

Blind Modulation Recognition in Complex Electromagnetic Environment

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ABSTRACT

With the continuous development of wireless communication technology, the wireless electromagnetic environment is increasingly complex, which results in the difficulty of modulation recognition of communication signals. In this paper, combining the advantages of ResNet and DenseNet, we propose a blind modulation recognition model based on deep learning. In this model, we reduce the two-dimensional convolution neural network in ResNet into the one-dimensional convolution neural network and then embed it into DenseNet. The identity mapping of ResNet and the dense connection of DenseNet, which strengthen feature propagation and encourage feature reuse and reduce the number of parameters, make the model take full advantage of multi-layer features to improve the ability of feature extraction and reduce the computational complexity. The experimental results on the RadioML2016.10b dataset show that the recognition accuracy of the model can reach 93.7% at high SNR.

Keywords: automatic modulation recognition, cognitive radio, one-dimensional convolutional neural network, ResNet, DenseNet, deep learning

1. INTRODUCTION

Automatic modulation recognition plays an important role in cognitive radio and non-cooperative communication systems. With the continuous development of wireless communication technology, the types and parameters of signal modulation in a wireless communication system are exploding. Traditional methods of signal modulation recognition need to know the signal and channel parameters in advance, which may not be accurate in a poor communication environment. Therefore, it is necessary to propose a robust modulation recognition method for communication signals.

The existing methods of signal modulation recognition could be divided into two categories: one is based on the likelihood function; the other is based on the feature. Although the method based on the likelihood function is the best way to reduce the probability of misclassification, due to the requirement of precise parameters, the computational complexity is very high, so it has poor robustness in practical application. Compared with the traditional method based on the likelihood function, the feature-based method needs more preprocessing. Deep learning technology has been widely used and has made great achievements in image processing and speech recognition. Many researchers have applied the deep learning method to signal modulation

recognition. The authors introduced the classical methods and development trend for automatic modulation recognition [1]. In [2], the authors use CNN to recognize signal modulation mode, with the recognition accuracy of 87.4%. The CLDNN-based method [3] is used to recognize signal modulation mode, and the recognition accuracy is 88.5% at high SNR. A blind modulation recognition method of overlapping co-channel signals based on CapsNet is proposed in [4]. The deep belief network (DBN) is studied in [5] to recognize the modulation of signals, the recognition accuracy is 92.12% when SNR = 18dB. A deep hierarchical network (DHN) is proposed in [6] for signal modulation recognition and achieves the highest recognition accuracy of 93.1% when SNR = 12dB.

2. SYSTEM AND SIGNAL MODEL

Automatic modulation recognition is the intermediate process of signal detection and demodulation in the receiver. At the transmitting end, the transmitter sends the signals to the wireless channel through the transmitting antenna. The signal is affected by the noise source and channel fading in the transmission process. Finally, the signals are received by the receiver. After preprocessing, the modulation mode of the signal is recognized by the modulation recognition model. The system model is shown in Figure 1.

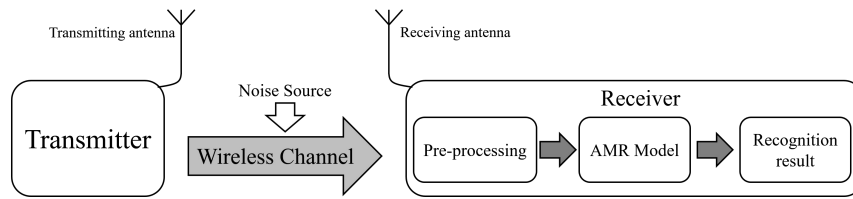


Figure 1 System Model.

For the receiver, the received signal is shown in equation (1), i.e. signal model. $s(t)$ is a continuous signal sent by the transmitter, or a series of discrete bits modulated into a sinusoidal signal. $c(t)$ reflects the multipath fading and frequency selective fading in the wireless channel, and $n(t)$ represents the noise source, such as Gaussian white noise; “*” represents convolution operation.

$$r(t) = s(t) * c(t) + n(t) \quad (1)$$

3. THE ARCHITECTURE OF MODULATION RECOGNITION MODEL

In [7], the ResNet is proposed. The most important residual unit is shown in Figure 2 (a). The residual unit forms the identity mapping by short-cut connection, which can realize the addition of input and output. This kind of addition will not add extra parameters and computational complexity to the model but can accelerate the training speed and improve the training performance of the model. To improve the ability of the model's feature extraction, the DenseNet is proposed in [8]. The structure of Dense Block is shown in Figure 2 (b), each layer in the network structure gets additional inputs from all the previous layers and transmits its own features to all the subsequent layers. Unlike ResNet, before it passes the features into a certain layer, they are combined by concatenation on the channel.

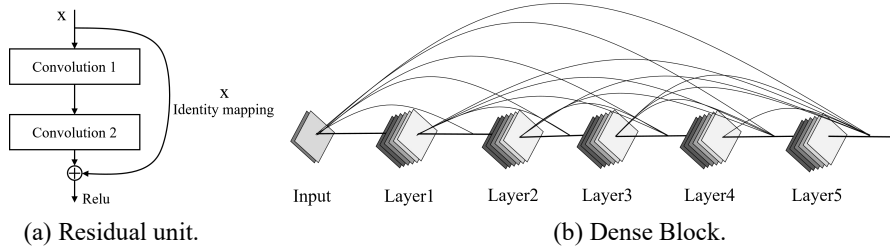


Figure 2 The architecture of residual unit and Dense Block

In this paper, combining the advantages of ResNet and DenseNet, the two-dimensional convolution in ResNet is reduced to a one-dimensional convolution and embedded in DenseNet, and the modulation recognition model of the communication signals is obtained, as shown in Figure 3. The model consists of input layer, six ResNet blocks, two full connection layers, and output layer. Beginning with the

first ResNet block, we connect the output of each ResNet block to the input of its subsequent ResNet block. The connection between the output of the first ResNet block and the input of the third ResNet block is the direct addition, which is the addition in ResNet. The others are concatenating on the channel, which is the same way in DenseNet.

