A Novel Algorithm for HRRP Target Recognition Based on CNN

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Abstract. Compared with traditional methods, deep neural networks can extract deep information of targets from different aspects in range resolution profile (HRRP) radar automatic target recognition (RATR). This paper proposes a new convolutional neural network (CNN) for target recognition based on the full consideration of the characteristics (time-shift sensitivity, target-aspect sensitivity and large redundancy) of radar HRRP data. Using a convolutional layer with the large convolution kernel, large stride, and large grid size max-pooling, the author built a streamlined network, which can get better classification accuracy than other methods. At the same time, in order to make the network more robust, the author uses the center loss function to correct the softmax loss function. The experimental results show that we have obtained a smaller feature within the class and the classification accuracy is also improved.

Keywords: Range resolution profile (HRRP) · Radar automatic target recognition (RATR) · Convolutional neural network (CNN)

1 Introduction

Radar automatic target recognition (RATR) is an indispensable means of detection in modern information warfare. With the development of radar imaging technology and information processing technology, RATR based on high range resolution profile (HRRP) recognition has become one of the hot spots of research [7]. The HRRP is one-dimensional projection of the target in the radar observation direction obtained by wideband radar, which reflects abundant information of the scatterers contained in the target [3]. Radar HRRP target recognition refers to extracting the robust target features from HRRP which is reflected from the target and received by the radar sensor, and utilizing the features to automatically recognize the target types or models.

How to extract the robust target features from HRRP plays an important role in HRRP recognition. Features extracted using traditional methods such as sparse representation classification criteria [9] and manifold learning (ML) [8] do

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not effectively represent the complete information of the target. These features are artificially designed and depend on actual experience and application context. In recent years, deep learning has become a research hotspot in various fields, as well as in the HRRP recognition. In [6], the proposed deep learning approach employs deep convolutional neural networks to automatically extract features from the HRRPs and experimental results show that this method achieves good recognition even at low signal-to-noise ratios. In [1], a deep network is developed to replace the shallow algorithms and Stacked Corrective Autoencoders (SCAE) is further proposed for HRRP ATR considering HRRP's characteristics. In summary, compared with the traditional pattern recognition method, the deep learning method helps to avoid over-reliance on prior knowledge to abstract features, and can automatically obtain the deep expression features of the target through feature learning.

In summary, there are traditional methods and deep learning methods in the field of radar HRRP target recognition, the deep learning methods avoid overusing hand-crafted feature, and the deep learning method can achieve better performance. However, most of deep learning based methods are designed by drawing lessons from the rules of other fields, without considering the characteristics of the data. Thus, we design a structure for radar HRRP recognition based on the characteristics of HRRP data. The advantages of this framework are:

(1) We formed the structure by several convolutional layers and max-pooling layers, and large convolution kernels are used to overcome the time-shift sensitivity of the HRRP data. Convolution operation with stride is used to reduce data redundancy, and we used max-pooing layer to overcome target-aspect sensitivity of HRRP data. This network has very few parameters (5W).
(2) When the target is transformed in full-angle domain, the use of max-pooling is not enough to overcome these changes, so we use center loss to correct the softmax loss. It can make the output of network have more reasonable distribution, which will improve the recognition accuracy of the model.

