Specific emitter identification of radar based on one dimensional convolution neural network

Yao Xiao¹, and Xi zhang Wei*¹
¹School of Electronics and Communication Engineering, Sun Yat-sen University, Guangzhou, Guangdong, 510006, China
²School of Electronics and Communication Engineering, Sun Yat-sen University, Guangzhou, Guangdong, 510006, China
¹Corresponding author’s e-mail: xiaoy268@mail2.sysu.edu.cn
*Corresponding author’s e-mail: weixzh7@mail.sysu.edu.cn

Abstract. Specific Emitter Identification (SEI) of radar has become a focus point of research and difficulty in the field of electronic reconnaissance, and the application of Automatic Dependent Surveillance Broadcast (ADS-B) signal in Identification Friend or Foe (IFF) system is beginning to raise increasing concern. At present, the research of deep neural network in the field of target recognition mostly focuses on the modulation pattern recognition of signal, but there are few applications for the specific emitter identification. In order to overcome the shortcoming that the effect of the traditional method is not excellent, a radar emitter target recognition method based on one-dimensional (1D) convolutional neural network is proposed for ADS-B signal in this paper. Taking the sequence data of ADS-B pulse signals as the training and testing samples of emitter target identification, the frequency domain features of ADS-B signal are obtained by Fast Fourier Transform (FFT), and the target identification is achieved by combining the convolution neural network with the fine feature extraction. The result of simulation demonstrates that the specific emitter identification based on frequency domain and one-dimensional (1D) convolutional neural network has an excellent recognition performance, which effectively resolves the shortcomings of the traditional method of feature extraction and low classification accuracy.

1. Introduction
Radar emitter target identification is one of the main functions of radar countermeasure system, which has the important function of electronic support and intelligence reconnaissance. Because it is increasingly difficult to identify the target based on the traditional method of electronic reconnaissance and recognition, the specific emitter identification of radar can accurately provide important military information about the enemy radar, which has a wide application prospect. The nuances of the hardware of different individual radiation sources will eventually be reflected in the signals emitted by the radiation sources. If we can extract the subtle characteristics that reflect the individual attributes of the emitter equipment from the signals of different radiating sources, which is also called fingerprint information, we will distinguish the corresponding radiating source equipment from the intercepted radiating source signals quickly, so as to realize the identification and classification of specific emitter of radar. The ADS-B signal in this study has been widely used in the field of civil aviation, such as air traffic control, air-to-air coordination, and so on. In the field of electronic reconnaissance and electronic
countermeasure, the application of ADS-B signal in the direction of IFF is just beginning to attract more and more attention.

Preliminary extraction of one-dimensional fingerprint signal characteristics can be divided into time domain and frequency domain. In the time domain, reference [1] proposed the extraction algorithm of radar pulse amplitude unintentional modulation feature, which was used to characterize the actual radar pulse property. In reference [2], an emitter identification based on the instantaneous phase of radar radiation source and its transformation fatures was proposed. Reference [3] proposed an individual radar emitter identification based on pulse radar intential frequency modulation characteristics. Time domain features are easy to obtain, but susceptible to multipath effects and noise. And fingerprint identification rate is relatively low in low SNR environment. Due to the different time of initial sampling points, different samples of the same category produce distinct time domain characteristics, which is easy to cause classification errors. Frequency domain feature is a common feature used for emitter identification. In reference [4], the effectiveness of using frequency feature of emitter signal to identify target radar type was studied. On this basis, this paper proposes a Fast Fourier Transform (FFT) method to extract and process ADS-B sample data, which can transform the time-domain characteristics that are not easy to recognize into the frequency-domain characteristics with greater feature distinctions.

