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Convolutional neural network-based modulation recognition technique for communication signals

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Abstract. The last decade has seen breakthroughs in communication technology. The increasingly complex signal transmission environment has placed higher demands on signal modulation recognition. Traditional modulation recognition approaches cannot guarantee satisfactory recognition accuracy. Fortunately, with the continuous advancement of deep learning algorithms, convolutional neural network-based communication signal modulation recognition techniques have become the mainstream of current research. Therefore, this paper first reviews the development history of signal modulation recognition techniques and introduces the concepts of signal modulation theory. It includes ASK, PSK and FSK modulation methods, which are common today. Subsequently, I analyze the principles of signal modulation recognition and the implementation method of CNN in modulation recognition. To further explore the shortcomings of CNNs, I propose two optimized models, the residual network model and the CLDNN model. After comparing the performance, the former has higher performance, but its computational complexity is higher while the latter takes into account the high recognition accuracy while still reducing the network parameters as much as possible to keep the complexity at a low level.

Keywords: signal modulation, deep earning, CNN, residual network, CLDNN.

1. Introduction

1.1. Background

Modern communication technologies have brought digital life into millions of homes. the revolutionary advances in digital access technology over the past decade, signal modulation techniques have gained widespread attention in recent years [1]. The standardization process for 5G is accelerating in the face of increasingly complex requirements [2]. Meanwhile, with the exponential growth of the amount of data to be computed and the increasing demand for computational power and recognition accuracy, a series of deep learning models have emerged, such as VGG Net [3], Google Net [4], Res Net [5], Alex Net [6], etc.

Certainly, the increasingly complex electromagnetic environment undoubtedly places higher demands on the reliability and interference immunity of signal modulation techniques. The signal will inevitably undergo nonlinear distortion and aberration during transmission [7]. In order to cope with the complex environment and at the same time improve the efficiency of signal transmission band utilization, a variety of signal modulation techniques have sprung up into the public eye. Although these modulation techniques can be more flexible according to a region's specific environment, which brings users a good experience, the variable modulation techniques undoubtedly pose a greater challenge to the signal receiver.Therefore, an efficient signal modulation identification technique has emerged. It is intermediate between signal receivers and demodulators and greatly alleviates the latter's difficulty in coping with multiple modulation methods in complex environments [8]. There is no doubt that this technology can play a crucial role both in the military and in the population's daily life.

Nowadays, algorithms for digital signal modulation techniques have become very popular. With the birth of new technologies such as machine learning, the signal modulation recognition technology combined with convolutional neural network has become a hot research topic because it has many advantages that traditional modulation techniques cannot match.

1.2. Recent progress

Traditional signal modulation techniques are broadly classified into two types. One of them is difficult, which requires the extraction of signal features and modulation based on them.The other technique is based on decision theory, which is complex and difficult to guarantee accuracy. The above two methods can certainly implement modulation techniques, but they both have drawbacks. In order to remedy these drawbacks, recent research has attempted to incorporate deep learning into the modulation process because of its ability to extract features from different signals suitable for modulation recognition.

Convolutional neural networks (CNNs) and deep neural networks (DNNs) are often discussed together. It is concluded that when comparing the performance of these two in the wireless domain, there is little difference in performance between them for the same test dataset. The final validation loss was 0.874 for all signals with signal-to-noise ratio and the classification accuracy was around 66.9% [9].

Of course, this classification accuracy is obviously not satisfactory enough, so researchers at Purdue University innovatively introduced a convolutional long-range deep neural network (CLDNN) on top of the convolutional neural network in order to improve the accuracy [11]. Not surprisingly, the model was able to achieve 88.5% recognition accuracy in a high signal-to-noise environment in the task of signal modulation recognition. Two deep learning models based on convolutional neural networks, Alex Net and Google Net, are two deep learning models based on convolutional neural networks. The idea proposed in the literature [12] draws on these two models. An improvement in accuracy in the field of wireless signal modulation recognition can be observed, which is 97.3%. Convolutional neural networks are simple in structure and easy to implement. Based on this, Zufan Zhang et al. keep trying to improve its performance. Their proposed automatic modulation classification feature fusion scheme can achieve recognition accuracy of up to 92.5% in a low signal-to-noise ratio environment [13]. Both of the above schemes break the ninety percent recognition accuracy. However, they both rely on a separate pre-processing of the signal. This makes them computationally more resource intensive and the models more challenging to implement [12, 13].