2 HRRP Target Recognition System

2.1 HRRP Data Description and Preprocessing

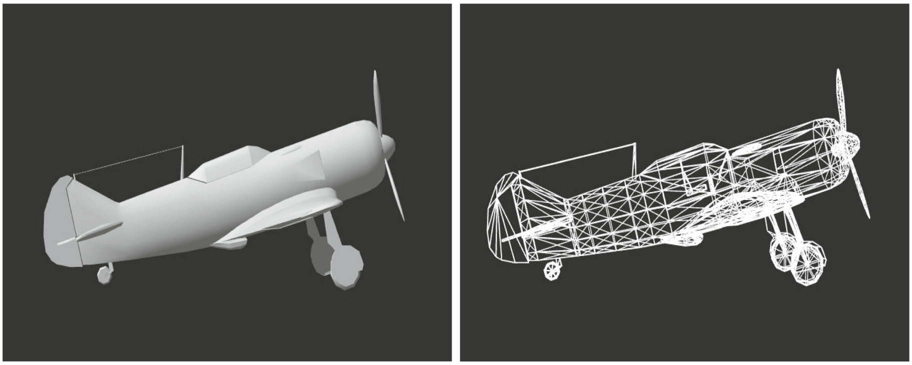
HRRP is the amplitude of the coherent summations of the complex time returns from target scattering points in each range cell. Accurate echo data needs to be calculated from the scattering characteristics of the electromagnetic wave according to the target, but the precise electromagnetic wave scattering characteristics are difficult to describe. When the radar resolution is much smaller than the target size, the target can be modeled as a set of independent scattering centers [2,5]. A HRRP is the amplitude of the coherent summations of the complex echoes from scattering centers of the target in each range cell onto the radar line of-sigh (LOS) [4]. The radar echoes of the ith range cell can be described as:

$$x_i = \Psi_i(f) = \sum_{k=1}^{N} a_{i,k} \exp\left(j\frac{2\pi f}{c} r_{i,k}\right) = \sum_{k=1}^{N} a_{i,k} \exp\left(j2\pi f \tau_{i,k}\right) \tag{1}$$

where f represents the center frequency of the radar signal. N indicates the number of target scattering points in the ith range cell. $a_{i,k}$ represents the complex scattering intensity of the k scattering point in the ith range cell. c represents the speed of light. $r_{i,k}$ indicates the radial distance from the kth scattering point to the radar in the ith range cell. $\tau_{i,k}$ denotes the arrival time of the kth scattering point in the ith range cell. HRRP data can be expressed as:

$$\mathbf{x} = \left[|x_1|, |x_2|, \ldots, |x_n|\right]^T \tag{2}$$

where n is the dimension of the HRRP data. This paper carries out HRRP identification of aircraft models. A certain type of aircraft and its scattering points model are shown in Fig. 1(a) and (b), respectively.



(a) (b)

Fig. 1. HRRP model: (a) Aircraft model; (b) Scattering points model.

Due to the movement of the target and the changes in radar detection environment, there are three problems with HRRP data, namely time-shift sensitivity, amplitude-scale sensitivity, and target-aspect sensitivity of HRRP. In order to solve the problem of amplitude-scale sensitivity, we have preprocessed the data, that is, normalized amplitude.

2.2 The Simple Convolutional Neural Network with Center Loss for HRRP Recognition

Convolutional neural networks (CNN) can automatically extract the high-order abstract features of the target and have achieved great success in the field of target recognition. Generally, a CNN consist of one or more pair of convolution and pooling layers and finally ends with a fully connected layer. To our best knowledge, convolutional layers have some translation invariance and max-pooling layers have some rotation invariance. When we use radar HRRP to recognize radar targets, we will encounter several problems that need to be considered: time-shift sensitivity, amplitude-scale sensitivity, and target-aspect sensitivity of HRRP.

Architecture: As shown in Fig. 2, we used a simple network for radar HRRP recognition and adopted center loss and softmax loss as joint supervision. Loss functions introduced in Section Loss Function. In this network, we used convolutional layers to overcome the time-shift sensitivity of radar HRRP and used max-pooling layers to overcome the amplitude-scale sensitivity. In the feature mapping part, there are two conv-pooling sub-blocks which are cascaded to a fully connected layer. The convolutional layer in the first conv-pooling sub-block is 7×1 with stride 3, followed by tanh nonlinear units, and the neuron number is 32. The following max-pooling grid is 8×1. The second convolutional layer have 64 5×1 neurons with stride 2, followed by tanh nonlinear units. The Second max-pooling layer gird is 4×1. The output of the two conv-pooling sub-blocks are concatenated as the input of the first fully connected layer and the output dimension is 32, followed by relu nonlinear units. The second fully connected layer is the classification layer, and the output dimension is the target class numbers 4.

