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RESEARCH ARTICLE

Modulation Signal Classification Algorithm Based on Denoising Residual Convolutional Neural Network

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ABSTRACT Traditional denoising algorithms are easy to lose signal details, resulting in low recognition accuracy of modulated signals. A modulation signal classification algorithm based on denoising residual Convolutional Neural Network (DRCNet) is proposed. DRCNet inserts a soft threshold function as a nonlinear transformation layer into the deep architecture to build a soft threshold learning network (STLNet). STLNet obtains an appropriate threshold according to the signal-to-noise ratio of the input signal samples, which is used to remove useless noise features, thereby effectively denoising the signal.This paper builds a serial network (RCTLNet) connected by Convolutional Neural Networks and Long-Short-Term Memory Networks. RCTLNet uses the convolutional neural network to extract the spatial features of the signal samples, and uses the long and short-term memory network to extract the temporal features of the signal samples. And then realize the classification and identification of the modulated signal. Experiments show that the recognition accuracy of the proposed modulated signal classification model is 92%, which is 7% higher than that of the Convolutional Long-Short Term Memory Network (CNN-LSTM).

INDEX TERMS Automatic modulation classification, convolutional neural network, denoising network, long-short term memory network.

I. INTRODUCTION

In the wireless system, the modulation method will change with the change of the environment. It is necessary to perform Automatic Modulation Classification (AMC) [1] on the modulated signal. Traditional modulation signal identification methods can be brought down to two categories [4], one being the decision theoretic approach [2], [3], [4] and the other the feature based approach [5], [6], [7]. In the decision theoretic approach, AMC is presented as a multiple hypothesis testing problem. In the Conventional feature-based approaches, AMC uses expert functions such as cyclic moments for modulation classification.

Modulated signal classification methods using deep learning have achieved better performance than traditional modulated signal recognition methods. Deep learning have been successful attempts in some areas such as natural language processing, video detection, image classification and voice signal processing. Ma et al. [8] and Wang et al. [9] applied Convolutional Neural Networks (CNN) to the task of radio modulation recognition. Simulation results show that CNN demonstrates better accuracy results, and provides more flexibility compared to current day expert-based approaches.But increasing the depth of the network beyond the range will bring about problems such as gradient disappearance or explosion. The Residual Neural Network (ResNet) [10] enhances feature propagation in neural networks by creating shortcut paths between different layers of the network, greatly alleviating the problem of vanishing or exploding gradients.To further improve the performance, the Recurrent Neural Network (RNN) [10] is proposed to explicitly learn the complex relationship of time-dependent signals under various noise conditions on Rayleigh Fading Channels. Long-Short Term Memory (LSTM) [11], [12] is a temporal recurrent neural network used to classify the modulation patterns of short-length signals. A new data-driven model for AMC

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based on LSTM [13] is proposed. The model learns from the time domain amplitude and phase information of the modulation schemes present in the training data without requiring expert features like higher order cyclic moments.Recently, a Convolutional Long-Short Term Memory Network (CNN-LSTM) has been introduced in, where it combines the architectures of CNN and LSTM into a deep neural network by taking advantageof the complementarity of CNNs, LSTMs, and DNNs. It can more effectively explore the spatiotemporal correlation of the signal. But the original signal is not processed using a noise reduction algorithm.

At the same time, traditional denoising algorithms can suppress the noises by applying appropriately designed filters and soft threshold values, such as the wavelet-based denoising algorithms [14] and the filter-based denoising algorithm [15]. However, traditional denoising algorithms might not work well in practical systems. On the one hand, traditional denoising algorithms need to understand the characteristics of noise to determine key parameters such as thresholds, which brings great challenges to practical systems that usually work in noise-changing environments. On the other hand, the components in the system usually operate under imperfect conditions, and the noise can be white noise with uniform frequency distribution, or it can be random with unknown statistical characteristics, and it may even be correlated.

In recent years, intelligent denoising methods based on deep learning have been proposed to improve denoising performance. With the help of deep neural network, after time-consuming offline training, the noise can be suppressed in real time in the online deployment state. Yoonsik Kim et al. proposed a single-model CNN denoiser by gating the CNN's feature maps according to the noise level [16]. Yi Wang et al. proposed a novel Channel and Spatial Attention Neural Network (CSANN) for image denoising. In CSANN, They concatenate the noise level with the mean and maximum value of each channel as input, and propose a convolutional network to learn the relationship between channels [17]. Hailiang Zhu et al. [18] proposed a deep learning-based classification structure to enhance modulated signals. The structure consists of a denoiser and a classifier. A residual learning-based generative adversarial network (GAN) denoiser implicitly removes potential interfering signals from the original modulated signal to understand the distribution of noise and finally enhance the original modulated signal.

