A Signal Recognition Algorithm Based on Compressive Sensing and Improved Residual Network at Airport Terminal Area

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Abstract: It is particular important to identify the pattern of communication signal quickly and accurately at the airport terminal area with the increasing number of radio equipments. A signal modulation pattern recognition method based on compressive sensing and improved residual network is proposed in this work. Firstly, the compressive sensing method is introduced in the signal preprocessing process to discard the redundant components for sampled signals. And the compressed measurement signals are taken as the input of the network. Furthermore, based on a scaled exponential linear units activation function, the residual unit and the residual network are constructed in this work to solve the problem of long training time and indistinguishable sample similar characteristics. Finally, the global residual is introduced into the training network to guarantee the convergence of the network. Simulation results show that the proposed method has higher recognition efficiency and accuracy compared with the state-of-the-art deep learning methods.

Key words: compressed sensing; deep learning; residual network; modulation recognition

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0 Introduction

The continuous increase of various civil aviation radio stations at the airport terminal area makes the electromagnetic environment more and more complex, and also leads to more serious frequency conflict interference[1]. The United States (NextGen), Europe (SESAR) and International Civil Aviation Organization (ICAO) Doc9854 have proposed a vision for a new generation of navigation systems, including utilizing the digital communications to reduce the impact of interference in airspace[2]. And the modulation recognition method is widely used in the field of digital communications. How to capture and interpret the communication signal effectively plays a major role in ground-to-air communication.

Traditionally, the decision theory is based on hypothesis likelihood ratio and the methods are based on higher-order statistics and feature extraction[3-4]. However, the feature extraction is time-consuming and these methods have not been able to meet the demands of high precision and efficiency in the era of data explosion. So that state-of-the-art methods based on deep learning have emerged. The application in the field of communication brings brand-new opportunities and changes. A modulation recognition method based on deep belief network (DBN) was proposed in Ref.[5] to classify the two-dimensional images of universal correlation functions of common digital modulation signals. Converting signal into constellation method and recog-

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nizing by convolution neural network (CNN) were proposed in Ref. [6] which obtained more accurate results than the support vector machine (SVM) and also avoided the manual selection of features. Instead of converting signals into an images, the in-phase component and orthogonal component sampling point data proposed in Ref. [7] were directly used as the input of CNN and the stability of the deep learning method was proved at low signal-to-noise ratio (SNR). The reference data set of modulation recognition learning was given in Ref. [8]. A simulation data set simulated in a more realistic radio environment was proposed in Ref. [9], which includes 24 kinds of modulation signals. Deep residual network is widely used in the field of computer vision. Through the method of cross-layer connection, the residual network (RN) can avoid the problem of feature graph loss[10-11]. RNs for time series radio classification were proposed in Ref. [12] to reduce the training time, but they did not significantly improve the recognition accuracy.

In signal modulation recognition, compressive sensing (CS) is introduced to preprocess the signal to retain the most useful information before inputting the signal into the neural network. The possibility of using measurement signals without reconstruction for detection was provided in Ref. [13]. Spectrum detection based on eigenvalues for compressed unreconstructed signals was proposed in Ref. [14], which greatly reduced the computational complexity, but did not affect the probability of signal detection.

Residual neural network can solve the problems that the model training time is too long and the similar features of the sample are hardly to distinguish, which finally lead to a certain enhancement for the recognition accuracy of samples. The image is two-dimensional convolution while the signal is one-dimensional one. The use of neural networks to classify signal modulation is based on the idea of image classification. In this work, the received signal is regarded as a single channel "picture", and a method based on the improved RN to identify the signal modulation is proposed. Firstly, the received signal is compressed in the preprocessing to extract most of the useful information. Furthermore, the scaled exponential linear units (SELU) activation function is introduced to construct the RN structure. Global residual is introduced to solve the problem of network convergence. Simulation results show that the proposed method has higher recognition efficiency and accuracy.