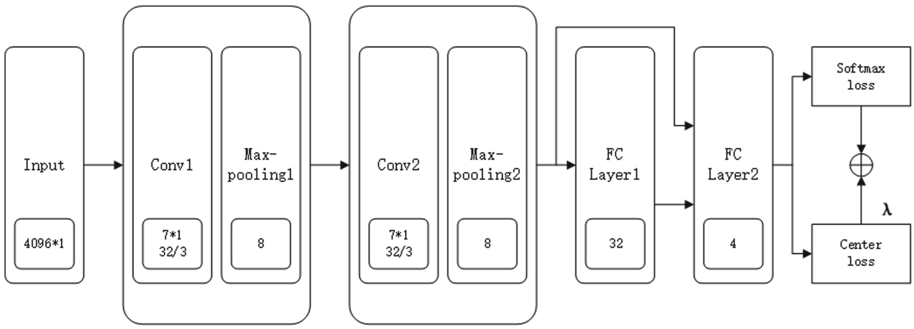


Fig. 2. Proposed simple CNN for radar HRRP recognition.

Loss Function: Generally, in image classification tasks, we use the softmax loss function to calculate the loss. The traditional softmax loss function does not restrict the distance between classes and within classes, and it is easy to produce the phenomenon that the distance within class is larger than the distance between features, leading to unsatisfactory recognition effect. Inspired by face recognition method, we use center loss function to correct softmax loss to meet the requirements of radar HRRP target recognition. The softmax loss function is presented as follows:

$$L_s = -\sum_{i=1}^{m} \log \frac{e^{\mathbf{W}_{y_i}^T \mathbf{x}_i + \mathbf{b}_{y_i}}}{\sum_{j=1}^{n} e^{\mathbf{W}_j^T \mathbf{x}_i + \mathbf{b}_j}} \tag{3}$$

where $\mathbf{x}_i \in R^d$ denotes the ith deep feature, belonging to the $\mathbf{x_i}$th class. d is the feature dimension. $\mathbf{W}_j \in R^d$ denotes the jth column of the weights $\mathbf{W} \in R^{d\times n}$ in the last fully connected layer and $\mathbf{b} \in R^n$ is the bias term. n is the number of class and m is the batch size. The center loss this paper used is defined as:

$$L_c = \frac{1}{2} \sum_{i=1}^{m} \|\mathbf{x}_i - \mathbf{c}_{y_i}\|_2^2 \tag{4}$$

where $\mathbf{c}_{y_i} \in R^d$ denotes the y_ith class center of deep features. It should be updated as the deep features changed and computed by averaging the features of the corresponding classes. This formulation can characterize the intra-class variations effectively.

We used center loss to correct softmax loss to train the CNNs for discriminative feature learning. The expression of the loss function used in this paper is as follows:

$$L = L_s + \lambda L_{center} \tag{5}$$

where λ is a hyper parameter that used for balancing the two loss functions. By using this loss function in training process can make the model learn the classification features of smaller intra-class distance.

3 Experimental Results

In this paper, four aircraft HRRP data are simulated. The radar signal bandwidth is 150 MHz, the sampling frequency is 200 MHz and the center frequency is 9.7 GHz. There are 2048 samples of each aircraft and each sample contains 4096 sample points. We randomly divide the training set and test set by 50%. Take one sample for each type of aircraft, as shown in Fig. 3.

In training process, the goal is to minimize the corrected softmax loss (shown in Eq. 3). We used adaptive moment estimation optimizer, and the batch size was set to 512. The dropout regularization before the first fully connected layer was set to 0.3. The training process was stopped after 500 epochs. In testing process, the center loss did not calculate. A complete experimental process includes randomly dividing data sets, training and testing. We took the average of the results of 10 experiments as the final result. The classification results, evaluated using confusion matrix, are listed in Table 1. It is observed that the overall accuracy (OA) is 99.14%.