Based on the above problems, this paper builds a classification model of modulation signal based on denoising residual Convolutional Neural Network.

1) A denoising residual Convolutional Neural Network (DRCNet) is proposed. Firstly, the soft threshold function is inserted into the deep architecture of the network as a non-linear transformation layer. Then appropriate thresholds are given for signals with different Signal-Noise Ratios (SNR) to eliminate useless noise features. Finally residual connections are introduced in DRCNet to improve the optimization performance of the neural network.

2) A neural network (RCTLNet) for modulated signal recognition is proposed.Firstly,RCTLNet is a concatenated network consisting of Convolutional Neural Networks and Long-Short Term Memory Networks. Then CNN and LSTM are used to extract spatial and temporal characteristics of signals. Finally, residual connections are used to increase network depth and improve recognition accuracy, thereby realizing the classification and recognition of modulated signals.

3) A classification model (DRC+RCTLNet) of modulation signal is proposed. Firstly, the preprocessed modulated signal is sent to DRCNet for denoising processing to improve the accuracy of the subsequent modulated signal identification. Then, the denoised signal is divided into training set and test set in proportion. And the training set and test set are sequentially input into RCTLNet for training and testing. Finally, the modulation type identification is realized.

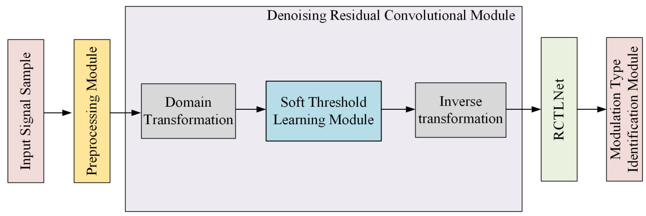


FIGURE 1. Architecture of DRC+RCTLNet.

For convenience, the remainder of this article is organized as follows. Section II presents the signal model. In Section III, details of the proposed algorithm are elaborately described. Next, the experiment and result analysis are provided in Section IV. Finally, Section V concludes the whole article.

II. PROPOSED AMC ALGORITHM

The modulation signal classification algorithm based on DRCNet includes a preprocessing module, a denoising residual convolutional module, a soft threshold learning module, and a modulation type identification module. The overall network architecture is shown in FIGURE.1.

A. SIGNAL MODEL

Modulation recognition can be viewed as a multi-classification problem, where the original signal is observed at the receiver [22]. The general expression for the received baseband signal is

$$r(t) = h(t) * s(t) + n(t) \tag{1}$$

where $r(t)$ represents the received signal at the receiving end, $s(t)$ represents the transmitted signal at the sending end, $h(t)$ represents the channel impulse response, $*$ represents the convolution operation, and $n(t)$ represents the Additive White Gaussian Noise. $h(t)$ is expressed as

$$h(t) = \alpha(t)e^{j(2\pi f_0 t+\theta_0(t))} \tag{2}$$

Combining equation (1) and equation (2), $r(t)$can be expressed as

$$r(t) = \alpha(t)e^{j(2\pi f_0 t + \theta_0(t))} * s(t) + n(t) \tag{3}$$

where $\alpha(t)$ represents the Rayleigh Weakened Channel, f_0 and $\theta_0(t)$ represents the frequency and phase offset. f_0 and $\theta_0(t)$ are caused by different Doppler Effects and local oscillators, respectively.

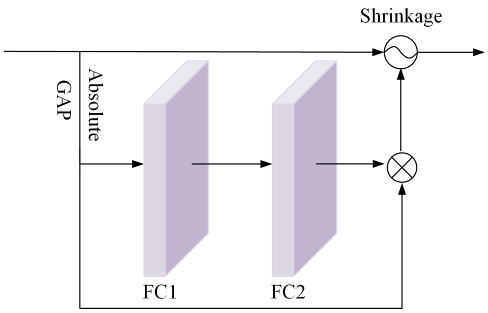


FIGURE 2. Structure of STLNet.

B. DRCNet

The soft threshold function [20] is an important shrinkage function, as

$$y = \begin{cases} x - \tau & x > \tau \\ 0 & -\tau \le x \le \tau \\ x + \tau & x < -\tau \end{cases} \tag{4}$$

where x is the input feature, y is the output feature, and τ is the threshold. The soft threshold function is to set the near-zero features to zero instead of setting the negative features to zero, which can preserve the useful negative features.The soft threshold learning network (STLNet) can give an appropriate threshold according to the SNR of the signal samples. So that the useless features related to noise can be eliminated to remove the noise signal. The structure is shown in FIGURE.2.