1 Signal Model

Combined with the very high frequency (VHF) communications in the airport terminal area, it is assumed that the received signal is $r(t)$, which can be written as

$$r(t)=s(t)\times c+n(t) \tag{1}$$

where $s(t)$ is a modulated signal, c represents the path loss, and $n(t)$ the white Gaussian noise. The measurement value is obtained by CS as follows

$$\boldsymbol{y}=\boldsymbol{\Phi r} \tag{2}$$

where $\boldsymbol{r}$ is $N\times 1$ vector of Nyquist sampling denoting signal $r(t)$, $\boldsymbol{y}$ the $M\times 1$ measurement signal, and $\boldsymbol{\Phi}\in \mathbf{C}^{M\times N}(M\ll N)$ the measurement matrix. During one cycle, the atom with the largest inner product for the measurement matrix and residual is found and incorporated into the estimation support set. The single atomic selection process can be represented as

$$i=\underset{1\leqslant i\leqslant N}{\arg\max}\left|\left\langle \boldsymbol{\phi}_i,y_r\right\rangle\right| \tag{3}$$

where $\boldsymbol{\phi}_i$ is the ith line vector of measurement matrix $\boldsymbol{\Phi}$.

Discrete cosine transformation (DCT) matrix is selected as the sensing matrix in the absence of prior information about the signal. Most of the energy information of the time-domain signal can be compressed into a small number of DCT domains[15], as represented by

$$\phi(k,i)=c(k)\cos(\pi(2i+1)k/2N) \tag{4}$$

where $k\in(0,M-1)$, $i\in(0,N-1)$, and $c(k)$ is the matrix coefficient. Hence, we arrive at the measurement signal notation of

$$\boldsymbol{y}=[y_1,y_2,\cdots,y_M]^{\mathrm{T}}=[s_1+n_1,s_2+n_2,\cdots,s_M+n_M]^{\mathrm{T}} \tag{5}$$

To prevent over-fitting, three parts data are divided into train set, test set and cross-validation set, $\boldsymbol{y}=[y_1\ y_2\ y_3]^{\mathrm{T}}$, where y_1 is a training model of training set, y_2 the validation set, and y_3 a test set.

2 Improved Residual Network

The proposed residual network and global skip connection are introduced in this section.

2.1 The proposed residual network

Instead of the original rectified linear unit (RELU), the residual unit based on SELU activation function (R-SELU) is constructed to solve the problem of "neuronal death" at the negative gradient, as shown in Fig.1.

In the residual unit, the input of the first residual unit is set to x_l, then the structure of the residual unit is

$$x_{l+1}=x_l+F(x_l,w_l) \tag{6}$$

$$F(x_l,w_l)=w_l\sigma(w_{l-1}x_{l-1}) \tag{7}$$

where σ is the activation function and $F(x_l,w_l)$ the function of residual unit.

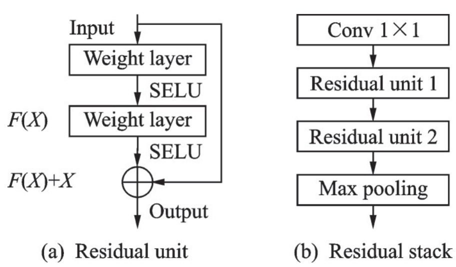


Fig.1 Residual block structure

For any input of unit, the relationship between multiple residual units can be obtained by

$$x_L=x_l+\sum_{i=1}^{L-1}F(x_i,w_i) \tag{8}$$

Assuming that J is loss function, then the calculation expression for the error back-propagation is followed by

$$\frac{\partial J}{\partial x_l}=\frac{\partial J}{\partial x_L}\cdot\frac{\partial x_L}{\partial x_l}=\frac{\partial J}{\partial x_L}\left(1+\frac{\partial}{\partial x_l}\sum_{i=1}^{L-1}F(x_i,w_i)\right) \tag{9}$$

$\dfrac{\partial J}{\partial x_L}$ ensures that the information can be directly back to x_L, so $1+\dfrac{\partial}{\partial x_l}\sum_{i=1}^{L-1}F(x_i,w_i)$ solves problem of vanishing gradient.

A 6-layer residual neural network is constructed based on the above residual blocks. The structure diagram is shown in Fig.2.