In the field of signal recognition and classification, traditional template matching methods, such as pattern matching based on pulse parameters such as PRI, RF and other signals, couldn’t express individual differences precisely after these quantized features. Researchers have proposed k-nearest neighbor (KNN) [5] [6], support vector machine (SVM) [7][8], K-means and other machine learning methods. In reference [9], k-means method was used for clustering, and in reference [10], a radar signal recognition algorithm based on Kernel Fuzzy C-Means was proposed. Although these two methods are simple and cost low, the recognition effect is not ideal. In reference [10], support vector machine was used to classify and identify radar signals, and the recognition effect was improved. With the extensive application of deep learning, some deep learning algorithms such as feedforward neural network, convolution neural network (CNN) [11], deep neural network (DNN) and others were also introduced into signal recognition, but most of the current research focused on the modulation pattern recognition of signals [12]. A typical algorithm in the artificial neural network is back propagation (BP) neural network. Its network structure is simple, with forward transmission to obtain output error, and backward transmission to update parameters. Reference [13] studied the fault diagnosis algorithm based on BP neural network. BP neural network algorithm is very easy to fall into local convergence, which makes the learning time of the algorithm longer. The detection performance of the network is poor, and the test recognition rate is low.

Convolutional neural network (CNN) is a machine learning method which can combine feature extraction with classification and recognition. It has been widely applied to classification and recognition of images and speech signals [14][15]. The most prominent advantage of the convolutional neural network is that it does not need manual selection, and features can be automatically learned from the original data. By adjusting and optimizing the parameters of the convolutional kernel through training, features can be automatically obtained after the weight training, so as to realize the classification and recognition of data. The most outstanding advantage is that the classification effect is exceptional. With the application and research of deep learning in various fields, convolutional neural network has also been gradually carried out in radar target recognition, such as SAR imaging radar recognition [16][17], high resolution range profile recognition [18] and other fields, and has shown good performance in the above radar image recognition. Reference [19] focused on the target recognition of one-dimensional range image radar, and adopted the classification and recognition method of target high resolution range profile of one-dimensional convolutional neural network to carry out the research, and achieves a good recognition effect. Reference [20] studied the HRRP recognition method based on one-dimensional convolutional neural network (CNN), trained CNN to automatically learn useful features from HRRP and classify them, with excellent network performance. Therefore, for ADS-B signal, this paper proposes target identification of radar radiation source based on one-dimensional convolutional neural network. References [19] [20] studied the one-dimensional radar target recognition, but the ADS-
B signal has not been involved yet. Therefore, for the ADS-B signal, this paper proposes the specific emitter identification of radar target based on the one-dimensional convolutional neural network.

This paper studies the specific emitter identification of radiation source method based on the convolutional neural network (CNN) signal target, and applies deep learning algorithms to the signal target individual recognition field. The data set composed of different ADS-B signal data is constructed to train and test the network. The frequency domain signal is extracted from the time domain sequence sample by fast Fourier transform. One-dimensional convolution neural network structure is used to classify and identify multiple types of ADS-B target signals, and the classification effect is compared with that of support vector machine and BP neural network. The experimental result shows that the one-dimensional convolutional neural network is suitable for ADS-B emitter target classification and identification. It can generalize the same kind of target data and has better target recognition effect. What’s more, the identification effect of frequency domain signal is better than the time domain signal.

In addition, the use of one-dimensional convolution neural network for ADS-B emitter classification can effectively combine feature extraction and identification.

2. Model of ADS-B signal and FFT

2.1 Model of ADS-B signal

In this training, ADS-B is the experimental object. First of all, the biggest feature of ADS-B is that it adopts broadcast rather than point-to-point communication, so the signal is easy to obtain, which provides great convenience for data collection and sample production. At the same time, this signal has a clear message leader, which is convenient to pick up the fingerprint information from above, so as to identify quickly.

The data length of ADS-B signal is 120 μs, the header is 8 μs, the response message data block is 112 μs, and the sampling rate is 25 MHZ. The ADS-B message data block format is encoded using Pulse Position Modulation (PPM), which divides the first half of each transmitted Pulse into 1 and the second half into 0, as shown in figure 1.

![Figure 1 Time series waveform of ADS-B signal.](image)

The ADS-B message preamble contains four pulses, each lasting for 0.5 μs. The interval between the second, third and fourth pulse and the first transmission pulse is 1.0 μs, 3.0 μs and 4.5 μs respectively. ADS-B message data block should start 8 μs after the first transmission pulse. The next 112 μs is divided into 112 ADS-B message bits by average interval, and the pulse with width of 0.5 μs should be in the first half or the second half of each interval.