In order to minimize the computational complexity under the precondition of high recognition accuracy, a new model based on residual networks was proposed [14]. This multimodal WSMF approach has many improvements in performance compared to the traditional AMC-CNNs model. The scholars led by Jun Wang combined the denoising ability of denoising autoencoder with the feature extraction ability of CNN to propose a machine learning method based on denoising autoencoder (DAE) and CNN for Gaussian noise classification of signals. In simulations, the model shows a 58% improvement in judgment accuracy for a signal-to-noise ratio of 84 dB compared to a neural network without a denoising autoencoder [13]. This is because the combination of autoencoders achieves dimensionality reduction of the data, reducing the algorithm's complexity and thus improves the recognition performance.

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The traditional modulation recognition techniques are maximum likelihood hypothesis testing and statistical pattern discrimination, respectively. The former relies on decision trees, while the latter relies on statistical methods of feature extraction. These two methods are time-consuming and laborious with low recognition accuracy. Therefore, they are gradually being replaced by automatic modulation techniques based on deep learning in the process of technology development. Although various neural network algorithms continue to make breakthroughs in recognition accuracy, there are still various problems in signal modulation method recognition, such as computational complexity and single network structure.

2. Principle

In modern communication, signal modulation technology is a crucial part of the process. Signal modulation converts the raw input signal into a high frequency signal through a series of transformations. The purpose of this is to reduce signal interference during long-distance transmission. A typical example is that two signals with similar original frequencies can interfere significantly with each other during transmission. The mutual influence between them is significantly reduced by shifting them to a higher frequency band farther apart through linear spectrum shifting. Of course, the advantages of signal modulation are much more than that.

The basic principle of signal modulation is to embed a baseband signal into a carrier by changing certain carrier characteristics to create a modulated signal. In digital communication, there are different modulation methods depending on where the information is carried in the signal, and they have different performance. Several of them are described in detail below.

2.1. ASK modulation technology

Amplitude keying, also known as amplitude shift keying, is the most common type of amplitude modulation for analog signals. In this modulation mode, the amplitude is treated as a variable, while the frequency and phase remain constant. In this way, the information is represented by the amplitude of the carrier wave.

Amplitude keying means digital information is transmitted by modulating the carrier amplitude change, while the frequency and initial phase remain unchanged. ASK modulation is a one-dimensional modulation, all information is carried by the signal amplitude A[n], if the carrier amplitude has M values, the number of bits each modulation symbol can carry is $log_2 M$, and the bit rate is $\frac{log_2 M}{T}$, where T is the symbol period.

Generally, the modulated signal is sent in the following form.

$$x(t) = A_m \cos(2\pi f_c t + \phi), t \in [0, T] \tag{1}$$

The miss-symbol rate is used to represent the probability of demodulation error, and for M-element ASK modulation, its miss-symbol rate can be expressed as follows

$$P_e = \frac{2(M-1)}{M} Q\left(\sqrt{\frac{3SNR}{(M-1)(2M-1)}}\right) \tag{2}$$

This uses the Q function to represent the mis-sign rate. Further, the following equation for the BER can be obtained based on the conversion relationship between bits and symbols.

$$P_b \approx \frac{1}{\log_2 M} P_e \tag{3}$$

BER is an important criterion for judging the quality of demodulation systems.

2.2. PSK modulation technology

Phase shift keying (PSK), unlike ASK, is a modulation method in which the amplitude is kept constant, but instead the phase difference signal is continuously changed. During the information transmission, the information of the synthesized wave is carried entirely by the phase θ. Binary phase shift keying (BPSK) is the best understood type of PSK because it has only two phases, 0° and 180°, to represent the 0 and 1 information respectively.

Quadrature Phase Shift Keying (QPSK) is more advantageous from the perspective of bandwidth utilization, which transmits in binary. This because it allows a signal to represent multiple bits. In contrast to BPSK, this common coding technique uses a phase shift value of 90°. This means that a symbol will need to be represented by two bits of binary.

The band communication number expression is.

$$x(t)=\sum_{n}^{\infty} \mathrm{A}[n]g(t-nT)\cos(2\pi f_c t+\theta[n]) \tag{4}$$

To visualise the modulation mapping relationship, a constellation diagram is often used, and Figure 1 shows the PSK constellation diagram in this form..

