Radar signals recognition based on attention and denoising residual network

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Abstract. To solve the problem that complex radar emitter signals are difficult to identify under low signal-to-noise ratio, this paper proposes a novel radar signal recognition method based on an improved deep residual network. In this method, two IQ signals are used as the input of the method, which saves time for generating time-frequency images, and then the signal features are extracted through an improved deep residual network. A nonlinear transform layer is inserted into the network to automatically confirm the threshold value, and then the soft threshold method is used to denoise. The importance of features is weighted by attention unit, and then classified by softmax classifier. The experiments based on five kinds of radar signal datasets show higher accuracy at low signal-to-noise ratio compared with other methods. The experiments also verified its overall accuracy can still exceed 90% even at extremely low signal-to-noise ratio of -16dB.

1 Introduction

Radar signal recognition is a technology in the field of radar electronic countermeasure, which is used to infer the function and performance of radar and assess its threat level. With the emergence of various new radar systems and the increasingly complex electromagnetic environment, electronic reconnaissance and electronic countermeasure systems are facing severe challenges.

Radar signal recognition technology is divided into two main categories: signal recognition based on feature engineering and signal recognition based on deep learning. Manual extraction of radar features requires a lot of radar signal processing knowledge, which has some drawbacks such as high targeting and low signal-to-noise ratio failure. Paper [1] used a feature extraction method with low complexity for radar signal, and uses decision tree to identify the signal. Paper [2] used partial link number clustering and random forest algorithm to sort radar signals. In recent years, more and more scholars attempt to use deep learning to complete automatic classification. Papers [3-4] used time-frequency transformation to convert radar signal classification problems into image

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classification, and then use improved convolution neural network or deep residual network [5] to identify different types of signals. However, these methods require a lot of preprocessing time and have poor real-time performance. Papers [6-7] used an improved convolution neural network and papers [8-10] used an improved residual network to input the radar signal directly as the network input, which eliminates the time to generate the image and has a good performance, but the recognition rate of the radar signal is not good at extremely low signal-to-noise ratio.

Thus, in order to enhance the feature learning ability of radar signal and achieve high recognition rate in high noise environment. And in order to solve the problem that some redundant and useless features are extracted when using deep residual network for feature extraction, resulting in the decline of recognition rate. This paper proposes a new two-dimensional deep residual network with attention mechanism and soft thresholding denoising. The features are extracted from the two-dimensional radar signal after denoising and focusing on the key information in the extracted features.

2 Improved recognition algorithm

2.1 Denoising residual network

Residual neural network is an improved convolutional neural network proposed by paper [5]. The network is composed of residual blocks, which simplify the network calculation through a "skip connection", and solve the problems of network degradation and gradient disappearance with the deepening of network layers. Its mathematical expression is shown in formula (1):

$$H\left(x\right)=F\left(x\right)+x, \tag{1}$$

Where x represents input, $H\left(x\right)$ is the output, and the $F\left(x\right)$ denotes residual mapping.

Usually, the intercepted radar signal contains a lot of noise. When using the soft thresholding algorithm to denoise, setting an appropriate threshold requires a lot of experience. The expression of soft threshold is shown in formula (2):

$$y=\begin{cases} x-\tau & x>\tau \\ 0 & -\tau\le x\le\tau \\ x+\tau & x<\tau \end{cases}, \tag{2}$$

Where y denotes the output, x is the input, and τ indicates that the threshold is a positive number. Paper [11] proposed a deep residual shrinkage structure, which designed a small neural network to automatically learn the noise threshold of each channel and then use a soft threshold algorithm. Therefore, this paper integrates this structure as a denoising layer into the residual network to improve the feature learning ability of the residual network under low signal-to-noise ratio. The unit structure of the deep residual shrinkage network is shown in Figure 1. In the threshold learning network, the input vector takes the absolute value, and then through the global average pooling (GAP), the one-dimensional vector is obtained. Then, this one-dimensional vector is passed through the full connection layer twice to obtain the weight z of each channel, and then a scalar σ with a range of (0,1) is obtained through the sigmoid activation function. Its mathematical expression is shown in equation (3):

$$\sigma = \frac{1}{1+e^{-z}}, \tag{3}$$

Finally, multiply σ by the average value of GAP result $\left|x_{i,j,c}\right|$ to obtain the soft threshold value τ . In short, the determination of the threshold is shown in formula (4):

$$\tau = \sigma \cdot average_{i,j,c}\left|x_{i,j,c}\right|, \tag{4}$$

where τ is the threshold and i , j , c represent the width, height and number of channels of the feature map x .