The input of STLNet is the feature obtained through the transformation of convolution layers. The input of STLNet is processed by absolute value operation and global average pooling (GAP) firstly. Secondly it is transmitted to fully connected layers (FC) and processed by BN operation and the ReLU function after the first FC. Then apply the sigmoid function at the end of fully connected layers to obtain a scale parameter in the range of (0,1). The scale parameter can be expressed as

$$\nu = \frac{1}{1 + e^{-z}} \tag{5}$$

where z is the output of the FCs, an ν is the corresponding scale parameter.

Lastly the average value of $|f_{a,b,c}|$ multiplied by the scale parameter to get the threshold. The learned threshold can be expressed as

$$f_{out} = \begin{cases} 0, & \left|f_{a,b,c}\right| \le \tau \\ sign\left(f_{a,b,c}\right)\left(\left|f_{a,b,c}\right| - \tau\right), & \left|f_{a,b,c}\right| > \tau \end{cases} \tag{6}$$

where f_{out} is the output feature, and $sign(\cdot)$ is the sign function.

A DRCNet is designed by connecting 4 convolutional layers and STLNet in series, as shown in FIGURE.3.The BN operation [23] is performed before convolutional layers to normalize the distribution of the input data and enhance the generalization ability of DRCNet. In the first two convolutional layers, the signal is learned and domain transformed firstly. The useful features in the signal are transformed into a domain with a large absolute value, and the useless features are transformed into a near-zero domain. Secondly STLNet gives an appropriate threshold according to the SNR of the signal, and uses a shrinking function to convert features close to zero to zero, that is, remove noise-related features. Then the features output by the shrinking function are inversely transformed in the following two convolutional layers, and will be restored to the original signal domain to obtain a denoised signal.Lastly residual connections [24] are introduced in DRCNet to improve the optimization performance of the neural network and speed up the convergence speed of the denoising network.

C. RCTLNet

LSTM is a gated recurrent neural network. The LSTM unit has the same input and output as the ordinary recurrent neural network, but introduces more parameters and a system consisting of input gate, forget gate and output gate to control the information flow, as shown in FIGURE.4.

Gates in the LSTM unit are defined as

$$\begin{aligned} i_t &= \sigma(W_i h_{t-1} + U_i x_t + b_i) \\ f_t &= \sigma(W_f h_{t-1} + U_f x_t + b_f) \\ o_t &= \sigma(W_o h_{t-1} + U_o x_t + b_o) \end{aligned} \tag{7}$$

where σ is the sigmoid activation function, i_t, f_t and $o_t$are the input gate, forget gate and output gate respectively, h_{t-1} is the output of the past time step, x_t is the input of the current time step, b_i, b_f and b_o are the deviations of the input gate, forget gate and output gate respectively, W_i, U_i, W_f, U_f, W_o and U_o are the weight matrices of the input gate, forget gate and output gate respectively. The three gates allow the LSTM unit to store and access information, thus avoiding the vanishing gradient problem.

RCTLNet is a deep network structure composed of 4 convolutional layers, 2 LSTM layers and 2 fully connected layers,as shown in FIGURE.5.

If the input is x, the outputs of the 4 convolutional layers are

$$\begin{aligned} \boldsymbol{o}_{conv1} &= f(\boldsymbol{W}_{c1} * \boldsymbol{x} + \boldsymbol{b}_{c1}) \\ \boldsymbol{o}_{conv2} &= f(\boldsymbol{W}_{c2} * o_{conv1} + \boldsymbol{b}_{c2}) \\ \boldsymbol{o}_{conv3} &= f(\boldsymbol{W}_{c3} * o_{conv2} + \boldsymbol{b}_{c3}) \\ \boldsymbol{o}_{conv4} &= f(\boldsymbol{W}_{c4} * A_1 + \boldsymbol{b}_{c4}) \end{aligned} \tag{8}$$

where $f(\cdot)$ is the Relu function, W_{ci} is the weight of the corresponding layer, and $\boldsymbol{b}_{ci}$ is the bias vector of the corresponding layer, A_1 is the combined eigenvector of o_{conv1} and o_{conv3}.

