Feature Extraction and Classification of Radar Targets Based on High Resolution Range Profiles

Danyang Liu
College of Electronic Science
National University of Defense Technology
Changsha 410073, China
3468417209@qq.com

Yu Liu
College of Electronic Science
National University of Defense Technology
Changsha 410073, China

Yu Lan
College of Electronic Science
National University of Defense Technology
Changsha 410073, China

Yongfeng Zhu
College of Electronic Science
National University of Defense Technology
Changsha 410073, China

Jianxiong Zhou
College of Electronic Science
National University of Defense Technology
Changsha 410073, China

2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP) | 978-1-6654-7857-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICSP54964.2022.9778691

***Abstract*—High resolution range profile contains important structural features of the target. It is often used to classify radar targets. Hence, the feature extraction based on high resolution range profile is important. The neural network is often used as the classifier to recognize radar targets based on the features of high resolution range profile. In this paper, a set of features suitable for High Resolution Range Profile recognition are proposed, which have low dimension and good real-time performance without translation sensitivity and amplitude sensitivity. Combined with the signatures, a neural network for target recognition was generated based on the ground target simulation data. Then the adaptability of the network to signal-to-noise radio and elevation angles were discussed. Finally, the filed data were used to verify the universality of the proposed method.**

Keywords-feature extraction; high resolution range profiles; neural network; targets classification; radar ground targets;

I. INTRODUCTION

Radar automatic targets recognition technology has wide applications in civil and military fields. High Resolution Range Profile (HRRP) is the projection of the target's strong scattering center on the radar line of sight, which reflects the characteristics of the physical structure of the target. Target recognition based on HRRP has the characteristics of easy acquisition, interpretation, small computational load, and good real-time performance. The high-resolution radar can reduce the average power of ground clutter. It also can recognize ground targets in its complex environment. Therefore, HRRP is often used to classify ground targets[1].

Research on HRRP recognition mainly includes data preprocessing, feature extracting based on HRRP, and classifier designing[2]. The neural network is often used as the classifier to recognize radar targets based on the features of HRRP[3]. The HRRP has translation sensitivity and amplitude sensitivity, which can be solved by data preprocessing and feature extracting. So how to extract features of the targets has become a key point in radar target recognition. There are many feature extraction methods for HRRP, which are mainly divided into non-parametric methods and parameterized methods[4]. The typical representative of non-parametric method is using HRRP directly, which has no amplitude sensitivity. Thesis[5] elaborates the feasibility of directly using HRRP as the feature vector, and proposes a range profile recognition method based on matching degree. The typical representative of parameterized method is Relax algorithm[6-7]based on simple scattering center model, which is a spectrum estimation algorithm based on nonlinear minimum variance criterion proposed in literature[8]. The parameterized method has low dimension and high precision performance.

This paper proposes ten features suitable for HRRP recognition, which have low dimension and excellent real-time performance without translation sensitivity and amplitude sensitivity. Extracted features are used as input of neural network, which is composed of three layers, including input layer, hidden layer, and output layer. Simulation grounds data and measured ground data are adopted for experiments to test the recognition network's adaptability.

II. HRRP RECOGNITION ALGORITHM

A. *The nature of HRRP*

HRRP is the projection of the target's strong scattering center on the radar line of sight. Its features reflect the physical structure characteristics of the target, such as size, structure, and geometric shape. Hence, HRRP is often used to classify radar targets. HRRP recognition mainly includes data preprocessing, feature extracting based on HRRP, and classifier design.

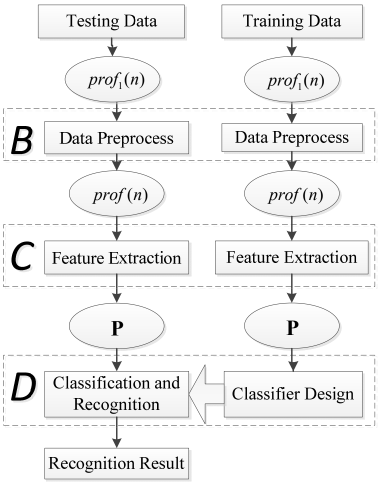


Figure 1. HRRP recognition algorithm process.