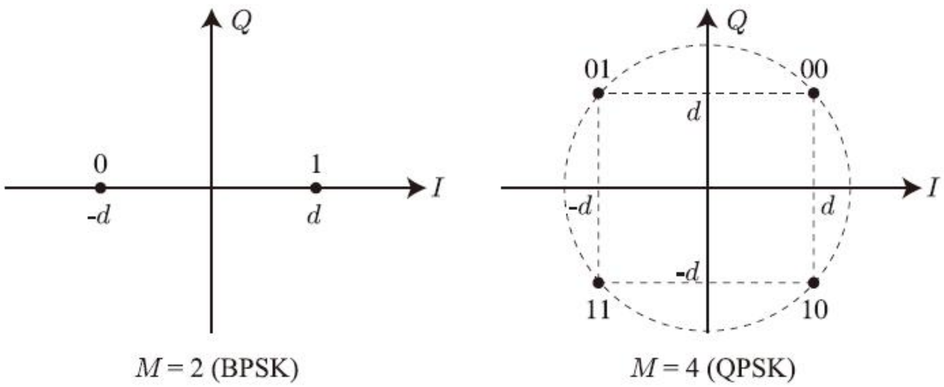

Figure 1. PSK's constellation chart.

Similarly, the mis-signature rate of PSK can still be represented by the Q function, where the mis-signature rate of BPSK is.

$$P_e=Q\left(\frac{\sqrt{2}A}{\sigma}\right)=Q\left(\sqrt{2\mathrm{SNR}}\right) \tag{5}$$

In Equation 5, σ represents the standard deviation of the noise power. The same form expressed in terms of signal-to-noise ratio is given.

3. Principle of convolutional neural network

3.1. Deep learning theory

Deep learning methods are based on neural networks, a machine learning technique that can effectively extract complex data features and therefore has wide application value in signal modulation recognition. The core of deep learning lies in training neural networks to extract target features for efficient and accurate task completion.

Over the past decades, deep learning has made remarkable progress from the birth of theory to practical applications. Today, the technology has achieved remarkable results in areas such as personalized recommendation systems and image and speech recognition. However, the potential of deep learning goes much further than that. In the future, it will be useful in many more areas and thus remains one of the hot spots for research.

3.2. Convolutional neural networks

As the name implies, a neural network system is like a nerve unit in the human body. It is structurally similar to a network of nerves and has a similar learning capability. After being trained with a certain amount of data, a complete neural network system can have the ability to determine new data features autonomously and take a certain level of processing. The following is the structure of a neural unit. As the name implies, a neural network system is like a nerve unit in the human body. It is structurally similar to a network of nerves and has a similar learning capability. After being trained with a certain amount of data, a complete neural network system can have the ability to determine new data features autonomously and take some degree of processing. The following is the structure of a neural unit.

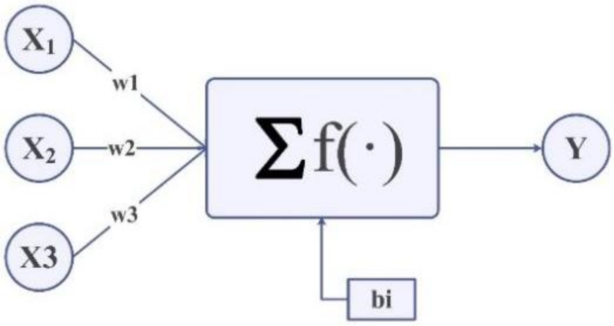

Figure 2. The structure of a neural unit.

Figure 2 shows the mathematical model of a neural network unit, from which it is clear that each neuron cell is composed of a synapse, an adder, and an activation function. At the left end of the picture, each synapse is connected to an input value X_i, which is given different weights by W_i and enters the adder together. Before the summation, a b_i is also introduced as a bias term. The introduction of the activation function makes the operation of the model nonlinear, and through these steps above, the mathematical expression of the final output Y can be obtained as.

$$\mathrm{Y} = \mathrm{f}\left(\sum_{i=1}^{n} W_i X_i + b_i\right) = f\left(W^T X\right) \tag{6}$$

In the above equation, $W = [b, W_1, \dots, W_n]^T, X = [1, X_1, \dots, X_n]^T$.

A complex multilevel structure can constitute an efficient neural network system. In the structure, the previous layer processes the input data and feeds the extracted learning results to the next layer, and so on. As the number of training layers increases, the characteristics of the data gradually emerge. The originally disordered and complex data will be represented by the neural network system through its unique abstract features.

CNN is a popular model among the many deep learning-based neural network models. It is suitable for dealing with network structured data and applies to the signal modulation recognition system targeted in this paper. Based on the neural cell model mentioned above, CNN also has a pooling layer for reducing computation and improving the system's robustness, and a fully connected layer linking the neurons in the front and back layers.