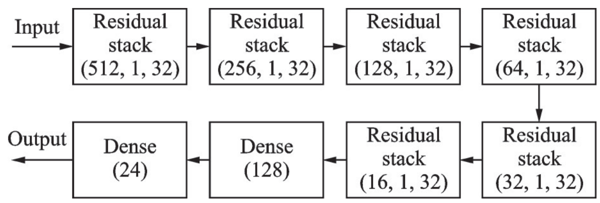


Fig.2 Structure of ResNet network

The expression of each layer of the above network structure is followed by

$$\begin{cases}F_1(X)=\sigma(W_1*y+b_1)\\F_2(X)=\sigma[W_2*F_1(X)+b_2]\\\quad\vdots\\F_{n-1}(X)=\sigma[W_{n-1}*F_{n-2}(X)+b_{n-1}]\end{cases} \tag{10}$$

where y is the low dimensional measurements of compressed signals, b the basis, W convolution kernel, the number n and the size $k\times k\times c$. c is the number of channels. When $n=1$, $W_1=3\times1\times1$. "*" is convolution operation.

$$y'=F_n(X)=W_n*F_{n-1}(X)+b_n \tag{11}$$

where y' is the reconstructed measurements of the last convolutional layer.

2.2 Activation function

The activation function used for the full-connection layer is SELU

$$\mathrm{selu}(x)=\begin{cases}\lambda x & x>0\\\lambda(\alpha\mathrm{e}^x-\alpha) & x\leqslant0\end{cases}\quad \lambda>1 \tag{12}$$

As can be seen from Eq.(11), when the gradient is greater than 0, the positive half-axis gradient is greater than 1, which is well solved in the RELU activation function. It is not simple to set 0 at the negative half-axis, which solves the case of neuronal death. The introduction of the SELU activation function solves the problem of indistinguishable similar features in the sample. The activation function used by the output layer is

$$\mathrm{soft\,max}(\boldsymbol{x})_i=\frac{\exp(\boldsymbol{\theta}_j^{\mathrm{T}})x(i)}{\sum_{l=1}^{k}\exp(\boldsymbol{\theta}_j^{\mathrm{T}})x(i)} \tag{13}$$

Using training set T to train classifiers is to find appropriate parameters to minimize some loss functions of classifiers. The cross entropy loss function is generally used as

$$J(\theta)=-\frac{1}{N}\sum_{i=0}^{N}[y_i\lg\hat{y}_i+(1-y_i)\lg(1-\hat{y}_i)]=$$
$$-\frac{1}{N}\left[\sum_{i=0}^{N}\sum_{j=1}^{k}1\{y_i=j\}\lg\frac{(\exp(\boldsymbol{\theta}_j^{\mathrm{T}})x(i)}{\sum_{l=1}^{k}\exp(\boldsymbol{\theta}_j^{\mathrm{T}})x(i)}\right] \tag{14}$$

where $1\{y_i=j\}$ means that when $y=j$, the value is 1, otherwise the value is 0. The smaller the value of the loss function, the more accurate the result of the classification training set.

However, Eq.(14) is not a strict convex function, which does not guarantee that it has a unique solution. Increasing the weighted attenuation term $\frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j=0}^{n}\theta_{ij}^2$ penalizes excessive attenuation value, then, the new loss function is

$$J(\theta)=-\frac{1}{N}\left[\sum_{i=0}^{N}\sum_{j=1}^{k}1\{y_i=j\}\right.$$
$$\left.\lg\frac{(\exp(\boldsymbol{\theta}_j^{\mathrm{T}})x(i)}{\sum_{l=1}^{k}\exp(\boldsymbol{\theta}_j^{\mathrm{T}})x(i)}\right]+\frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j=0}^{n}\theta_{ij}^2 \tag{15}$$

Using the iterative optimization method to solve Eq. (15) , the gradient equation can be obtained as

$$\nabla_{\theta_j}J(\theta)=-\frac{1}{N}\sum_{i=0}^{N}[x^{(i)}(1\{y_i=j\}-$$
$$p(y_i=j|x(i);\theta))]+\lambda\theta_j \tag{16}$$