The specific process is shown in Fig. 1. B, C, and D in Fig. 1 represent subsections B, C, and D in this section. The $prof_1(\text{n})$, the $prof(\text{n})$, and the $\mathbf{P}$ respectively are the original input HRRP, the preprocessed HRRP, and the feature vector of HRRP.

B. HRPP preprocessing

Before feature extracting, the preprocessing of the HRRP is important, including normalization and noise suppression.

1) Normalizing HRRP: The $prof_1(\text{n})$, $n = 0,\cdots,N-1$ is as the original input data and σ^2 as its average noise power.We normalized the maximum amplitude of $prof_1(n)$:

$$E_p = \max_n\{prof_1(n)\} \tag{1}$$

$$prof_2(n)=prof_1(n)/E_p \tag{2}$$

where, E_p is the maximum of HRRP, and $prof_2(n)$ is the normalized HRRP.

This paper adopts peak signal-to-noise ratio, which is the most critical. It is defined as (3). The added noise signal is lower than the peak signal-to-noise ratio except at the peak.

$$SNR = 10\times\log10({E_p}^2/\sigma^2) \tag{3}$$

2) Suppressing Noise: We perform noise suppression processing on the normalized HRRP:

$$prof(n) = prof_2(n)\cdot\text{sgn}(prof_2(n) - A_{noise}) \tag{4}$$

where, $A_{noise} = \text{x}\times\sigma/E_p$, x is the input coefficient. The obtained $prof(n), n = 0,\cdots,N-1$ is the amplitude range profile.

C. Feature Extracting of HRRP

We can directly extract the target length, the number of strong scattering centers, and other features from the range profile to form a feature vector. Define T as the set of peak positions on the range profile that exceed the threshold:

$$T = \begin{Bmatrix} n/\,prof(n) > A_{noise}\alpha, \\ prof(n) > prof(n+1), \\ prof(n) > prof(n-1) \end{Bmatrix},\quad n = 1,\cdots,N-2 \tag{5}$$

where, $A_{noise}\alpha$ represents the threshold for extracting strong scattering centers, $\alpha = 1$.

The center of gravity of the range profile is defined as:

$$n_c = \sum_n n\cdot prof(n) \Big/ \sum_n prof(n) \tag{6}$$

The n_c is rounded to the nearest whole number.

We directly extracted the following range profile signal features from HRRP.

$$P_1 = length(T) \tag{7}$$

$$P_2 = \{\sum U[prof(n) - A_{noise}\alpha]\} \tag{8}$$

$$P_3 = T(end) - T(1) \tag{9}$$

$$P_4 = \sum_{n=1}^{n_c} prof(n) \Big/ \sum_{n=n_c+1}^{N} prof(n) \tag{10}$$

$$P_5 = \sum_n \left|prof(n) - mean(prof)\right|^2 \tag{11}$$

$$P_6 = \sum_{\text{n}=1}^{N-1} \left|prof(n) - prof(n-1)\right|^2 \tag{12}$$

$$P_7 = -\sum_n prof(n)\cdot\ln(prof(n)) \tag{13}$$

$$P_8 = \sqrt{\sum_n (n-n_c)^2\, prof(n)} \tag{14}$$

$$P_9 = \sqrt[3]{\sum_n (n-n_c)^3\, prof(n)} \tag{15}$$

$$P_{10} = \sum prof(n)/N \tag{16}$$

where, P_1 is the number of strong scattering centers, P_2 is the number of peak distance units, P_3 is the length of the range profile, P_4 is the range profile skewness, P_5 is the range profile variance, P_6 is the difference range profile energy, P_7 is the entropy of range profile, P_8 is the second moment of range profile, P_9 is the third moment of range profile, P_{10} is the mean of range profile.