In practical engineering applications, convolutional neural networks usually increase the depth of convolutional and pooling layers as much as possible while considering the cost, and set multiple convolutional kernels and choose more appropriate activation functions to ensure the overall performance of the network. In addition, the use of residual connection technique and batch normalization technique can also do further optimization and improvement of CNN networks.

4. Signal modulation identification technology

There is no doubt that signal modulation recognition is a very tedious function. The following Figure 3 shows the overall framework of the signal modulation recognition system.

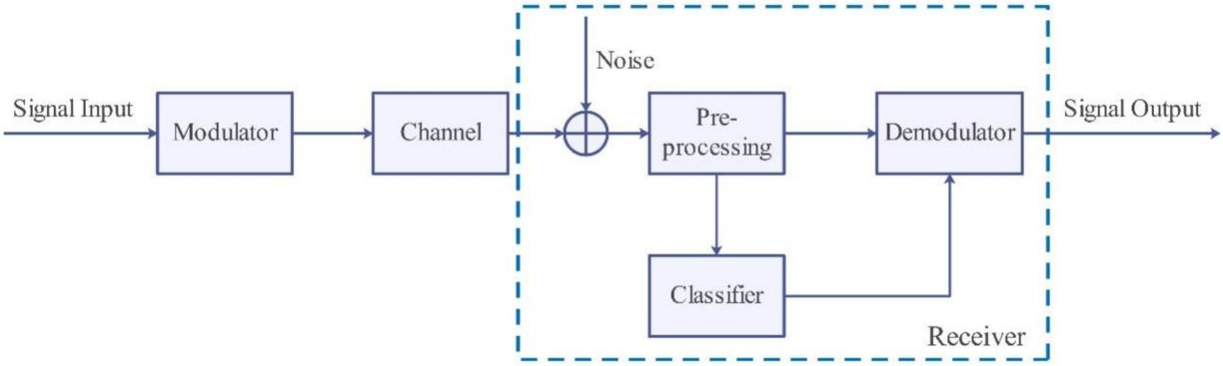

Figure 3. Modulation identification system model.

In order to achieve satisfactory performance, not only multiple steps need to be coordinated, but also various external factors, such as channel estimation, signal synchronization, etc. need to be taken into account in practical applications. In this section, we will first discuss the application of CNNs in signal modulation recognition, followed by the improvement of RES and CLDNN networks, respectively. Finally, the performance of the three networks will be compared.

4.1. Application of CNN in signal modulation recognition techniques

4.1.1. Pre-processing of data. Before training the model, the obtained dataset needs to be processed. The purpose of this approach is to convert the signal data into a form suitable for CNN processing. Take RadioML 2016.10a as an example. It has a total of about 220,000 modulated signals. There are many modulation types, and 11 modulation types are generally considered, including three analog modulation and eight forms of digital modulation.

For ease of processing, these one-dimensional data are usually chosen to be processed in the form of a spectrogram. The literature [16] provides ideas to achieve the above effect by noise reduction through low-pass filters thus.

4.1.2. Building convolutional neural network models. For training purposes, a convolutional neural network structure needs to be designed to identify the modulation method [17]. It includes multiple layers, the exact structure of which is shown in Figure 4.

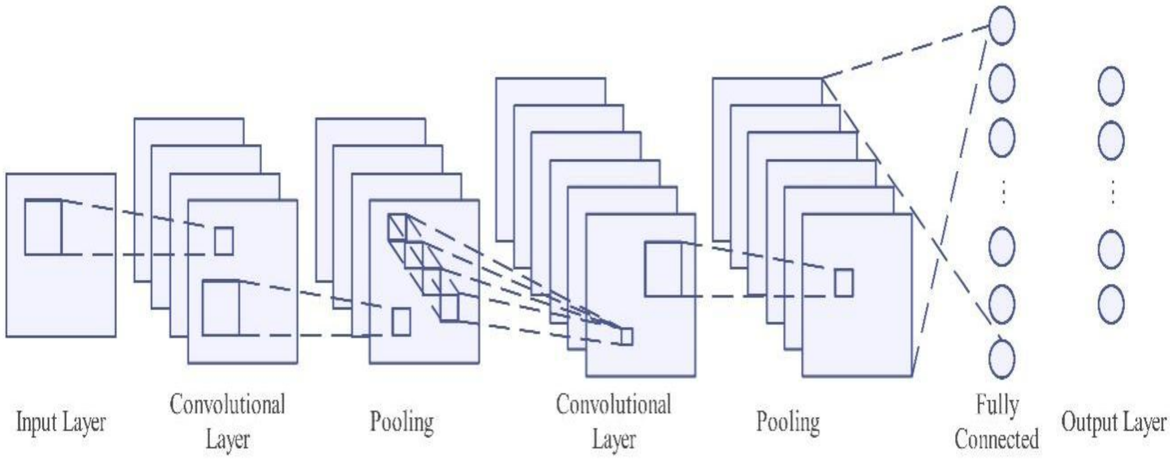

Figure 4. CNN network structure.