The time domain signal of ADS-B is located by the first four pulses of the preamble. In order to eliminate the impact of message sampling on identification, this paper selects the location segment as the identification segment. The message preamble is as follows:
2.2 Fast Fourier Transform

For one-dimensional time series data of ADS-B signal, each time point of signal acquisition from different samples varies. According to the Fourier Transform property of the linear time invariant system, time shift operation on the time domain signal does not affect the frequency characteristic of the signal. As can be seen from the distribution of the signal in the time domain and frequency domain, the frequency domain features of ADS-B signals of the same kind are concentrated in some points, which are more obvious than those of the time domain. Therefore, the discrete Fourier transform (DFT) is applied to transform the time domain information into the frequency domain information for analysis, which can effectively extract the features.

The finite length sequence can also be discretized into finite length sequence in frequency domain by DFT:

\[ f(x) = a_0 + \sum_{n=1}^{\infty} (a_n \cos n\pi x / L + b_n \sin n\pi x / L) \]  

(1)

However, the calculation is too large to deal with the problem in real time. When the number of points is large, the calculation of DFT will increase greatly, which significantly reduces the processing efficiency of the computer system. So fast Fourier transform (FFT) is introduced. Fast Fourier transform (FFT) is a fast algorithm of discrete Fourier transform. The basic idea of FFT is to decompose the original N-point sequence into a series of short sequences. By making full use of the symmetric and periodic properties of the exponential factors in the DFT calculation formula, the corresponding DFT of these short sequences can be obtained and properly combined, so as to achieve the purpose of eliminating the repeated calculation, reducing the multiplication operation and simplifying the structure, thus greatly reducing the calculation amount of DFT.

In this paper, FFT method is used to preprocess the data, transform the time-domain signal into the frequency-domain signal, and then input the neural network for feature extraction.

3. One dimensional convolutional neural network

The typical convolution neural network is composed of input layer, convolution layer, pooling layer, full connection layer and classifier. The convolution layer can extract the input image features layer by layer, the pooling layer can extract the secondary features of the feature map, the full connection layer will connect the features and send them to the classifier, and finally realize the classification. Different network structures produce different models and bring different classification effects. At present, there are many mature convolutional neural network structures. Since the earliest Lenet-5 model was proposed, many excellent CNN models such as Alex Net, VGG Net, Res Net and Google Net have emerged.

The structure of the classic model Lenet-5 is shown in the figure 3.
Figure 3 The model of Lenet-5.

Compared with the traditional two-dimensional convolution neural network structure, the difference of one-dimensional convolution neural network is that the convolution kernel and the feature block after convolution are vectors rather than matrices.

3.1 Convolution layer
Convolution is used to check the local region of the input signal for convolution operation, and corresponding features are generated. The most important feature of this layer is weight sharing, which greatly reduces the network parameters of the convolutional layer and effectively avoids the occurrence of overfitting. In the convolution layer, the feature graph of the previous layer carries out convolution operation with the convolution kernel, and then the feature graph of this layer is obtained through activation function.

For the one-dimensional CNN structure, let $x^0 = x^{in}$ be the original ads-b signal data input, then the feature extraction process of the network is

$$g_j^d(i) = \sum_{m=1}^{M} (x_{m-1}^d * w_{mk}^d) (i)$$  \hspace{1cm} (2)

$$x_j^d(i) = f(g_j^d(i) + b_j^d)$$  \hspace{1cm} (3)

In the formula: $\sum$ is the sum symbol, $*$ represents the one-dimensional convolution operation; $x_j^d$ is the first characteristic block of the output of the $d$-th convolutional layer; $M$ is the number of convolution kernels; $w_{mk}^d$ is the convolution kernel of the $d$-th shell; $b_j^d$ is the offset of $d$-th shell; $f(\cdot)$ is the activation function.