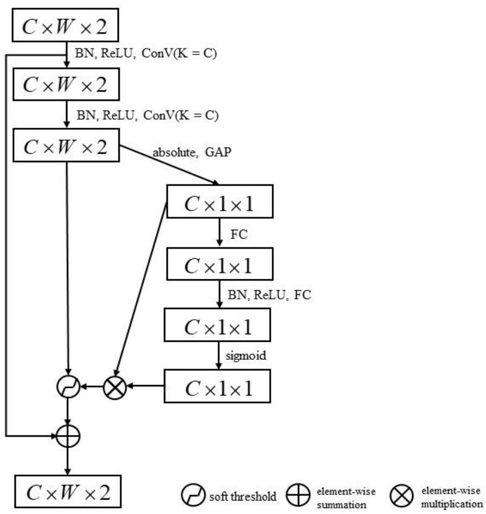


Fig. 1. The structure of a residual shrinkage net unit.

2.2 Attention mechanism

In order to obtain features better and reduce the influence of redundant features, attention mechanism is introduced in this paper. The idea of attention mechanism refers to the behavior of human beings in processing image information. Human beings will pay more attention to available favorable information and ignore other visible information. Paper [12] proposed SENet (Squeeze-and-excitation networks), which aims to dynamically adjust the weight of each channel through the SE module, so that the importance of different channels can be learned. The SE module first performs the Squeeze operation on the feature map obtained by convolution to get the channel-level global feature. The Squeeze operation is to perform global average pooling on the $W \times H \times C$ feature map U , and the resulting $1 \times 1 \times C$ feature map Z can be understood as having a global receptive field. As shown in formula (5):

$$Z_c = F_{sq}\left(U_c\right) = \frac{1}{H \times W}\sum_{i=1}^{H}\sum_{j=1}^{W}U_c\left(i,j\right), Z \in R^c, \tag{5}$$

Excitation of global feature Z is performed to get the weights for each channel through the linear layer and sigmoid activation function, and the weights are applied to each channel.

2.3 Model building

This paper proposed network structure is shown in Figure 2. The network structure is modified on the basis of ResNet34 and consists of input layer, denoising block, attention block and residual block. The denoising block contains the residual shrinkage structure as shown in Figure 1.That is, a soft threshold learning network is added to the residual block to reduce the noise. Each residual block consists of two convolution layers and two batch standardization layers. Convolution of input is equivalent to extracting signal features, and batch standardization layer accelerates network training. Attention blocks use SENet to learn the importance of each feature channel. The more useful information in the feature, the heavier the weight, and suppress the useless information. The result is output by the fully connected layer and the softmax function.

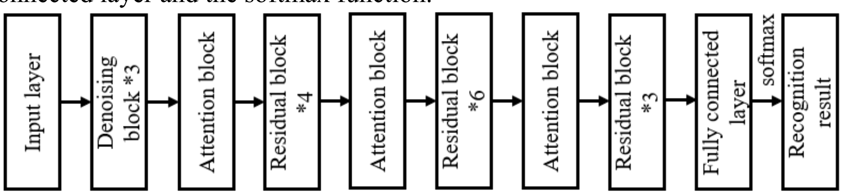


Fig. 2. Network framework

3 Experimental results and analysis

The data of network training is generated by MATLAB simulation with reference to relevant modulation parameter standards and signal model. The specific parameters of the dataset are shown in Table 1. Five kinds of radar emitter signals with Gauss white noise are generated. The signal-to-noise ratio ranges from -20dB to -11dB and the step is 1dB. Under a given signal-to-noise ratio, each signal type generates 1024 samples as a training dataset uses to train the model, and generates 512 samples as a test dataset to verify the model.

Table 1. Structure of the dataset.

Parameter name	Parameter value
Signal type	LFM,NLFM,FSK,QPSK,MPSK
Sample length	2048 Sampling point
Sample dimension SNR range	[2048, 2] -20 dB ~ -11 dB

3.1 Analysis of algorithm simulation performance

This section verifies the recognition performance of this model for five types of radar emitter signals, and compares it with the other two radar emitter signal recognition models based on depth residual network. Paper [9] uses an improved ResNet in which each residual block consists of three convolution layers and three batch standardization layers to enhance the feature extraction of radar emitter signal. Paper [10] uses the expanded residual network to ensure that no subtle features are lost to improve the recognition rate of radar emitter signal. Figure 3 shows the recognition accuracy of different algorithms in different SNRs. As shown in the figure, the overall recognition accuracy is positively correlated with SNR, and the recognition accuracy of signal increases with the improvement of SNR. Under the same SNR, the accuracy of the algorithm in this paper is higher than that in Paper [9] and [10]. The results show that the algorithm has good anti-noise ability. When the SNR is greater than -16dB, the accuracy of the model in this paper is higher than 90%, and then the accuracy increases slowly.