To clearly demonstrate the functions of the various levels, Table 1 shows them.

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Table 1. Functions of CNN network layers.

Input layer	Processed modulated signal data
Convolutional layer I	Feature extraction and filtering of the input data
Pooling layer	Stability and robustness to assist in extracting signal features
Convolutional layer II	Deep feature extraction of the data output from convolutional layer I
Fully connected layer	Judgment of the modulation method based on signal characteristics
Activation function	Assists in capturing non-linear relationships in signals
Loss function	Measuring the gap between predicted results and actual labels

4.1.3. Training and evaluation. For the processed data, it is usually divided into a training set and a test set in the ratio of 8:2. Subsequently, the training set is used to train the CNN with the following steps:

1. Initialize model parameters
2. Truncate the data set into segments of equal length
3. Randomly select a segment and input the segment data as a vector signal
4. Obtain the predicted label distribution by the model
5. Calculate the difference between the predicted and true values with the help of loss function
6. Continuously update the parameters during the back propagation process
7. Repeat the above steps until the loss function values remain converged

Once the model is obtained, the performance of the model can be evaluated with the help of a test set. Commonly used performance test metrics include accuracy, confusion matrix, etc. In addition, the robustness of the model can be analyzed with the help of different signal-to-noise ratios signals. Finally, increasing the convolutional layer depth can further improve the performance. Of course, depending on how the model performs on the test set, it is also possible to change to a more appropriate form of activation function. These are all the steps of CNN in signal modulation recognition.

4.2. Modulation recognition combined with residual networks

4.2.1. Residual networks. Since residual networks were introduced in 2016 [5], it was once considered the best performing network structure. This is since it introduces residual links that allow the network to skip certain layers, thus allowing to learn the objective function more easily. The Figure 5 bellow illustrates its network structure

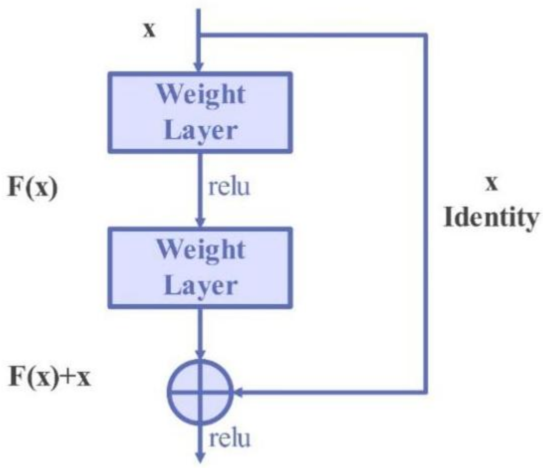

Figure 5. The structure of residual networks.

Specifically, a traditional CNN network can be represented as the function shown below.

$$Y = F(x) \quad (8)$$

F(x) is expressed as the mapping function of the network layers. However, the gradient disappearance problem becomes particularly serious as the number of layers deepens [18], which indirectly constrains the depth of the CNN network from being too deep, otherwise it will be difficult to train. ResNet, conversely, is a pioneer in introducing the concept of residual linking, which converts the original mapping relationship to residual mapping.

$$Y = F(x) + x \quad (9)$$

The difference with the CNN mapping relationship is that the input needs to be additionally summed with the residual mapping before the output. In this way, the original problem of learning the function F(x) directly is converted into a problem of trying to learn the difference between the function F(x) and the input x. By doing so, a jump in learning can be achieved, which helps to eliminate the gradient disappearance problem and improve the stability of the network training.

4.2.2. CNN combined with residual network for modulation recognition. When residual networks are used with CNNs, the data are usually converted to a time-frequency domain representation in the pre-processing data stage, and then the relationship between modulation type and signal features is learned by training the residual network model. Its operation process is relatively similar to the one mentioned in the previous section. However, due to the introduction of the residual network, the problem of gradient disappearance and network degradation of the network is alleviated, which allows the network to be trained deeper while still achieving good performance in signal modulation recognition tasks.

Referring to the steps in the literature [10], I tested the model with and without the residual network, judged on the basis of the validation loss of both, to produce Figure 6.