The commonly used activation functions are relu, sigmoid and tanh. In this paper, we use the linear rectification function, namely relu activation function, because compared with the traditional activation function, such as sigmoid function and tanh function, relu activation function can produce more sparsity. When the input is positive, there is no gradient saturation problem. In addition, the relu activation function has only linear relationship, so the calculation speed is much faster and the performance of the algorithm is improved. The expression of relu function is shown in formula (3):

$$f(x) = \max(0, x)$$  \hspace{1cm} (4)

It can be seen that the interval function less than 0 is 0, and the interval greater than 0 is $f(x) = x$.

3.2 Pooling layer
It is necessary to periodically introduce a pooling layer between convolutional layers of CNN structure. In order to reduce the amount of data in the neural network calculation and the overfiting phenomenon of the model, and improve the calculation speed, the pooling operation is often used to reduce the dimension of the data. Because the dimension of the input ADS-B data is often high, and the convolution layer has a large number of overlapping areas in the process of window sliding convolution, the output feature block has a large number of redundant information. The introduction of pooling layer can reduce the redundant information and thus reduce the amount of calculation.

Set the input data of the pooling layer as the $p \times 1$ dimensional matrix, $X = [x_1, x_2, \cdots, x_p]^T$, the
pooling size as \( t \), and the step size as \( s \), then the output data after the pooling operation is the \( q \times 1 \) dimensional matrix, \( Y = [y_1, y_2, \ldots, y_q]^T \). There are two kinds of pooling methods: maximum pooling method and average pooling method. The global average pooling layer averages each eigenvector of the last convolution layer. Compared with the full connection layer, the global average pooling layer can enhance the correlation between the vector graph and the target category, and is more suitable for the convolution structure. Moreover, there is no training parameter to be optimized in the global average pooling layer, which can greatly compress the network model, reduce the network computation, effectively prevent over fitting, and make the learned feature more robust. Therefore, the average pooling is adopted in this pooling.

3.3 Dropout layer
In order to further avoid the over fitting phenomenon of the model, dropout method is also used in this time, which randomly sets the neuron weight in the network to zero. That means some hidden layer neurons in the network are deleted randomly. This method can reduce the sensitivity of neural network to small data changes and improve the accuracy of data processing.

3.4 Full connection layer and softmax layer
In the all connected layer, each neuron is connected with all the neurons in the upper layer. After multi-layer convolution and pooling, convolution neural network outputs the target in the form of class, so a full connection layer is needed to map the output eigenvector to class. The full connection layer can pull the output of the previous layer into a column vector, integrate the local information with category differentiation in the convolution layer or pool layer, and use it to integrate the features extracted from the previous layer. This layer plays the role of classifier in the whole convolutional neural network. Therefore, after the output of the full connection layer, the classifier is connected. In this paper, softmax classifier is selected. Softmax classifier can be used to solve the problem of multi classification. This model is a supervised learning algorithm, the categories of the input samples should be very clear, the same sample can’t belong to multiple categories at the same time.

The expression of the input vector \( z \) of the fully connected layer is

\[
(z = [(x_1^1)^T, (x_2^2)^T, \ldots, (x_p^i)^T]^T
\]

In the above formula: \( (x_i^j)^T \) is the transposition of the \( i \)-th output vector of the last layer of pooling layer. That is the input vector \( z \) of the full connection layer is the splicing of all output vectors of the last layer of pooling layer. The mapping process of all connected layer is nonlinear. For the case of \( C \) classification number, the full connection layer maps the input high-dimensional vector \( z \) to the output vector \( U \) of \( C \times 1 \) dimensional size as the input of softmax classifier. The expression to get the output vector \( U \) is as follows

\[
U = W \ast z
\]

Where: \( W \) is the weight vector of the full connection layer.

In the process of softmax classification, the probability of classifying the input data \( x \) as category \( i \) is

\[
f_i(U) = \frac{\exp(U(i))}{\sum_{i=1}^{C} \exp(U(i))}
\]

Where: \( f_i(U) \) is the probability when the input category is \( i \), \( U \) is the output of the full connection layer of the classifier, \( U(i) \) is the \( i \)-th component of the output vector \( U \) of the full connection layer, and \( C \) is the number of classifications.