2.3 Global skip connection

In the residual block, the relationship between the input and the output can also be written in a simple way as

$$x_{ll+1}=\sigma(g(x_{ll};W_{ll})+x_{ll}) \tag{17}$$

where x_{ll} and x_{ll+1} are the input and the output of the residual block, respectively. $g(\cdot)$ is the joint operation between the convolution layers and W_{ll} represents all contained parameters. Since $\sigma(\cdot)$ is nonlinear, $g(x_l;W_l)+x_l$ is not always greater than zero.

$$\sigma(g(x_{ll};W_{ll})+x_{ll})\neq\sigma(g(x_{ll};W_{ll}))+\sigma(x_{ll}) \tag{18}$$

Residual block does not accurately learn the residual between the input and the output $x_{ll+1}-x_{ll}$, so the overall residual x_L-x_{ll} is also inaccurate.

Since the input and output of this work are similar, zero padding is used to keep the data dimension consistent. The overall model of the training network is shown in Fig.3. Received signal is compressed using the signal model method to reduce the redundancy and divided into dataset and label. The dataset is based on the constructed residual network and the global residual connection is introduced. Through the full connection layer with SELU as the activation function, the regression output is carried out, the loss function is calculated, and the training network is evaluated. By introducing global skip connection, the residual neural network detects the residuals from the overall network existing between input and output, which leads to a faster convergence rate.

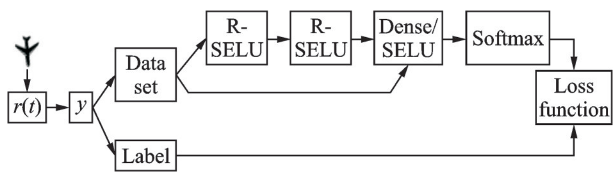


Fig.3 Structure diagram of overall training network

3 Experiments and Analysis

3.1 Experiment settings

To verify the validity of the proposed method, the open dataset named RML2018.01a in Ref.[9] was used. 74 million signals were extracted, in which 60% data were the training set, 20% data were the cross-verification set and the final 20% data were the test set. These extracted data set were divided into 24 parts and preprocessed, including compressing and denoising. The dataset parameters used are listed in Table 1.

Experiments were conducted on Google's open cloud platform to overcome the inconvenience caused by the hardware limitation. For the sake of

Table 1 ResNet network layout

Parameter	Value
Dataset dimension	2 555 904 × 1 024 × 2
Modulation pattern	24
SNR range/dB	−20—30
SNR interval/dB	2
Total dataset amount	740 000
Signal number for each modulation pattern	4 096
Modulation modes for each pattern	2
Sampling signal length	1 024
Measurement signal length	128

simplicity, the simulation environment configuration is shown in Table 2.

Table 2 Simulation environment configuration

Issue	Version number
Tensorflow version	1.14.0
Keras version	2.2.4
Python version	Python3.6
Cloud platform	Google Colaboratory
GPU	NVIDIA Tesla K80

After many experiments, the first training time of the whole model is longer by using the setting of hardware conditions. The ResNet network layout is shown in Table 3.

Table 3 Resnet network layout

Layer	Output dimension	Kennel_size	Pool_size
Input			
Residual_stack	(512,1,32)	(3,2)	(2,2)
Residual_stack	(256,1,32)	(3,1)	(2,1)
Residual_stack	(128,1,32)	(3,1)	(2,1)
Residual_stack	(64,1,32)	(3,1)	(2,1)
Residual_stack	(32,1,32)	(3,1)	(2,1)
Residual_stack	(16,1,32)	(3,1)	(2,1)
Dense/ SeLU	128		
Dense/ SoftMax	24		

Dropuout was selected to enhance the generalization ability and robustness of the network. Adam optimizer, an extended algorithm of stochastic gradient descent, was selected in the process of parameter updating, which has excellent performance in practice. Hyper-parameter settings of the training network are shown in Table 4.