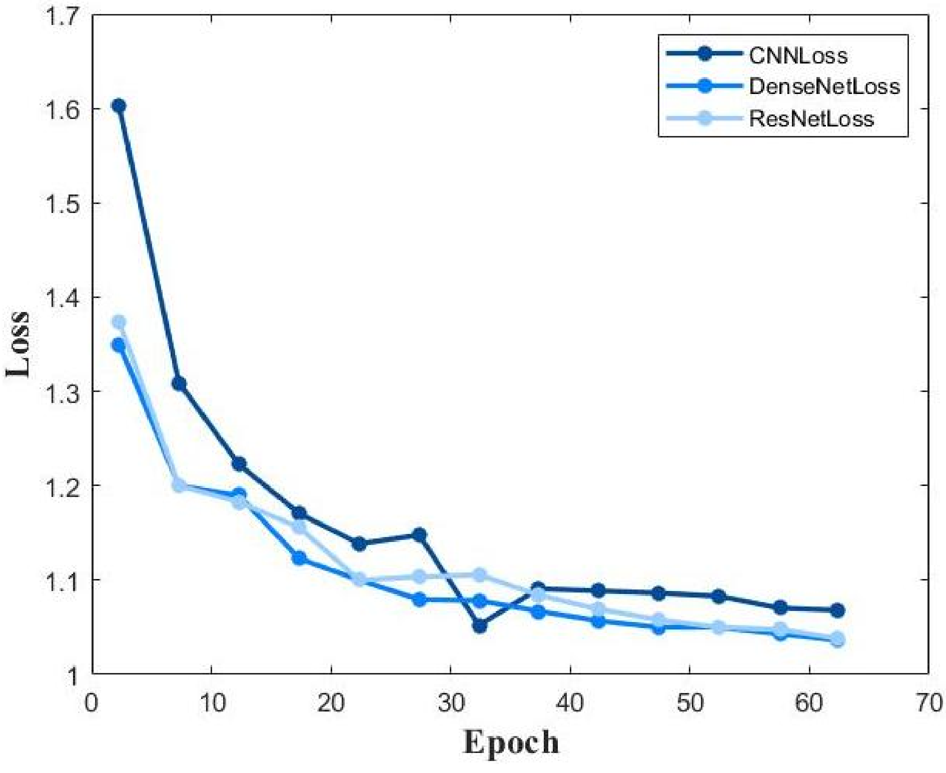

Figure 6. Comparison of validation loss of networks with Residual networks or not.

Evidently, the verification loss of the model incorporating the residual network is 14% lower than that of the CNN at the beginning of the training and decreases significantly from the beginning of the training, reaching a steady state after about 20 training rounds. In contrast, the CNN-only modulation recognition approach not only has a slightly higher verification loss than the network with residual networks, but also requires more cycles to reach steady state.

Therefore, it can be concluded that the residual network improves the recognition performance of the network to some extent by eliminating the gradient disappearance problem. However, it should also be noted that the time cost of using the residual network approach is much higher than that of the CNN modulation recognition technique because the former has a deeper network structure and thus will require more computational resources during the training process.

4.3. CLDNN-based modulation recognition

4.3.1. Model of CLDNN. Although CNN models can extract abstract features from huge amount of irrelevant data. The recognition accuracy is not satisfactory. The simple CNN model is used together with the CLDNN model formed by combining a long short-term memory network and a fully connected deep neural network (DNN) [19]. This model inherits the ability of CNN to extract features

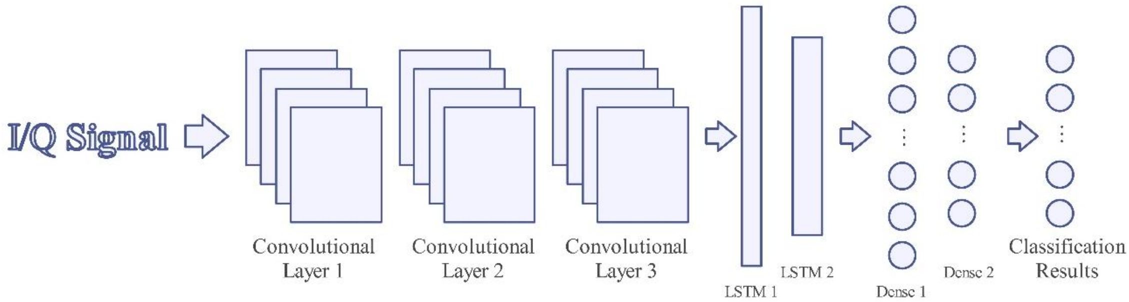

Figure 7. CLDNN network structure.

while substantially improving the recognition accuracy.