4. Simulation experiment

4.1 The data sample
After the one-dimensional time series of ADS-B signal is synchronized and normalized, the location segment of the signal used for fingerprint identification is selected. Generally, 400 time series points are selected as the original time domain input data of this target identification. Then the FFT method is used
to preprocess the data. By using the FFT function of numpy function library, the frequency-domain signal after conversion and the time-domain signal before conversion are the same discrete sequence composed of 400 sampling points, ensuring that the data sets before and after FFT processing are compatible with the convolution neural network of the same structure.

The ADS-B signal training data set used in the experiment includes 50 target categories, 120 samples in each category, and 6000 samples in total. Each sample contains 400 ADS-B complex signal values continuously sampled in time series. In the experiment, 80% of the training set, namely 4800 samples, is used to train the neural network model, and the rest samples are used to test the classification accuracy of the model. As with the training set, each sample contains 400 consecutive ADS-B complex signal data.

4.2 Construction of one-dimensional convolution neural network model

The one-dimensional convolution neural network includes input layer, two convolution layers, one pooling layer and two fully connected layers. The activation function of convolution layer uses the relu function, because the relu function can not only improve the convergence speed but also effectively avoid the over fitting problem. The last fully connected output connected softmax classifier. The size of the original input layer is 200, the number of convolution cores of the first convolution layer is 16, and the size is 1*2; the number of convolution cores of the second convolution layer is 32, and the size is 1*2, and the size of the pooling layer is 1*2. In this neural network, all one-dimensional convolution layers use the relu activation function. The dropout function can effectively prevent over fitting phenomenon in the training process. In this experiment, dropout ratio is set to 0.2, that is, 20% neuron weight of dropout layer is randomly assigned to zero. The number of neurons in each layer is set to 100. The results of the output layer enter the softmax classifier. According to the output values of the layer, the model classifies the samples into one of the most likely categories. The batch normalization process is added to the network, which can not only accelerate the convergence speed of the model, but also alleviate the problem of "gradient dispersion" in the deep network to a certain extent, so as to make the training of the deep network model easier and more stable.

The process of network training is back propagation error. The gradient value of error function to weight W and bias B is calculated layer by layer and the weight W and bias B are updated. It should be noted that when the error back propagation algorithm is applied in CNN, the pooling layer and the convolution layer have different processing methods than when the error is transferred in the reverse direction. Since there is no nonlinear mapping function in the pool layer, the derivative of activation function of pool layer is 1. The optimizer adopts Adam optimization algorithm this time. Adam is a first-order optimization algorithm which can replace the traditional stochastic gradient descent (SGD) process. It can update the weights of neural networks iteratively based on the training data. The loss function uses the cross entropy loss function, and the learning rate is set to 0.001. The batch size of the training sample is set to 200, the number of epochs is 100, and the test recognition rate of the radiation source target through one-dimensional convolution neural network is calculated.

4.3 The simulation results

The number of individual target categories of radiation sources is 5, 10, 20, 30, 50 and 70 respectively. The results are shown in Table 1:

| Number of target categories | 5   | 10  | 20  | 30  | 50  | 70  |
|-----------------------------|-----|-----|-----|-----|-----|-----|
| 400-point recognition rate in frequency domain | 97% | 97% | 91% | 89% | 88% | 83% |
| 400-point recognition rate of original time domain | 25% | 22% | 19% | 18% | 15% | 13% |
From the results of table 1, it can be seen that there are obvious characteristics differences between different types of samples in frequency domain. After preprocessing of FFT, the recognition rate of neural network model is improved obviously. The experimental results show that the FFT method can effectively improve the recognition accuracy of the model compared with no preprocessing. When the number of categories is 5 to 10, the accuracy can reach over 95%; with the increase of the number of categories, the recognition rate slightly decreases, and the overall recognition rate is over 80%.

| Number of target categories | 5    | 10   | 20   | 30   | 50   |
|-----------------------------|------|------|------|------|------|
| CNN                         | 97%  | 97%  | 95%  | 89%  | 88%  |
| BP Net                      | 94%  | 91%  | 88%  | 84%  | 81%  |
| SVM (Linear Kernel)         | 90%  | 86%  | 85%  | 80%  | 78%  |
| SVM (RBF kernel)            | 93%  | 90%  | 87%  | 83%  | 80%  |

