Radar emitter signal recognition based on coordinated attention

Ding Jiajun; Yan Yunyang; Liu Yian
School of Artificil Intelligence and Computer Science
Jiangnan University
Wuxi, China
E-mail: ding97342956@163.com; yunyang@hyit.edu.com; Lya_wx@jiangnan.edu.cn

***Abstract*—Aiming at the problem that complex radar emitter signals are difficult to be recognized at low signal-to-noise ratio, a method based on improved coordinate attention network is proposed. Firstly, the radar signal is converted into a two-dimensional time-frequency image to reflect the signal feature information. Then the time-frequency image preprocessing and denoising by convolutional neural network. Finally, the coordinated attention network is used for feature extraction, and then the classification of radar emitter source signals are realized. Experiments results show that the proposed method can validly improve the accuracy of radar signal recognition under the condition of low SNR.**

Keywords-radar signal recognition; coordinate attention; time- frequency image; low SNR;

I. INTRODUCTION

With the appearance of multiple novel radar systems and the involate and changeable signal patterns, the identification of radar signals is facing severe challenges. At present, radar signal identification first requires feature extraction. But manual extraction of radar signal features needs to rely on a large amount of radar signal processing knowledge and has defects such as strong pertinence and failure under low SNR. Literature [1] uses trestle sparse self- encoder to recognize radar waveform. Literature [2] uses partial correlation coefficient clustering and random forest algorithm to complete the sorting of radar signals. Recently, scholars have tried to use deep learning to complete feature extraction. Literature [3] uses time-frequency transformation to transform signals into time-frequency images, and then uses improved neural networks to recognize different types of signals.

In summary, this paper uses the coordinated attention network to realize radar emitter recognition, and uses the denoising neural network to denoise the image, so as to enhance the feature learning ability of the algorithm under low SNR.

II. THEORETICAL MODEL

A. Time-frequency analysis

Time-frequency analysis shows the modulation characteristic information of radar signal. In this paper, Choi Williams distribution (CWD) is adopted, which can better suppress the influence of cross terms in time-frequency distribution and highlight the characteristics of radar signal time-frequency image. The mathematical expression of Cohen generalized class time-frequency distribution is shown in(1):

$$C_f\left(t,\omega,\phi\right)=\frac{1}{2\pi}\iiint e^{j(\xi\mu-\tau\omega-\xi t,\tau)}\phi\left(\xi,\tau\right)A\left(\mu,\tau\right)d\mu d\tau d\xi \quad (1)$$

where $\phi\left(\xi,\tau\right)$ is kernel function. The definition of exponential weighted kernel function used by CWD is shown in (2). $A\left(\mu,\tau\right)$ is the ambiguity function of the signal, as shown in (3):

$$\phi\left(\xi,\tau\right)=e^{-\xi^2\tau^2/\sigma} \quad (2)$$

$$A\left(\mu,\tau\right)=x\left(\mu+\frac{\tau}{2}\right)x^*\left(\mu-\frac{\tau}{2}\right) \quad (3)$$

where σ is scaling factor, $x\left(\mu\right)$ is time signal and $x^*\left(\mu\right)$ is complex conjugate of time signal. The definition of discrete CWD adopted in this paper is shown in(4):

$$CWD_x\left(l,\omega\right)= 2\sum_{\tau=-\infty}^{\tau=+\infty}e^{-j2\omega\tau}\sum_{\mu=-\infty}^{+\infty}\frac{1}{\sqrt{4\pi n^2/\sigma}}e^{-\sigma(\mu-l)/\left(4\tau^2\right)}x\left(\mu+\tau\right)x*\left(\mu-\tau\right) \quad (4)$$

B. Time-frequency image denoising based on DnCNN

DnCNN is a denoising convolutional neural network proposed by Zhang Kai [4]. Compared with traditional denoising methods, it can achieve blind denoising and no need to manually set parameters. The idea of residual learning is used to denoise images. The residual learning adopted by DnCNN is different from the residual unit in ResNet [5]. DnCNN uses residual units to predict residual images. It can be seen from Figure1 that the model includes convolutional layers, BN(Batch Normalization), and ReLU activation functions. The convolution layer mainly extracts features automatically through the convolution between the convolution kernel and the image, and uses BN to speed up the training speed, and the ReLU activation function provides nonlinear capabilities for the model.

