutional layer depth is 16, the convolution kernel size is $5 \times 5 \times 3$, and the output is a feature matrix with a dimension of $33 \times 512 \times 16$. After passing through the first maximum pooling layer, the dimension of the characteristic tensor is $16 \times 256 \times 16$. Then, it is put into the convolutional layer whose depth is 32 and the convolution kernel size is 4×4. After passing through the second pooling layer, the dimension of the feature tensor becomes $8 \times 128 \times 32$. After flattening, the convolutional layer passes through the fully-connected layer with 1024 points and then is sent to the softmax layer, 3 output nodes are obtained, corresponding to the probability of each category.

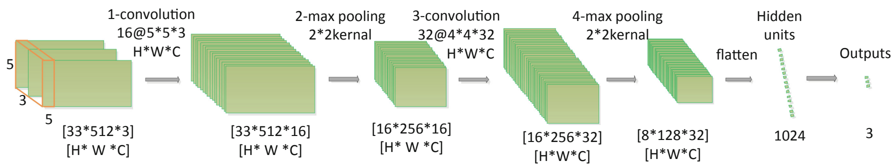

Fig. 4. CNN-based MVPHRRP model.

3 Simulation Results

The data used in this article comes from the AFRL CV data domes [8, 9]. The number of vehicle samples used for identification is 10. Simulation measurement parameters are shown in Table 1.

Table 1. Simulation measurement parameters

Parameter	Value	Parameter	Value
Center frequency	9.6 GHz	Number of samples	512
Bandwidth	2 GHz	Frequency step	≈ 0.48 MHz
Train azimuth	[0:1:359°]	Polarization	HH, HV, VV
Test azimuth	[0.25:3:357.25°]	Multi-view domain	0.25/0.5/1/2°
Elevation	30°		

In an ideal situation, the completeness of the multi-view HRRP sample library determines the recognition performance [10]. However, the performance is limited by the amount of data storage and computing overhead. When building the target database, find the fully polarized echo every 1° and extract the feature tensor according to the method proposed in this paper to obtain the sample set under different azimuth angles. Then expand the data set by adding noise. Figure 5 shows the vehicle imaging under different azimuth (Azis) with a multi-view angle of 2°.