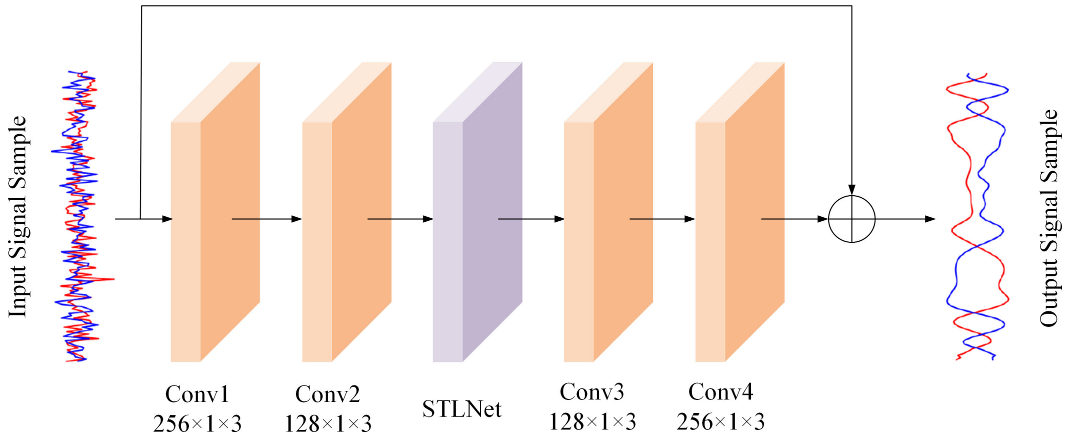


FIGURE 3. Structure of DRCNet.

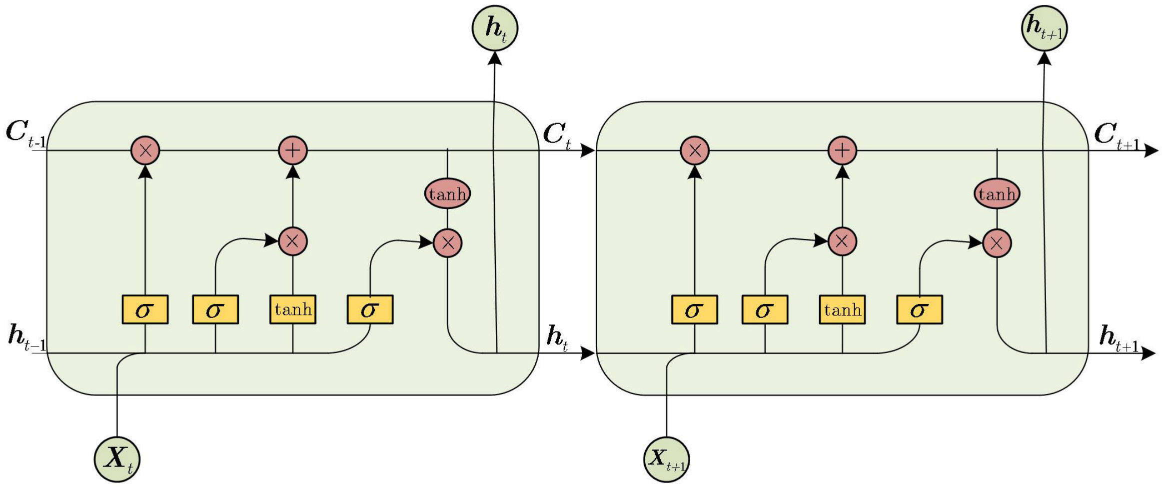


FIGURE 4. LSTM cell structure.

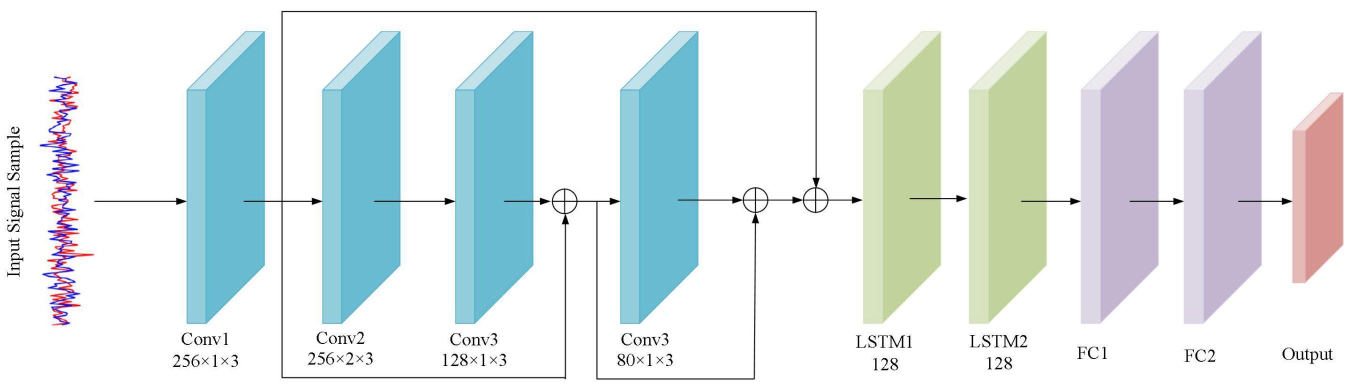


FIGURE 5. Architecture of RCTLNet.