Often the received radar signal is disturbed by noise, and its mathematical expression is shown in (5):

$$r\left(t\right)=o\left(t\right)+e\left(t\right) \quad (5)$$

$r\left(t\right)$ is the received radar signal, $o\left(t\right)$ is the original signal, and $e\left(t\right)$ is the noise signal. After the received radar signal is transformed by CWD, the obtained image will also contain the corresponding noise model.

$$Y=C_{wd}\left(s\left(t\right)+n\left(t\right)\right),X=C_{wd}\left(s\left(t\right)\right) \quad (6)$$

$$V=Y-X \quad (7)$$

where C_{wd} is CWD transform, Y is time-frequency image of radar signal containing noise, X is noise-free radar signal time-frequency image, and V is the residual mapping between Y and X. Different from the training method of directly learning the mapping function to directly map the noisy image Y to the most similar image of

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the noise-free image X, DnCNN takes the residual map V as the learning target of the network.

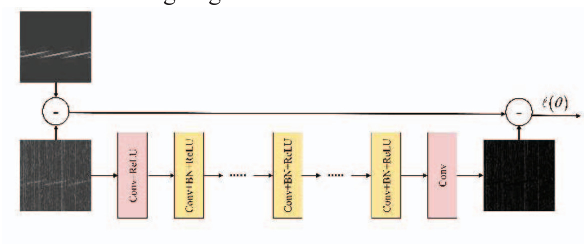

Figure 1. DnCNN denoising flowchart

As shown in Figure1, algorithm uses the time-frequency image y of the radar signal with noise and the corresponding residual image v as the output of the model for training. In the process of training the model, the output of the multi-layer convolutional layer is $\Re(y,\theta)$, and the mean square error (MSE) of the residual object v and $\Re(y,\theta)$ is used to construct the cost function:

$$\ell(\theta)=\frac{1}{N}\sum_{i=1}^{N}\left\|\Re(y_i,\theta)-(y_i-x_i)\right\|_F^2 \tag{8}$$

where x is noise-free image.

C. Coordinated attention network

Attention is an indispensable complex perceptual function of human beings. People tend to selectively focus on some information when and where needed, while ignoring other perceptible information. Similarly, the introduction of attention mechanism into neural network can make the network make more rational use of limited computing and processing resources. This paper uses coordinate attention[6] to improve the residual network to obtain ResCaNet, as shown in the figure 2. ResCaNet captures location and cross-channel information to improve the expressiveness of features in residual networks.

Coordinate attention encodes channel relations and dependencies of location information by coordinating attention generation and coordinating information embedding. The coordination information embedding uses two pooling kernels $(H,1)$ and $(1,W)$ to encode channel along the horizontal and vertical directions. Therefore, the output representation at channel c height h for a given X input is as shown in (9):

$$O_c^h(h)=\frac{1}{W}\sum_{0\le i<w}x_c(h,i) \tag{9}$$

Also the output at channel c width w can be expressed as:

$$O_c^w(w)=\frac{1}{H}\sum_{0\le j<H}x_c(j,w) \tag{10}$$

The above two transformations allow the block to acquire the dependencies in one spatial direction and maintain the precise positional relationship in the other direction, which is beneficial for the network to locate the position of interest. Coordinated attention generation first splices the vectors obtained by (9) and (10), and then obtains $l\in\mathbb{R}^{C/r\times(H+W)}$ through the 1×1 convolution transformation function F_1.

$$l=\sigma\left(F_1\left(\left[o^h,o^w\right]\right)\right) \tag{11}$$

where $[\ ,\ ]$ represents the splicing of two vectors along the spatial dimension and σ represents the activation function. The vector l is divided along the spatial dimension to obtain the $l^h\in\mathbb{R}^{C/r\times H}$ and $l^h\in\mathbb{R}^{C/r\times W}$, then two convolution transformation functions F_h and F_w are used to transform it into a vector with the same number of channels as the input to obtain u_h,u_w the attention weight.