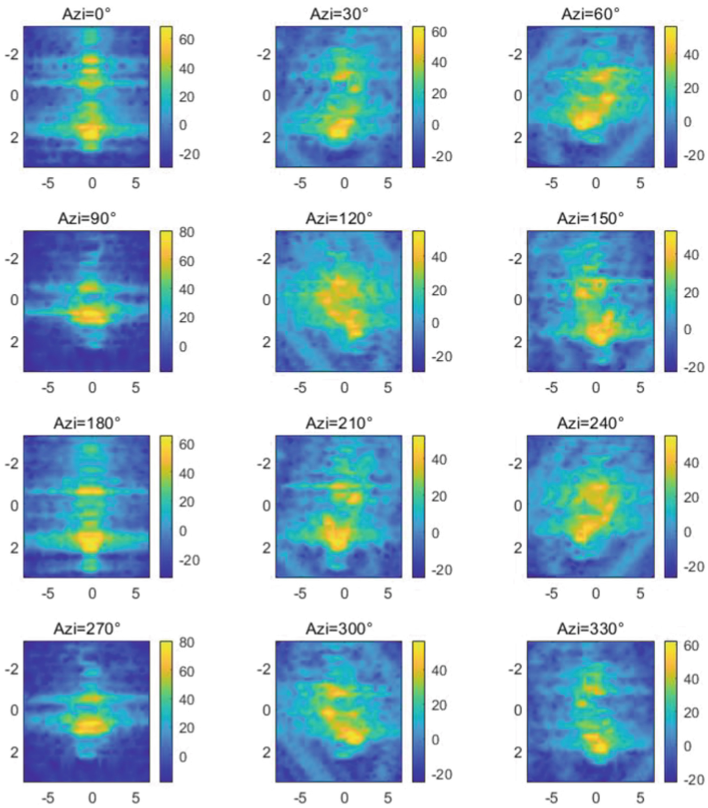

Fig. 5. Vehicle imaging under different azimuths

We choose Tensorflow framework to implement CNN construction, training and testing. And then we use the trained model to identify and verify the test data set. In order to illustrate the effectiveness of the feature tensor modeling method proposed in this paper, we compare the performance of multi-view single-polarization and multi-view multi-polarization target recognition. The method proposed in this paper is compared with multi-view HRRP intensity sequences of different polarization modes. And we verify polarization information extracted from Pauli decomposition is effective for enhancing the recognition performance.

First we select the multi-view multi-polarization feature modeling method in this paper to compare with the multi-view single-polarization feature method. We use the same CNN for training and conduct the experiment under the condition of multi-view angle of 2°. Unless otherwise specified, the multi-view angles selected in the experiment are all 2°, and the type of vehicles is 3. Without considering noise, Fig. 6 shows the relationship between the number of training epochs and the average recognition probability. It can be seen that the recognition effect of HV is the worst, lower than HH and HV. As the number of training epochs increases, the CNN learns more, and the recognition probability rises accordingly. Because the feature extraction technology of this method fits the multi-view and multi-polarization features, it can better characterize the target, which not only improves the probability of target recognition, but also reduces the training complexity. When the epoch number is 10, the method proposed in this paper has a performance improvement over single polarization, and multi-polarization information plays a positive role in target recognition.

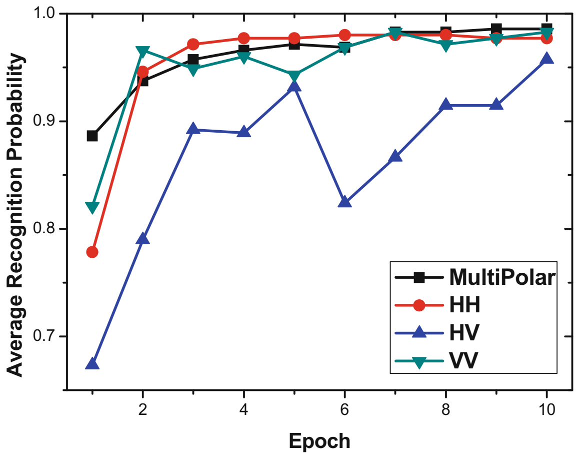

Fig. 6. Comparison of multi-view multi-polarization and single-polarization recognition.

Then we verify the influence of the number of targets on the recognition probability. Under the condition without noise, we select 3–10 types of vehicles for recognition, and verify the relationship between the recognition probability and the number of targets. As the number of training epochs increases, the probability of recognition is improved because of CNN learning. As shown in Fig. 7, the convergence is achieved when the epoch is 50 with the recognition probability of about 99%. And the accuracy is less affected by the change in the type number of targets. Therefore, CNN-based MVPHRRP has a strong robustness in the number of target categories.

To test the sensitivity of this method to noise, add Gaussian noise to the original echo and test the recognition performance under different SNR. As shown in Fig. 8, when the SNR is low, the recognition performance is poor. If the epoch is 50 and the SNR is 10, the recognition probability is 75.28%. When the SNR is higher than 20 db, the recognition probability is above 95%. CNN-based MVPHRRP has noise robustness, even in a noisy environment, it can still guarantee a certain recognition probability.

To compare the classification performance of the CNN-based MVPHRRP method with the traditional SVM classification method. Figure 7 and Fig. 8 also show the result of the comparison with the SVM method when the input parameters are the same. It can be seen that the classification performance of traditional SVM method is worse than the proposed method in the case of different number of targets and different SNR.