Table 4 Hyper-parameter settings of the training network

Hyper-parameter	Value
Optimizer	Adam
AlphaDropout	0.3
Min-Batah	1 024
Each training time/s	175
Epoch	100
Overall training time/h	2.95

3.2 Results and disussions

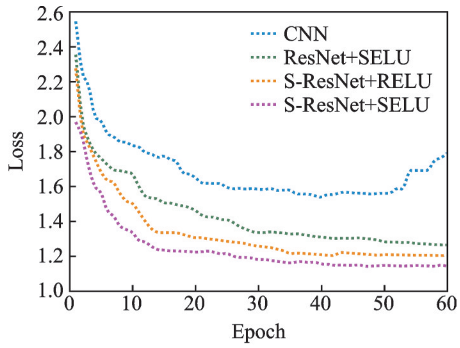
In this work, the conventional CNN, the ResNet+SELU method used in Ref.[9], the S-ResNet+RELU method and S-ResNet+SELU method constructed based on the RN proposed in this work are selected for comparative simulations.

Network loss trend of training dataset of four methods is shown in Fig.4(a). Considering the way of batch training, the curve will show ups and downs. At the same iteration number, it can be shown that the RN performs well. It can be shown that the loss function reduction rate of S-ResNet+SELU method is the fastest. At the time of epoch about 13, the loss function begins to converge and finally converges to 1.14. The loss function of S-ResNet+RELU method finally converges to 1.20, and the loss function of ResNet+SELU method tends to be flat in epoch 30 and finally converges to 1.28. The loss function trend of these three methods confirms the loss function change of the activation function in Fig.4(b). The loss function of CNN shows a "hook back" when epoch is 55, indicating that the network reaches a certain depth and the CNN appeares a gradient disappearance. The convergence trend of using RELU and SELU loss function in the improved network is basically the same, but it is easier to converge than using RELU activation function in the residual function.

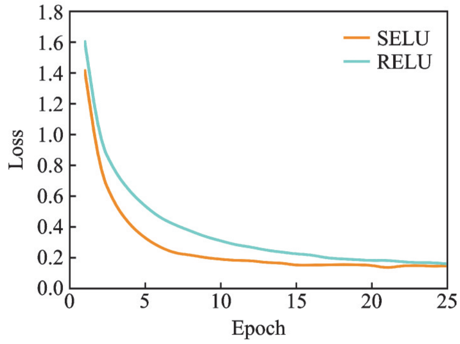
The recognition accuracy is the ratio between the correct number of samples predicted and the total number of samples, as

$$\mathrm{ACC} = \mathrm{prediction}/\mathrm{samples} \tag{19}$$

The four models are tested many times, the best results are recorded, and the accuracy is shown in Table 5.



(a) Variation of the training loss



(b) Convergence rate of activation function

Fig.4 Network loss trend of training dataset

Table 5 Accuracy comparison between the proposed methods and traditional methods on the dataset

Model	CNN	ResNet+SELU	S-ResNet+RELU	S-ResNet+SELU
Average accuracy /%	67.86	86.72	90.32	92.12

Under the condition that the improved residual block uses the SELU, the accuracy of the model using the RELU in the full connection layer is only 1.8% higher. However, SELU converges much faster than RELU, as can be seen from Fig.4(b).

The accuracy in the range of SNR of the four methods is shown in Fig.5.

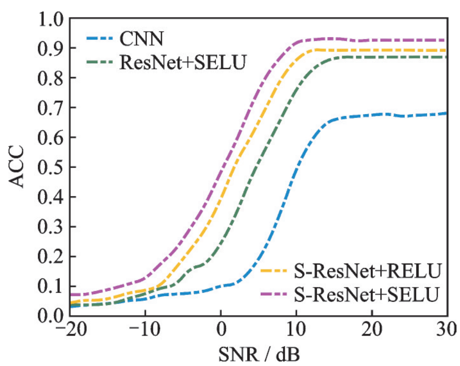


Fig.5 Accuracy trend of test dataset

When SNR is 10 dB, the three methods based on the RN achieve the best effect. At low SNR, the accuracy of the proposed method has been on top of the other methods. The higher-order modulation of the signal is less easily distinguished at low SNR, however, the recognition rate of the traditional residual module is low when it has similar samples, which explains the poor recognition effect of the ResNet+SELU in the low SNR. The S-ResNet+RESU and the S-ResNet+SELU can still achieve a recognition rate of 50% when SNR is 0, and the S-ResNet+SELU has reached 90.2% of the recognition accuracy at 8 dB.