$$u^h=\delta\left(L_h\left(l^h\right)\right),\ u^w=\delta\left(L_w\left(l^w\right)\right) \tag{12}$$

where δ is sigmoid function. Finally, the output Y of coordinate network can be expressed as formula (9):

$$y_c(i,j)=x_c(i,j)\times u_c^h(i)\times u_c^w(j) \tag{13}$$

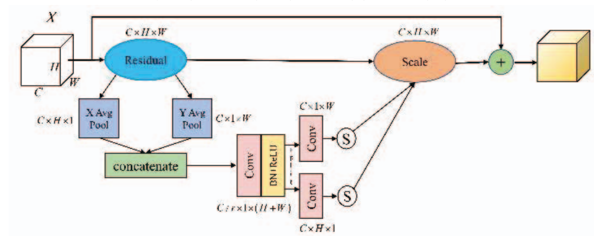

Figure 2. Schematic diagram of ResCaNet structure

D. Coordinated Attention Network

The model proposed in this paper is shown in Figure3. The first step is to convert the radar emitter signal into two-dimensional image by CWD transformation. The second step is to gray scale the time-frequency image, and use bicubic interpolation to reshape the size of the image to 128 * 128. The third step uses the trained denoising neural network to denoise the image. Finally, the denoised time-frequency image is sent to ResCaNet model for training.

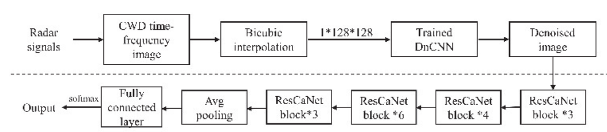

Figure 3. algorithm flow chart

III. EXPERIMENT AND ANALYSIS

A. Data preparation

Firstly, we generate nine kinds of radar signals with Gaussian white noise, with SNR ranging from -20dB to -11dB and step size of 1dB. Under the given SNR, each signal type generates 512 specimens as the training dataset and then generates 200 specimens as the test dataset. For each radar emitter signal, 200 time-frequency images with -20dB ~ -11dB noise and corresponding time-frequency images without noise are generated for training denoising neural network. Table 1 shows the detailed setting of the dataset.

TABLE I. RADAR PARAMETER SETTING

Signal type	LFM、NLFM、FSK、MPSK、QPSK、P1、P2、P3、P4
Signal form	CWD time-frequency image
SNR range	-20dB ~ -11dB

B. results and analysis

So as to further analyze the performance of the algorithms, the model in this paper is compared with the DRN model proposed in [3]. Considering that time-frequency image recognition is also an image classification problem, the proposed model is compared with the cutting-edge image classification neural network, namely the ECA network[7].

Figure 4 shows the correct rate of different models in different SNR. With the improvement of SNR, the recognition rate of signal is also rising. Under the same SNR, the accuracy of the model in this paper is more outstanding than that of ECA net and DRN. When SNR = -11dB, the accuracy of the three models is almost the same, reaching 98%. The results show that the model is insensitive to noise.

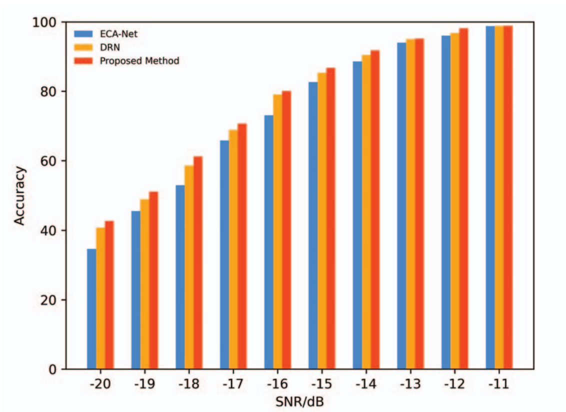

Figure 4. Schematic diagram of ResCaNet structure

Figure 5 shows the correct rate of different signal types for the three models under different SNR. It can be seen from Figure 5 that the algorithm in this paper has better recognition effect in most of the SNRs than the other two algorithms in the nine signals. All three models achieved 98% accuracy at SNR=-11. For FSK, QPSK, MPSK, NLFM and P3 signals, the recognition performance of the proposed model is better than the two contrasting methods. Among them, for the P2 signal, the performance of the three models is not much different and all are very high. Among them, the P3 and P4 models in this paper and the DRN model are pretty even under different SNRs, but the overall difference is not large. The recognition effects of LFM and P1 are not as good as DRSN in most cases, but better than the ECA-Net model.