Unlike the CNN structure, the feature data obtained from the three convolutional layers in Figure 7 are fed to the two LSTM layers to take advantage of the temporal correlation of the data. Each LSTM layer has a different number of memory units to capture the dynamic characteristics of the input signal. This compensates for the deficiency of CNN in capturing long-term dependencies in time series.

The LSTM is able to achieve these functions because it introduces the concept of forgetting gates and input gates.

$$f_t = \sigma\left(W_f * [h_{t-1}, x_t] + b_f\right) \tag{10}$$

Above is the equation of the forgetting gate. f_t is used to activate the forgetting gate, and the parameters need to be multiplied by the weight of W_f during the operation. The hidden state of the previous moment is represented by the equation h_{t-1}. b_f is the bias term. the Sigmoid activation function σ determines and decides which information is discarded from the cell state.

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \tag{11}$$

In contrast, there are input gates that determine which information is fed into the cell state. Where i_t is the activation value of the input gate. Combining these two concepts, candidate values can be calculated for updating the cell state.

$$C_t^{'} = tanh(W_C * [h_{t-1}, x_t] + b_C) \tag{12}$$

$$C_t = f_t * C_{t-1} + i_t * C_t^{'} \tag{13}$$

In CLDNN networks, the role of DNN is to do the final high-level abstraction and classification of the data. This is because each of its fully connected layers is in the form of input neurons connected to all output neurons, which ensures that it can better understand data features and learn more complex nonlinear structures, guaranteeing the recognition performance of the model and the generalization ability when recognizing unknown signals.

4.3.2. Modulation recognition of CLDNN. With reference to the above model architecture, two layers of LSTM with two fully connected layers are added after CNN for testing, and the loss function convergence curves are obtained as follows.

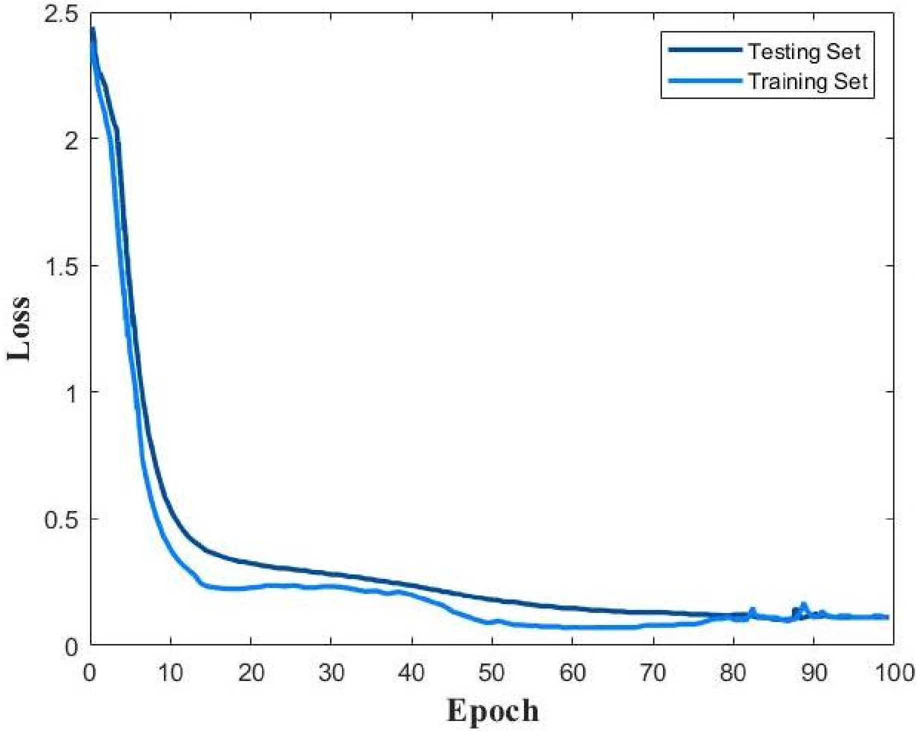

Figure 8. Convergence curve of the validated loss function of CLDNN.

As can be seen from Figure 8, although the validation loss is high at the beginning of the training, the loss function has largely converged and maintained at a low level by about 10 rounds of training.

4.4. Performance comparison

Further exploring the relationship between the models, I compare the performance of the three models mentioned in this paper.

Table 2. Comparison of validation loss of three models.