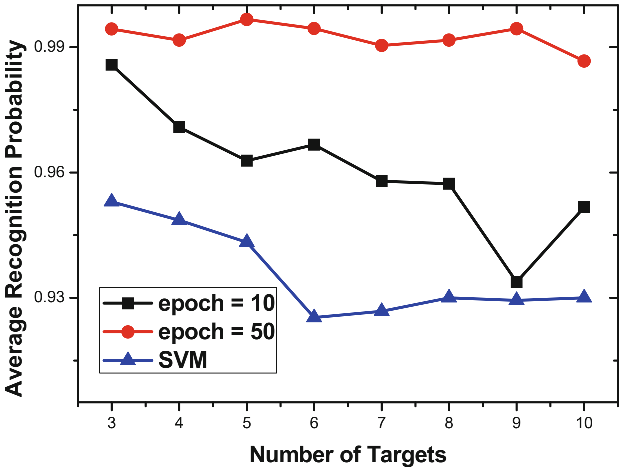

Fig. 7. Relationship between recognition probability and number of target categories.

Finally, we verify the relationship between multi-view angle and recognition probability. The experiment was conducted under the condition that the SNR is 30 db and the multi-view angle was 0.25, 0.5, 1.0 and 2.0°. As shown in Fig. 9, the results show that when the number of viewing angles increases, the recognition probability will increase. When the viewing angle is 2°, the recognition probability is above 98%.

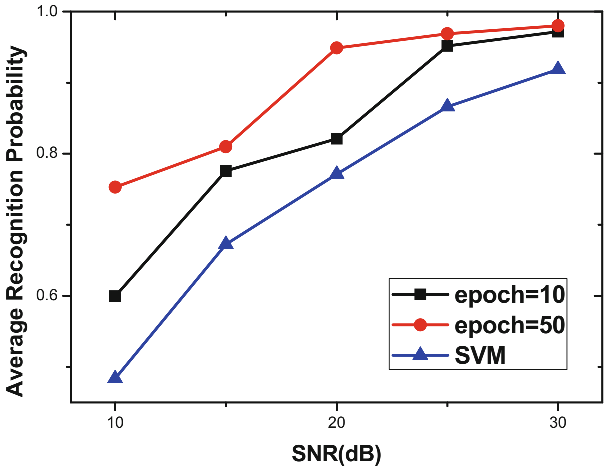

Fig. 8. Relationship between recognition probability and SNR.

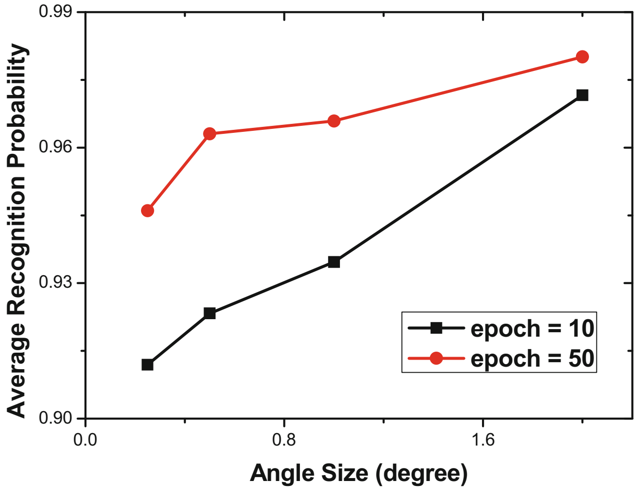

Fig. 9. Relationship between recognition probability and multi-view angle.

4 Conclusion

This paper uses polarization multi-view HRRP for complex target recognition. First, the feature tensor of the target is extracted, and a neural network classifier with strong separability is designed. It has the advantages of small storage capacity, fast calculation, high recognition accuracy and wide application range. The feature tensor modeling method in this paper comprehensively considers the deep joint of multi-view and polarization, which can extract the characteristics of radar echo more than the traditional method and reduce the training complexity. Through simulation experiments, it can be seen that CNN-based MVPHRRP improves the performance of radar target recognition with the characteristics of deep learning and this method has noise stability and strong robustness. However, the use of electromagnetic calculation as a means of simulating radar observation data needs to be further extended to the measured data to verify the feasibility of the method and contribute to visual radar perception.

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