The outputs of the 2 LSTM layers are

$$\begin{aligned} \boldsymbol{o}_{LSTM1} &= LSTM(\boldsymbol{o}'_{conv}, \boldsymbol{h}_{t1}) \\ \boldsymbol{o}_{LSTM2} &= LSTM(\boldsymbol{o}_{LSTM1}, \boldsymbol{h}_{t2}) \end{aligned} \tag{9}$$

where $\boldsymbol{o}_{conv}$ is the output vector of the global convolution layers, $\boldsymbol{o}'_{conv}$ is the one-dimensional feature after the Flatten operation, $\boldsymbol{o}_{LSTM1}$ is the output of the first LSTM layer, $\boldsymbol{o}_{LSTM2}$ is the output of the second LSTM layer

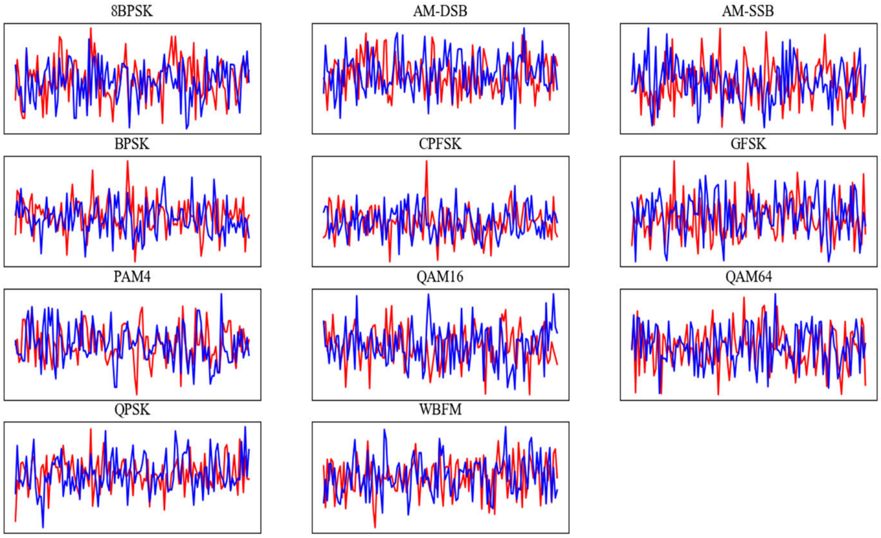


FIGURE 6. I/Q waveform of the relationship between each signal sample and the amplitude in some modulated signals.

The output of the first fully connected layer is

$$\boldsymbol{o}_{dense1} = f(\boldsymbol{W}_{d1}\boldsymbol{o}_{LSTM} + \boldsymbol{b}_{d1}) \tag{10}$$

The second fully-connected layer serves as the output layer and uses the Softmax function for classification. The output is

$$\boldsymbol{o}_{dense2} = \sigma(\boldsymbol{W}_{d2}\boldsymbol{o}_{dense1} + \boldsymbol{b}_{d2}) \tag{11}$$

where $\boldsymbol{o}_{dense1}$ is the output of the first fully connected layer, $\boldsymbol{o}_{dense2}$ is the output of the second fully connected layer, $\sigma(\cdot)$ is the Softmax function, and $\boldsymbol{b}_{di}$ is the bias of the corresponding layer, respectively.

RCTLNet uses CNN and LSTM to extract the spatial and temporal characteristics of signals respectively, and then realize the classification and identification of modulated signals. At the same time, multiple residual connections are introduced between different convolutional layers to avoid problems such as gradient disappearance caused by overfitting, and to improve the classification accuracy of the network.

III. EXPERIMENTS

This paper uses the dataset RML 2016.10a released by O'Shea and West [25] at the 6th GNU Radi0 Conference in 2016 for experiments.

A. DATASET

The dataset RML 2016.10a simulates center frequency offset, channel fading, and Additive White Gaussian Noise. and other actual influencing factors, the generated signal is very close to the actual communication signal, which has great research value.There are 11 modulation signal types in this dataset, Binary Phase Shift Keying(BPSK), Quadrature Phase Shift Keying(QPSK), 8 Phase Shift Keying (8PSK), Quadrature Amplitude Modulation 16 (QAM16),Quadrature Amplitude Modulation 64 (QAM64), Continuous Phase Frequency Shift Keying (CPFSK), Gaussian Frequency Shift Keying (GFSK),4-Level Pulse Amplitude Modulation (4PAM)), Amplitude Modulation-Double Side Band (AM-DSB), Amplitude Modulation-Single Side Band (AM-SSB), Wide Band Frequency Modulation (WBFM)).