It can be seen from the results in table 2 that SVM uses kernel function to map the raw data from the non-separable low-dimensional space to the high-dimensional space to achieve classification. When the number of target categories is small, the classification effect is better. From the perspective of kernel function, the recognition accuracy of RBF kernel is significantly higher than that of linear kernel. BP network realizes input-output mapping by adjusting the network weight and bias, and the recognition rate is higher than SVM classifier. CNN uses convolution layer to extract useful features for classification, with the highest recognition rate, and the recognition performance is still excellent when the number of categories increases.

| Training proportion | 20% | 30% | 50% | 70% | 80% |
|----------------------|-----|-----|-----|-----|-----|
| Average recognition rate | 76% | 83% | 86% | 86% | 88% |

It can be seen from the results in table 3 that the proportion of training and test samples will also affect the recognition results. When the training test proportion is 20%, the recognition rate is low; when the training proportion reaches more than 30%, the accuracy rate is improved; when the training proportion is higher than 50%, the average recognition rate is more than 85%.

| Input feature points after FFT | 200 | 300 | 400 |
|--------------------------------|-----|-----|-----|
| Average recognition rate       | 77% | 79% | 88% |

It is easy to see from table 4 that when the number of feature points increases from 200 to 400, the target recognition rate increases gradually.

| the size of Convolution kernel vector | 2*1 | 5*1 | 10*1 | 20*1 |
|--------------------------------------|-----|-----|------|------|
| Average recognition rate             | 88% | 86% | 84%  | 83%  |

From table 5, it can be seen that with the increasing of convolution kernel size, the recognition performance of the network gradually declines. When the convolution kernel size is 2, the network performance is the best; therefore, the small convolution kernel can be used to replace the large convolution kernel, and when the convolution kernel size increases, the number of weights in the network increases, and the time spent training CNN also increases.
Table 6 Average recognition rate of training samples in different batches (50 targets)

| batch | 20  | 50  | 100 | 200 | 300 |
|-------|-----|-----|-----|-----|-----|
| Average recognition rate | 89% | 90% | 86% | 85% | 86% |

It can be seen from table 6 that the number of batch training samples has a certain impact on the target recognition rate, and the recognition performance is optimal when the number of batch samples is 50; when the number of batch samples is greater than 50, the average recognition rate slightly decreases with the increase of the number of batch samples.

Table 7 average recognition rate of targets under different learning rates (50 targets)

| learning rate | 0.001 | 0.01 | 0.05 | 0.1 |
|---------------|-------|------|------|-----|
| Average recognition rate | 88% | 86% | 81% | 15% |

From table 7, it is found that when the learning rate is below 0.1, the recognition rate of the target individual is higher. And when the learning rate is reduced to 0.001, the network shows good performance. when it is over 0.05, the recognition performance is significantly reduced.

5. Conclusion

In this paper, convolution neural network in deep learning is applied to target recognition of radar. By constructing the network structure of one-dimensional convolutional neural network, the fingerprint identification of ADS-B signal emitter is carried out. In this method, ADS-B signal is taken as data sample, and the original data is preprocessed by FFT algorithm and input to one-dimensional convolution neural network for feature extraction. The feature dimension is reduced by pooling method, the over fitting is reduced by dropout method, and the final sample classification is realized by full connection layer and softmax. By changing the parameters of convolutional neural network to optimize its structure, such as improving the training test sample proportion, convolution kernel size, batch number, learning rate and other parameters, the target recognition rate was greatly improved. The result shows that the one-dimensional convolutional neural network model proposed in this paper can accurately identify the individual targets of different radar radiation sources. And compared with the original time domain sampling signal, the preprocessing method based on FFT can significantly improve the recognition accuracy of the model. The correct recognition rate can reach 97% when the target category is 10, and over 90% when the target category is 20. When the number increases to 50, the accuracy is more than 85%. Compared with SVM, BP neural network and other classifiers, convolutional neural network still has a stable and good recognition performance when the number of categories increases.