The above P_1~P_3 is based on extracting the characteristics of strong scattering centers, P_4~P_6 and P_{10} reflect the amplitude characteristics of range profile, P_7 is the entropy of range profile, P_8~P_9 are the second moment and the third moment respectively, reflecting the spatial distribution characteristics of the range profile.

So far, the feature vector $\mathbf{P}$ of range profile $prof(n)$ is successfully extracted, which is the collection of $P_1 \sim P_{10}$.

D. Classifier Implementation

The features proposed have low dimension and excellent real-time performance, so this work adopts simple neural network. Experiments in III show that this network can achieve great recognition of ground targets. According to the features matrix and target matrix, the parameters of neural network are obtained by training. This experiment adopts neural network classifier to classify features of HRRP. The algorithm is shown in Fig. 2.

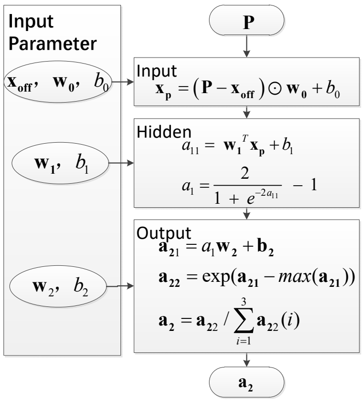


Figure 2. Neural network algorithm flow.

In Fig. 2, network input parameters obtained by training data are in the left border. The network is divided into input layer, hidden layer, and output layer. The input is the feature vector $\mathbf{P}$ corresponding to the target range profile with a size of 10×1 vector. The output is a vector $\mathbf{a}_2$ with a size of 3×1, whose three values are all between 0 and 1. The values represent the probability that the sample is judged as three types of targets respectively. The dimension in which the largest value is judged is the target type of the sample.

The above is the algorithm flow of using HRRP to recognize targets.

III. Classifier Test

In this section, simulation data and measured data are adopted for experiments to test the recognition performance of the classifier based on HRRP recognition.

A. Simulation Data Experiment

The simulation data used in the experiment are calculated by graphic electromagnetic computing platform. Simulation data parameters are shown in Table I.

TABLE I. EXPERIMENTAL SIMULATION PARAMETERS

Elevation angle	30°~40°，1° apart
Azimuth angle	0°~66°，0.1° apart
Frequency Range	4700MHz~5300MHz，7.5MHz apart

The frequency-dimensional Fourier transform is applied to the experimental data to obtain HRRP of the target at the given attitude angle. The three types of targets are shown in Fig. 5, which are Target 1, Target 2, and Target 3 from left to right.

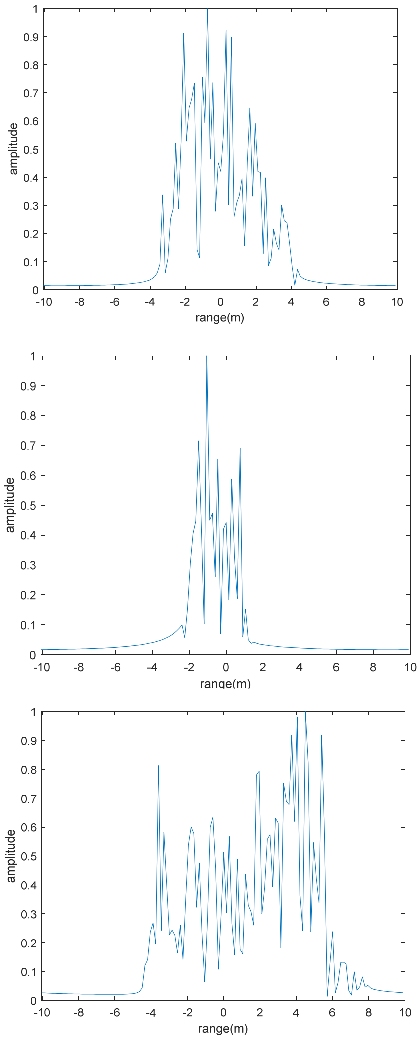


Figure 3. HRRP of target vehicle to be recognized

In this simulation experiment, three different vehicles are selected as the targets to be recognized, namely Target 1, Target 2, and Target 3. We select one HRRP randomly from each target vehicle. HRRPs are shown in Fig. 3. Since the data used is simulation data, it is necessary to add noise to the original range profile data. We adopt peak signal-to-noise ratio , which is defined as (3).