IV. CONCLUSION

Aiming at the difficulty of radar signal recognition under low SNR, a radar signal recognition method based on DnCNN and coordinated attention network is proposed in this paper. The algorithm uses CWD transform to transform the signal in time-frequency domain, and uses DnCNN network to denoise it. At the same time, the algorithm in this paper can automatically complete the feature extraction, so as to solve the problem of manual feature extraction.

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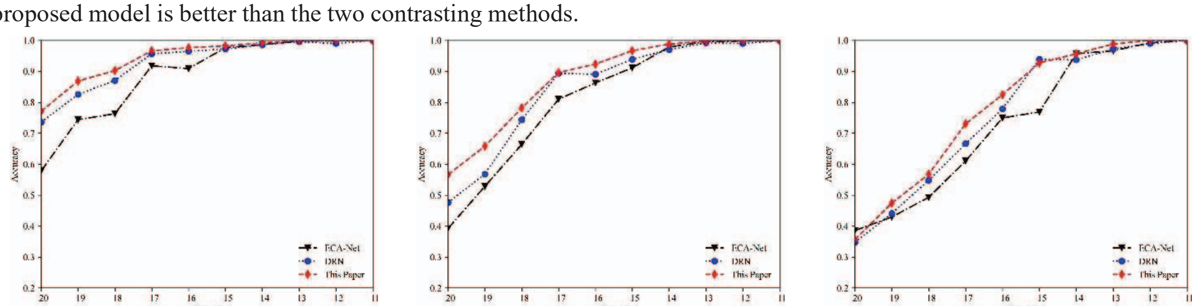

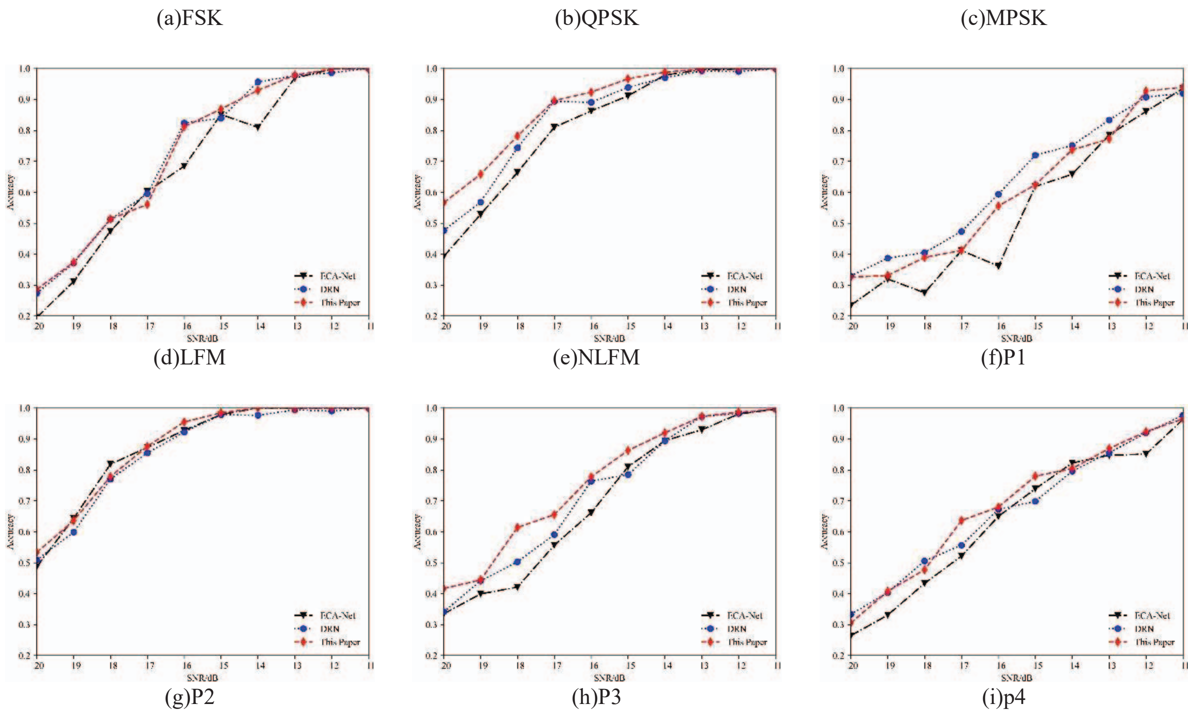

Figure 5. Schematic diagram of ResCaNet structure