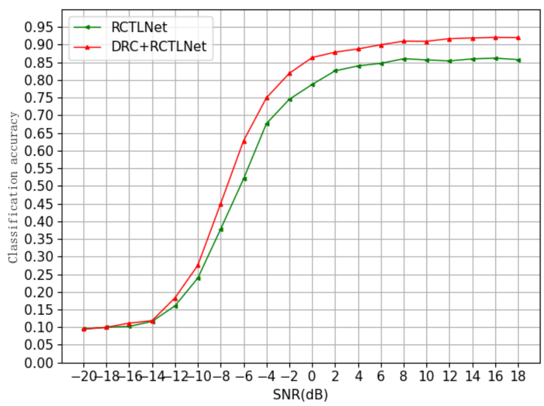


FIGURE 7. Classification accuracy of RCTLNet and DRC+RCTLNet.

FIGURE.6 shows the I/Q waveform of the relationship between each signal sample and the amplitude in some modulated signals. In the experiment, the 220,000 signal samples in the RML 2016.10a dataset are divided into training set and test set, of which the training set ccounts for 70% and the test set 30%. The training set is used to train the network and the test set is used to test the performance.

B. SETTINGS

The experiment is based on Nvidia GTX 1080Ti GPU to complete training and testing, and use python software to build the network. The parameter selection of the number of iterations, batch size, learning rate and dropout rate adopts the

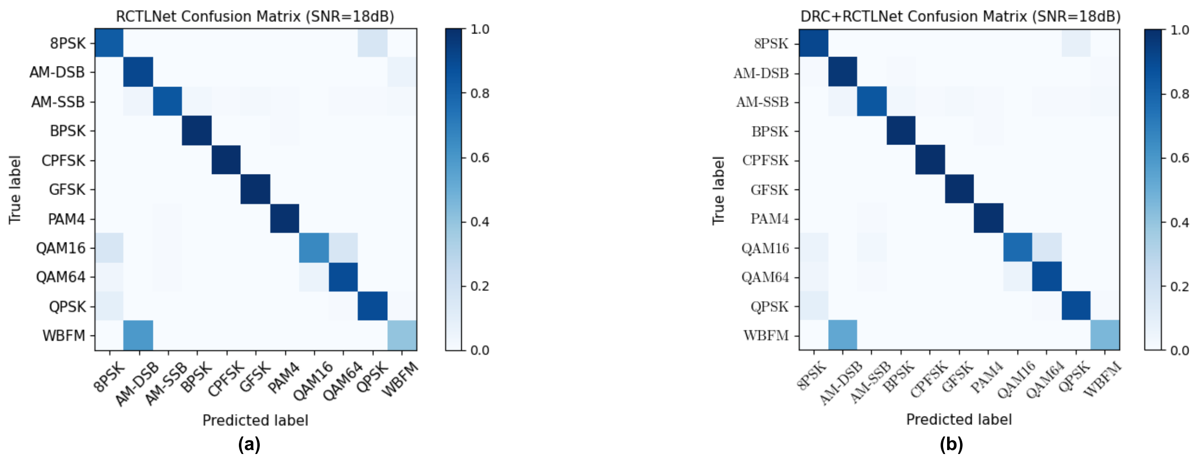


FIGURE 8. When the SNR is 18dB, confusion matrixs of RCTLNet and DRC+RCTLNet.

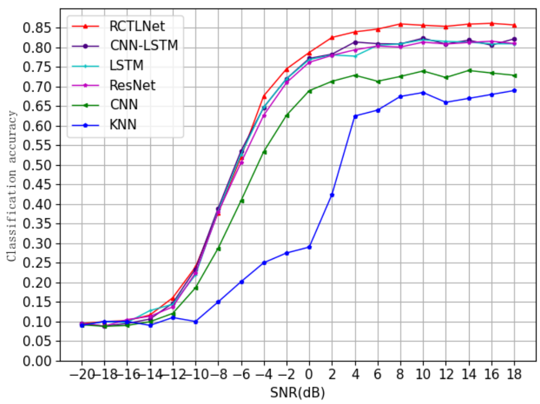


FIGURE 9. Modulation signal classification accuracy of each network.

automatic selection method of random search. The number of iterations is set to 100; the batch size is set to 512; the optimizer selects adaptive moment estimation; the default learning rate is 0.001; the dropout rate is set to 0.5.