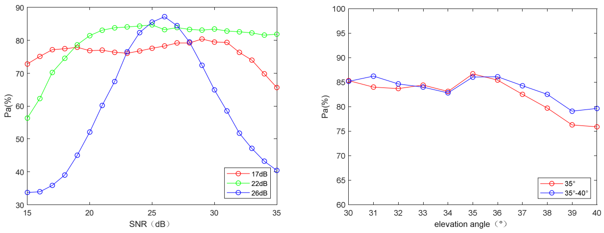
We firstly preprocess HRRP and extract features from the HRRP data to generate training data, and then obtain the classifier network parameters. Finally, the testing data and network parameters are imported into the classifier network to obtain the recognition results of the testing data.

In this paper, the average recognition rate of testing data is regarded as an important index of the recognition result, which is defined as:

$$P_a = \sum_{i=1}^{3} m_i / M \tag{17}$$

where, m_i is the correct recognition number of Target i for the testing data, and M is the total number of correct recognitions of three types of targets.

Different training data generate different classifier network parameters, which affect the average recognition rate of targets. By exploring the influence of SNR and elevation angle of training data on the average target recognition rate, we discuss the adaptability of the proposed recognition method.



(a) $SNR-P_a$ (b) Elevation angle - P_a

Figure 4. Average recognition rate curves

1) Signal-to-noise ratio: When the SNR of the training data is 17dB, 22dB and 26dB respectively, the corresponding three classifier network parameters are obtained by training. Under the condition of three network parameters, the data with different SNR are used for testing. Finally the average recognition rate of the testing data with different SNR is obtained under the premise of three parameters (Fig. 4(a)).

In Fig. 4(a), the abscissa SNR represents the signal-to-noise ratio of the testing data, and the ordinate P_a represents the total recognition rate of the testing data under the signal-to-noise ratio, constituting the $SNR-P_a$ curve. The red line, green line and blue line respectively represent the $SNR-P_a$ curves of classifier network parameters obtained from training data of three kinds of SNR .We consider that the P_a of testing data above 80% is an acceptable recognition result.

In Fig. 4(a), we can conclude that: *a)* The network with $SNR=22dB$ is relatively adaptable and can adapt to the testing data with $SNR=20\sim35dB$; *b)* Although the network with $SNR=17dB$ is adaptable for a wider range of the SNR of the testing data, the average recognition rate of the testing data is lower than 80%; *c)* Although the P_a of the network with $SNR=26dB$ is high when the SNR of testing data is equal to the SNR of the network, the P_a decreases when the SNR of testing data is not equal to the SNR of the network. Therefore, the adaptability of the network with $SNR=26dB$ is much lower than that of the network with $SNR=22dB$.

In this experiment, high average target recognition rate is not the only goal, but the robustness and adaptability are more important. Therefore, the network with SNR of 22dB has stronger adaptability and robustness and is more adaptable for SNR of training data.

2) Elevation angle: In this experiment, the SNR of testing and training HRRP data are all set as 22dB. Table I shows that there are 11 elevation angles in the simulation data. The training data in this experiment are divided into two types. The training data 1 is set to 35° elevation angle. Since the number of samples is too small, using the method of adding random Gaussian white noise with the same SNR to expand the size of sample. All 11 elevation angles are taken as training data 2 without sample expanding.

The profiles of elevation angles in Table I are used as the testing data to obtain the average recognition rate, from which the elevation angle-average recognition rate curve (Fig. 4(b)) can be drawn.