Name of the model	Number of rounds used for convergence	Final validation loss
CNN	35	1.06
Residual Networks	25	1.04
CLDNN	10	0.35

Table 2 shows the number of rounds required for the loss function to converge during the training process for the three models. It can be clearly seen that the model combining the residual network and CLDNN converges faster compared to the model using only CNN. Moreover, the final convergence value of CLDNN is much lower than the remaining two. This means that CLDNN has better performance in prediction, and it also has better generalization ability, because the lower validation loss means that the model performs better when facing unseen data. Therefore, its recognition performance was tested as follows.

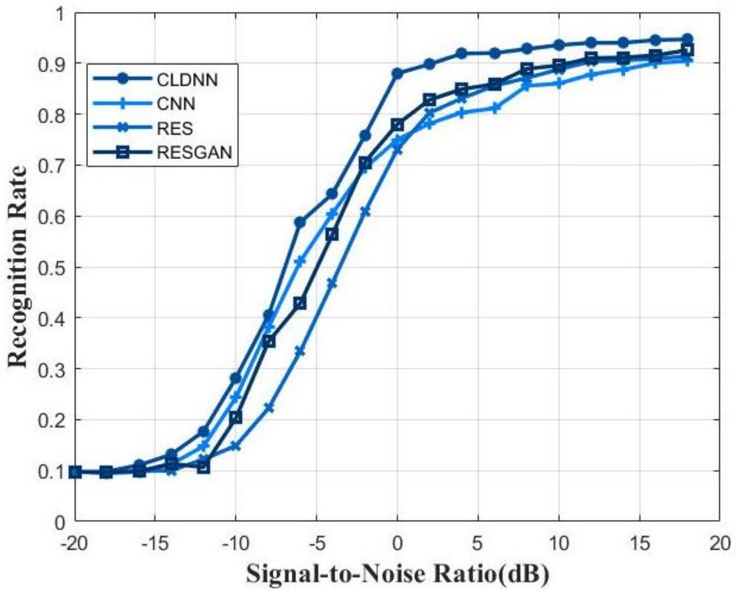

Figure 9. Comparison of recognition rates of different networks.

The signal-to-noise ratio represented by the horizontal axis can be clearly seen in Figure 9, which varies from -20 dB to 18 dB. The recognition accuracy of various models tends to increase as the signal-to-noise ratio increases. It achieves about 92% recognition accuracy at 4dB.

The recognition accuracy of the CNN model is surpassed by that of the RES model at 0 dB, which has 83% recognition accuracy at 4 dB. In contrast, the CNN outperforms it by 3 percentage points in that environment. This experimental result validates the theoretical derivation that RES has better recognition performance because of its deeper network structure.

However, the RES model takes up more resources in training, which is also a concern for me.

Table 3. Comparison of validation loss of three models.

Name of the model	Training time per batch/s	Number of training parameters
CNN	10.9	224331
Residual Networks	17. 1	246827
CLDNN	9.8	167243

In terms of training time, CLDNN is the fastest to train because it combines the features of CNN, LSTM and DNN to achieve better performance while maintaining relatively low computational complexity. In contrast, the residual network increases the computational complexity because it has more layers and has residual links. The CLDNN network is able to reduce the number of channels of input data by optimizing each network layer to each other, thus reducing the network parameters and complexity.

In general, compared with CNN, the residual network is slightly better than CNN in terms of performance, but has a higher computational complexity and requires a large amount of time cost in actual use. In contrast, the CLDNN model, as a comprehensive model, takes into account the high recognition performance while ensuring a low computational cost.

5. Conclusion

This paper introduces the signal modulation theory and proposes a convolutional neural network model commonly used for modulation recognition. Subsequently, two optimized models, the RES and CLDNN models, are proposed. The former model improves the performance but has a high computational complexity, while the latter model takes into account the high recognition accuracy while still reducing the network parameters as much as possible to keep the complexity at a low level.

Nevertheless, in the simulation, the best performing CLDNN could not reach 95% accuracy, which means that its accuracy still needs to be improved.

In practical applications, the signals will face harsh environments, which will lead to differences between the training data and the actual signals, further reducing the recognition accuracy of the network. Therefore, in the future, more advanced adaptive algorithms or online learning methods can be investigated to make CLDNNs face different signal environments with autonomous real-time adjustments and improved performance. In addition, although CLDNNs make full use of temporal correlation, the above three models still do not take full advantage of all the useful information in the signal. In further research, we can try to introduce more digital signal processing techniques, such as waveform analysis, time-frequency representation, etc. More information can be extracted from the signal to further improve the performance of the model.

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