The parameters of CNN, ResNet+SELU and the S-ResNet+SELU proposed in this work are compared, as shown in Table 6.

Table 6 Number of parameters

Method	CNN	ResNet+SELU	S-ResNet+SELU
Number of parameters	257 099	239 616	139 192

CNN uses 257 099 parameters, while ResNet+SELU uses 238 840 parameters. Furthermore, the number of parameters used in the proposed S-ResNet+SELU is 139 192. It is found that the number of used parameters is reduced by 99 648. In the process of model training, the method in this paper trains epoch that requires a mean detection time of 175 s, and the average time used by ResNet+SELU is 477 s. In hardware limitations, the detection time used in this paper is longer, and the training of the whole model takes about 2.95 h.

The confusion matrix is compared under different SNRs illustrated in Fig.6. When the three kinds of SNR are −2, 6 and 10 dB, the modulation mode can still be identified accurately. It is shown that the modulation modes of 32PSK, AM-DSB-WC, FM and OOK can be accurately identified when SNR is −2 dB. AM-DSB-WC is the modulation mode used in VHF communication system, and 256QAM and QPSK cannot be easily distinguished under low SNR because of their similar characteristics. When SNR is 6 dB, there are 16 modulation modes with

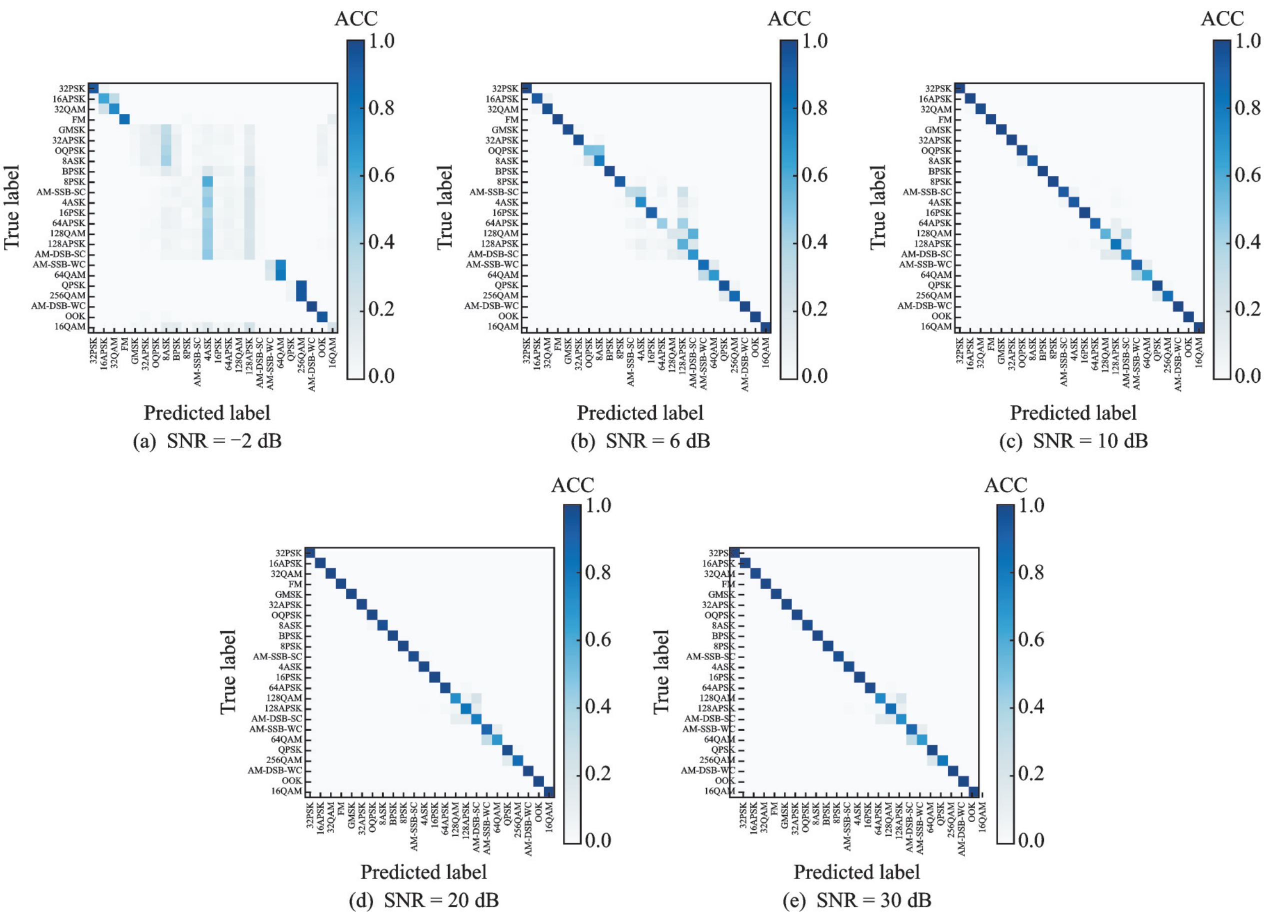


Fig.6 Confusion matrix of test set

the recognition rate of above 80%. When SNR is 10 dB, the confusion matrix can basically get pure diagonal lines, and most modulation modes can be recognized. However, 128QAM and AM-DSB-SC have 20% recognition error rate, 128APSK and 128QAM have 20% recognition error rate, 256QAM and QPSK modulation mode have about 10% recognition error rate. When SNR are 20 dB and 30 dB, there will still be shadows when the high-order PSK modulation is used. However, it has a good recognition effect for the analog modulation used in the traditional VHF communication, and this work will also provide a reference for the choice of digital modulation in the civil aviation VHF communication system in the future.

4 Conclusions