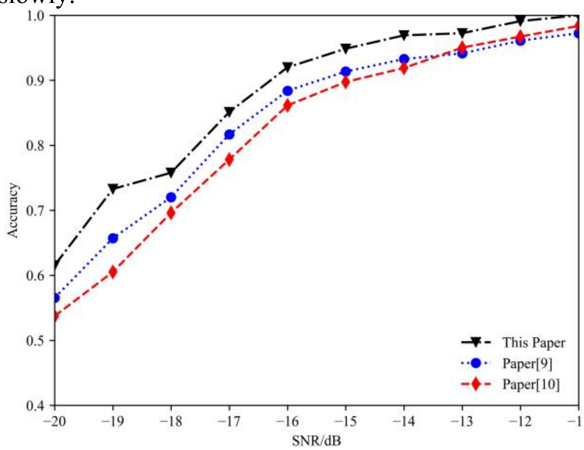
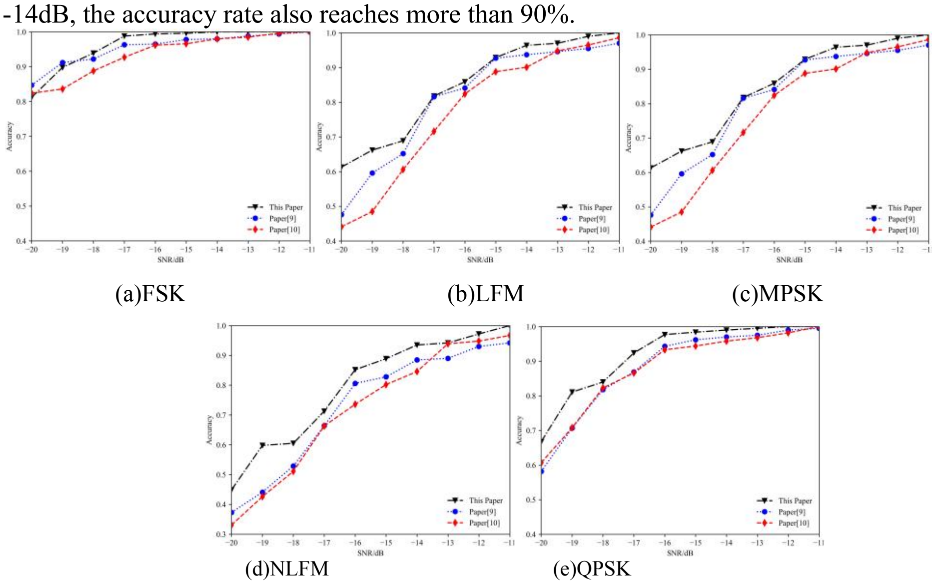


Fig. 3. Comparison of sorting results of different algorithms.

Figure 4 shows the recognition accuracy of three algorithms for different signal types at different SNRs. It can be seen from Figure 4 that the algorithm in this paper performs better than the other two algorithms in the five signals with FSK and QPSK having the best recognition performance. LFM, MPSK, and NLFM perform poorly under extremely low SNR, but the recognition performance increases rapidly with the increase of SNR, indicating that these three types of signals are relatively sensitive to noise. When the SNR is -14dB, the accuracy rate also reaches more than 90%.



(a)FSK (b)LFM (c)MPSK

(d)NLFM (e)QPSK

Fig. 4. Different radar signal recognition accuracy rate under different SNR

Figure 5 shows the recognition confusion matrix under the condition of SNR of -12dB using the algorithm in this paper. It can be seen from the figure that LFM is mainly mistaken for NLFM, and the corresponding NLFM is also mainly mistaken for LFM. Because LFM and NLFM are both frequency modulation signal, and some frequency information are interfered by strong noise. The loss and blurring of this small frequency information under low SNR conditions lead to confusion between signals.

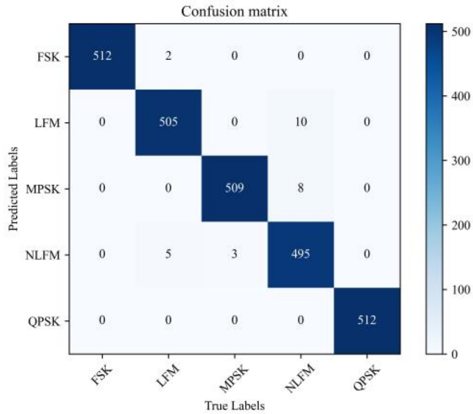


Fig. 5. Confusion matrix of the algorithm this paper.

4 Conclusion

This paper proposes a radar signal recognition algorithm based on an improved ResNet structure. A denoising unit is added to enhance the anti-noise ability of the network, which effectively solves the problem of feature extraction under low SNR and high signal quality requirement. The attention unit is integrated into the model to suppress redundant channels in the feature, which further improves the recognition progress of the neural network. Experimental results show that the model can realize high-precision recognition of different radar signals under the condition of low SNR, which provides a new idea for the recognition of radar signal under low SNR. In future work, we hope to propose a neural network based on small samples, which can further improve the accuracy of recognition while reducing training costs.

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