References

[1] D’Agostino, S. (2015) Specific emitter identification based on amplitude features. *2015 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*. IEEE, 2015:350-354

[2] Ru, X.H., Liu, Z., Jiang, W. L., et al. (2016) Recognition performance analysis of instantaneous phase and its transformed features for radar emitter identification[J]. IET Radar Sonar & Navigation, 2016, 10(5):945-952.

[3] Ye, H., Liu, Z., Jiang, W. (2012) Comparison of unintentional frequency and phase modulation features for specific emitter identification[J]. Electronics Letters, 2012, 48(14):875-877.

[4] Li Y.B, Wang Y.H, Lin Y. (2013) Recognition of radar signals modulation based on short time Fourier transform and reduced fractional Fourier transform [J]. Journal of Information & Computational Science, 2013, 10(16): 5171-5178.

[5] Zhong, Z., Zhu, M.L., Zhang, Chen., et al. (2011) Research on nearest neighbors classification techniques. Journal of Frontiers of Computer Science and Technology, 2011, 5(5): 467-473.

[6] Yan, L.T., Xiang, X.L. (2019) Application of k-nearest neighbor based on kernel in underwater
target recognition [J]. Applied Acoustics. (in Chinese)
[7] Guan, X., Guo, Q., Zhang, Z.C., et al. (2011) Radar emitter signal recognition based on kernel function SVM [J]. Journal of Projectiles Rockets Missiles and Guidance, 2011, 31(4): 188-191. (in Chinese)
[8] Gao, Z.B., Liu, Y.A. (2019) Recognition of SAR image based on NSCT and support vector machine [J]. Computer Measurement & Control, 2019(6). (in Chinese)
[9] Rong, L., Wang, H.N., Cui, Y.M., et al. (2011) Solar flare forecasting using learning vector quantity and unsupervised clustering techniques[J]. Science China, 54(8):1546-1552.
[10] Guo, Q., Nan, P., Zhang, X., et al. (2015) Recognition of radar emitter signals based on SVD and AF main ridge slice[J]. Journal of Communications & Networks, 17(5):491-498.
[11] Zeiler, M.D., Fergus, R. (2014) Visualizing and Understanding Convolutional Networks[M]. Computer Vision – ECCV 2014. Springer International Publishing.
[12] Ding, L., Wang, S., Wang, F., et al. (2018) Specific Emitter Identification via Convolutional Neural Networks[J]. IEEE Communications Letters, 2018:1-1.
[13] Zhang, W., Peng, G., Li, C., et al. (2017) A new deep learning model for fault diagnosis with good anti-noise and domain adaptation ability on raw vibration signals [J]. Sensors, 17 (2): 425.
[14] Ramaiah, N. P., Ijjina, E. P., & Mohan, C. K. (2015) Illumination invariant face recognition using convolutional neural networks. IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES). IEEE.
[15] Yu, N.G., Jiao, P., Zheng, Y.L. (2015) Handwritten digits recognition base on improved LeNet5[C] // IEEE Control & Decision Conference, Qingdao, China, 2015: 4871-4875.
[16] Housseini, A.E., Toumi, A., Khenchaf, A. (2017) Deep Learning for target recognition from SAR images[C]// 2017 Seminar on Detection Systems Architectures and Technologies (DAT). IEEE.
[17] Zhong, C., Mu, X., He, X., et al. (2018) SAR Target Image Classification Based on Transfer Learning and Model Compression[J]. IEEE Geoscience and Remote Sensing Letters, 2018:1-5.
[18] Lunden, J., Koivunen, V. (2016) Deep learning for HRRP-based target recognition in multistatic radar systems[C]// 2016 IEEE Radar Conference (RadarConf16). IEEE, 2016.
[19] Wang, R.C., Zhuang, Z.H., Wang, H.B., et al. (2019) HRRP classification and recognition method of radar target based on convolutional neural network[J]. Modern Radar,2019,41(5):33-38.
[20] Yin, H.Y., Guo, Z.H. (2018) Radar HRRP target recognition with one-dimensional CNN. Telecommunication Engineering, 2018, 58(10) : 1121-1126.