Figure 4 shows the distribution of deeply learned features (output of the first fully connected layer) under the supervision of different loss. The left is

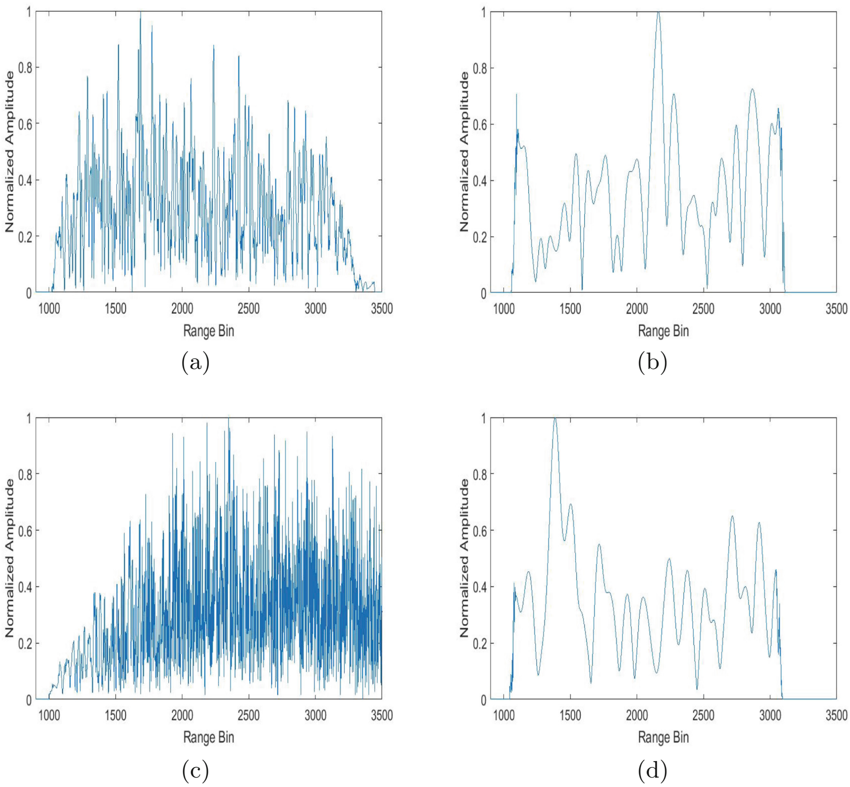
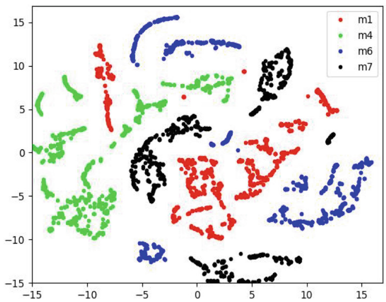


Fig. 3. HRRP signals for four aircraft.

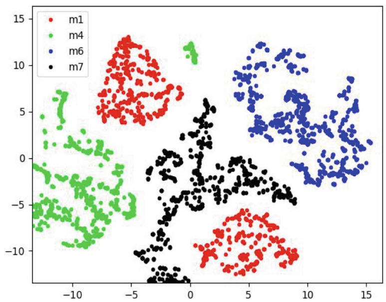
Table 1. The results of 4 radar HRRP targets recognition

T\Pre	1	2	3	4
1	1024	0	0	0
2	0	990	0	34
3	0	0	1024	0
4	1	1	0	1022

the feature trained by softmax loss, and the right is the feature trained by softmax loss and center loss. The distance within the class in the right graph is significantly smaller than in the left graph.



(a)



(b)

Fig. 4. The distribution of deeply learned features.

4 Conclusion

In this paper, a novel deep convolutional neural network recognition algorithm is designed and used for aircraft target recognition based on HRRP data. The proposed network has a large convolution kernel, a large stride convolution layer and large grid size max-pooling. In order to get a more robust network, the author uses the center loss function to correct the softmax loss function. The experimental results show that the method obtains the feature of smaller intra-class distance, and the recognition accuracy is very good, reaching 99.14%.

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