Aiming at the signal modulation pattern recognition, this work proposes an improved residual network based on SELU activation function combined with CS. It is shown to solve the problem of high computational complexity, complicated steps of the artificial feature extraction and slow convergence speed featured by the conventional residual network. The proposed algorithm firstly discards the redundant components when extracting information from the input signal using the measurement matrix. Then, when training the classification network, a residual unit and residual block structure based on SELU as the activation function is constructed. Furthermore, to solve the inaccuracy of residual learning and difficulty at network convergence, the concept of global skip connection is introduced. According to a series competing simulations, the proposed method is demonstrated to have the short training time, the faster convergence speed and the better recognition accuracy of the modulation mode when comparing with other four popular methods.

In view of the complex electromagnetic environment in the airport terminal area, the prospect of further research in this work is to design a recognition method for the performance detection of real signal sources based on deep learning spectrum sensing technology.

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Author contributions Prof. **SHEN Zhiyuan** designed the study, complied the models, conducted the analysis, interpreted the results and wrote the background of the study. Dr. **LI Jia** contributed to complying the models and data selection for analysis and simulation design. Ms. **WANG Qianqian** contributed to complying the models, conducting the simulation and discussion, and writing the manuscript. Ms. **HU Yingying** contributed to adding supplement for revised version and adjusting the paper format. All authors commented on the manuscript draft and approved the submission.

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一种基于压缩传感和改进机场残差网络的信号调制模式识别方法

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摘要:随着机场航站无线电设备数量的增加,迅速准确地识别通信信号的模式尤为重要。本文提出了一种基于压缩感知和改进残差网络的信号调制模式识别方法。首先,在信号预处理过程中引入了压缩感测方法,以丢弃采样信号的冗余分量,压缩后的测量信号作为网络的输入;然后,基于缩放的指数线性单位激活函数构造残差单元和残差网络,以解决训练时间长和样本相似特性难以区分的问题;最后,将全局残差引入训练网络以保证网络的收敛性。仿真结果表明,与前端的深度学习方法相比,该方法具有更高的识别效率和准确性。

关键词:压缩传感;深度学习;残差网络;调制识别