It can be seen from Fig. 4(b): *a)* For training data 2, P_a of most testing data are above 80%; *b)* For training data 1, in the testing data with elevation angles ranging from 30° to 38°, P_a is all above 80%. The elevation angle-P_a curve of training data 1 and training data 2 are roughly the same; *c)* P_a obtained by the network corresponding to training data 2 is generally slightly higher than that obtained by training data 1, but the difference is not significant. Based on the above conclusions, it is concluded that the recognition network proposed in this paper is not very sensitive to elevation angles of 30°~40°.

B. Filed Data Experiment

The experiments in this section use the filed HRRP data of three ground targets, such as corner reflectors and vehicles. The data band is X-band. The range resolution is 0.3m. The three types of targets are shown in Fig. 5, which are Target A, Target B, and Target C from left to right.

Figure 5. Target to be recognized

After training and testing, the recognition confusion matrix is obtained (Table II).

TABLE II. RECOGNITION CONFUSION MATRIX

	Target A(%)	Target B(%)	Target C(%)
Target A	82.44	31.65	2.88
Target B	16.73	68.35	0.00
Target C	0.83	0.00	97.12

The P_a of the three targets is 85.29%. In the left-hand column of Table II, the true identity of the target is stated. The three right-hand columns represent the probabilities of correctly and incorrectly identifying the target. And the gray boxes represent the correct recognition rate of each target.

The correct recognition rates of Target A and Target C are both very high. The radar cross section of the Target B is smaller than the other targets so the SNR is low, and the recognition performance is not good. Therefore, it can be verified that the recognition method in this paper is adaptable for ground target recognition.

IV. CONCLUSIONS

This paper proposes ten features which are suitable for ground target recognition based on HRRP. Extracted features are used as input of simple neural network. The recognition performance of ground targets is great.

According to the experiment of network adaptability to *SNR* and elevation angle, two conclusions are drawn. First, the recognition network built by the feature extraction method proposed in this paper is sensitive to the *SNR* of HRRP data. The relative best *SNR* (22dB) of the experimental data is obtained, which has good adaptability and robustness. Second, the recognition network has strong adaptability to the elevation angle of HRRP data, and the HRRP recognition with the network of the elevation angles of 30°~40° is acceptable.

According to the confusion matrix obtained from the measured data, it is concluded that the features and the network in this paper is suitable to classify the measured HRRP data of ground targets.

REFERENCES

[1] Liu, M. J., Zou, Z. F. (2009) Radar Target Recognition Based on Combined Features of High Range Resolution Profiles. C. In: 2009 2nd Asian-Pacific Conference on Synthetic Aperture Radar (APSAR2009). Xi'an. pp. 910-913.

[2] Mensa, D. L. (1981) High resolution radar imaging. M. Artech House.

[3] Ding, B., Chen, P. (2019) HRRP feature extraction and recognition method of radar ground target using convolutional neural network. C. In: 2019 International Conference on Electromagnetics in Advanced Applications (ICEAA). Granada. pp. 0658-0661.

[4] Shen, L. M. (2014) The Study on Radar HRRP Feature Extraction. J. Electronics Optics & Control, 21(5): 50-52,87.

[5] Li, H. J., Yang, S. H. (1993) Using range profiles as feature vectors to identify aerospace objects. J. IEEE Transactions on Antennas and Propagation, 41(3): 261-268.

[6] Li, H. J., Wang, Y. D., Wang, L. H. (1996) Matching score properties between range profiles of high-resolution radar targets. J. IEEE Transactions on Antennas and Propagation, 44(4): 444-452.

[7] Xing, M. D., Wu, R. B., Lan, J. Q., Bao, Z. (2004) Migration Through Resolution Cell Compensation in ISAR Imaging. J. IEEE Geoscience and Remote Sensing Letters, 1(2):141-144.

[8] Bao, Z., Xing, M. D., Wang, T. (2005) Radar imaging technique. M. Publishing House of Electronics Industry, Beijing.