C. EXPERIMENTS AND RESULT ANALYSIS

FIGURE. 7 shows the classification accuracy of RCTLNet and DRC+RCTLNet. The vertical axis is the classification accuracy, and the horizontal axis is the SNR. FIGURE.7 shows the classification accuracy of DRC+RCTLNet reaches 92%. The classification accuracy of DRC+RCTLNet is significantly higher than that of RCTLNet. And the improvement is more obvious at high SNR, at most about 6%. DRC+RCTLNet uses RCTLNet to identify the modulated signal, and uses DRCNet to effectively denoise the input signal samples, thereby obtaining a higher accuracy rate.

FIGURE.8 shows the confusion matrices of RCTLNet and DRC+RCTLNet with SNR of 18dB. It can be seen from FIGURE.8 that the denoising effect of DRCNet on RCTLNet is more obvious, and the Classification accuracy of each modulated signal is improved to a certain extent.

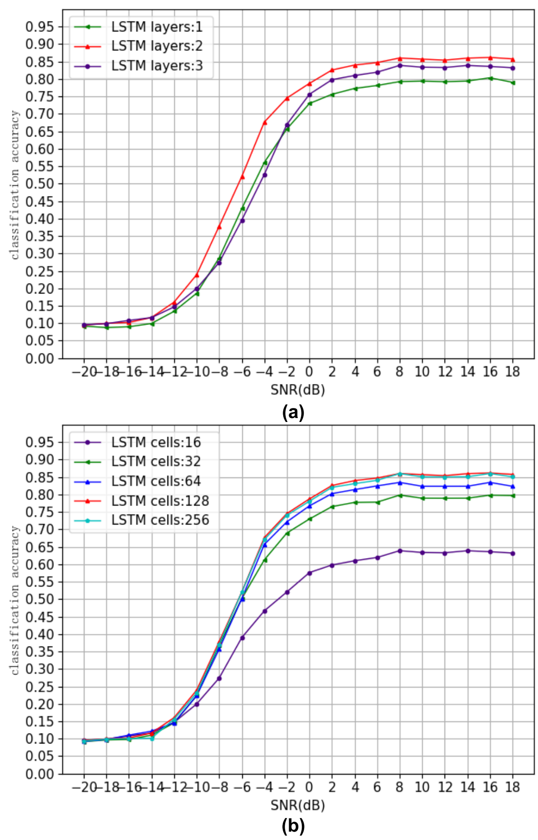
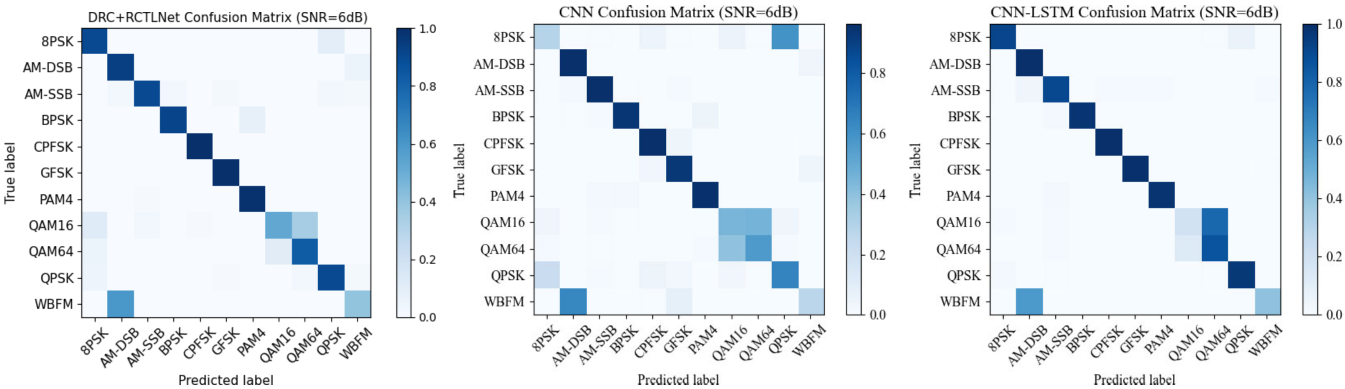


FIGURE 10. Effect of the number of LSTM layers and the number of LSTM cells on RCTLNet.

FIGURE.9 showns the modulation signal classification accuracy of RCTLNet, KNN [26], CNN [27], ResNet [15], LSTM [16] and CNN-LSTM [19].

KNN is not suitable for processing large-scale signal samples, resulting in poor classification accuracy, which only reaches 69%. The CNN network structure is simple and the network depth is shallow, resulting in a single extracted signal feature, and the network classification accuracy rate



(a) The confusion matrix of DRC+RCTLNet. (b) The confusion matrix of CNN· (C) The confusion matrix of CNN-LSTM.

FIGURE 11. **When the SNR is 6dB, confusion matrixs of DRC+RCTLNet, CNN and CNN-LSTM.**

is only 74%. LSTM is a temporal recurrent neural network that can extract temporal features in the network, with a high classification accuracy of 82%. On the basis of CNN, ResNet introduces skip-connections to increase network depth, alleviate problems such as gradient disappearance and gradient explosion, and improve network performance.Compared with CNN, the network classification accuracy of ResNet has been significantly improved, up to 83%. CNN-LSTM is a fusion of two heterogeneous deep models of CNN and LSTM, which can extract the temporal and spatial features of the signal to obtain better network performance, and the classification accuracy rate reaches 83%. Multiple residual connections increase the network depth, avoid the problems of gradient disappearance and gradient explosion, and further improve the network performance.

As can be seen from FIGURE.9, in the case of high SNR, the classification accuracy of RCTLNet can reach 86%, which is the highest among the networks used in the experiment.

FIGURE.10 shows the effect of the number of LSTM layers and the number of LSTM cells on RCTLNet. The classification accuracy of RCTLNet are analyzed with varying layer depth of LSTM from 1 to 3 and number of LSTM cells from 16 to 256.

The importance of the number of LSTM cells and layer depth of LSTM are further investigated by varying parameters. When the LSTM layer in RCTLNet selects 2 layers, the classification accuracy is the highest. When the LSTM layer selects 3 layers, the classification accuracy is lower. When the LSTM layer is selected as one layer, the classification accuracy is the lowest. At the same time, when RCTLNet adopts 2 layers of LSTM layers, the network classification accuracy rate obtained by selecting 128 cells in the LSTM layer is the highest.

FIGURE.11 show the confusion matrices of DRC+ RCTLNet, CNN and CNN-LSTM when the SNR is 6 dB.The diagonal line of the confusion matrix of DRC+RCTLNet is relatively clear, and the recognition rate of various

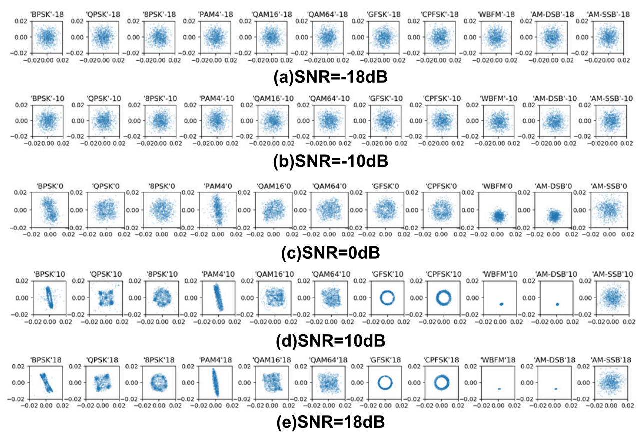


FIGURE 12. **Signal constellation diagram.**

modulation signals is higher than that of CNN and CNN-LSTM networks.

In the case of high SNR, the classification accuracy of DRC+RCTLNet model for most types of modulation signals is above 90%, and the classification accuracy of some modulation types can reach 100%, as shown in FIGURE.8 and FIGURE.11. There is aliasing between WBFM and AM-DSB, QAM16 and QAM64 signals, and there is almost no aliasing for other modulation types.

The aliasing phenomenon is analyzed through signal visualization. FIGURE.12 shows some signal constellation diagrams of the RML 2016.10a dataset. In the case of low SNR, the signal constellations of each modulation type are very similar, and the aliasing phenomenon improves as the SNR increases. In the case of high SNR, the signal constellation diagrams of most modulation types have different shapes and are not easily confused. However, the constellation diagrams of the WBFM and AM-DSB, QAM16 and QAM64 signals are very similar in the case of the same SNR, so these two groups of signals are easy to be confused and the recognition rate is not high.

IV. CONCLUSION

This paper proposed a modulation signal classification algorithm based on DRCNet. Firstly DRCNet is proposed,which is used to give appropriate thresholds for signal samples with different SNR, so as to improve the noise-related features. Secondly, RCTLNet composed of CNN and LSTM in series is proposed, while creating multiple residual connections between different convolutional layers to enhance feature propagation in the network. Experiments show that the network classification accuracy of RCTLNet is 86%, and the network classification accuracy of DRC+RCTLNet is 92%, which is significantly improved compared to the existing KNN, CNN, ResNet, LSTM and CNN-LSTM network models.

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