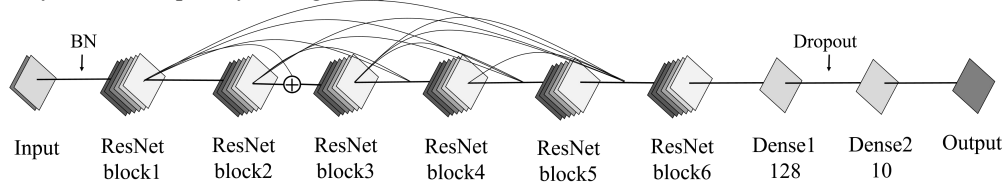


Figure 3 The architecture of the proposed model

We show the structure of the ResNet block in the proposed model in Figure 4. It composes each ResNet block of four residual units based on the one-dimensional convolutional

neural network. The number of convolution filters of six ResNet blocks is 32, all the convolution steps are 1, and the size of convolution filters are 7, 5, 3, 3, and 3 in order.

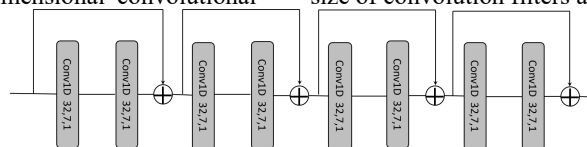


Figure 4 The architecture of ResNet block

To improve the recognition accuracy and robustness of the

model, we use some common optimization methods, such as

adding batch normalization processing layer, dropout layer, and Relu activation function in the model, and using Adam optimizer.

4. EXPERIMENT AND ANALYSIS

In this paper, we adopt the RadioML2016.10b dataset generated in [9] as the input data of the proposed model. The dataset includes 10 modulation modes, namely 8 digital modulation methods BPSK, QPSK, 8PSK, QAM16, QAM64, GFSK, CPFSK, PAM4, and 2 kinds of analog modulation methods WBFM, AM-DSB. The dataset is generated by the GNU radio platform and USRP hardware devices, fully

simulating signal transmission in real communication, such as multipath fading, frequency selective fading, and additive white Gaussian noise.

To demonstrate that the one-dimensional convolution has excellent processing ability for pre-processed modulated signals, we reduce the two-dimensional convolution of four models (CNN, ResNet, DenseNet, CLDNN) proposed in [4] to the one-dimensional convolution. Then, we get the modified models, and train and test them on the RadioML2016.10b dataset. As is shown in Fig. 5, compared with the original two-dimensional convolution-based models, the recognition accuracies of the modified models are improved obviously at high SNR, showing that the one-dimensional convolution is more suitable for processing sequence data.

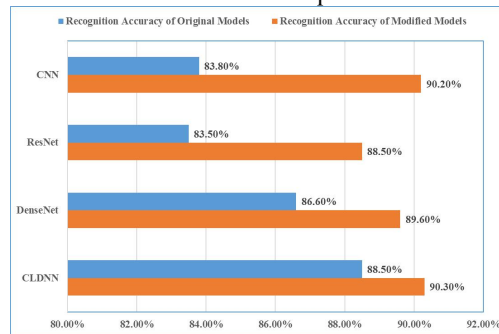


Figure 5 The recognition accuracy of the original and the modified models

The results of the four modified models compared with the proposed model are presented in Fig. 6. The recognition accuracies of the five models are positively correlated to the SNR. From the perspective of recognition accuracy, the algorithm of the proposed model is preferable to the other

four models. The recognition accuracy of the modified CNN is poor at low SNR. When $\text{SNR} > -6\text{dB}$, the recognition accuracy of proposed model is higher than that of the other four modified models, and achieved the highest recognition accuracy of 93.7% at $\text{SNR} = 16\text{dB}$.

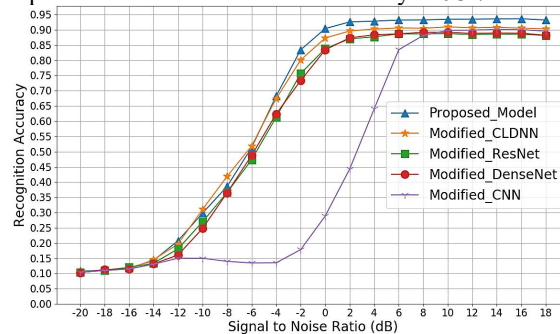


Figure 6 The recognition accuracy of the proposed model and the modified models

The four models mentioned in [4] do not distinguish QAM16 and QAM64 very well. At $\text{SNR} = 16\text{dB}$, we show the confusion matrix of the proposed model in Figure 7. The recognition accuracy of QAM16 and QAM64 is 97.6% and 97.3%, respectively, which shows that the proposed model

could well recognize QAM16 and QAM64 at high SNR. Besides WBFM being misidentified as AM-DSB under certain probability, other modulation modes can be well recognized as the correct modulation modes.

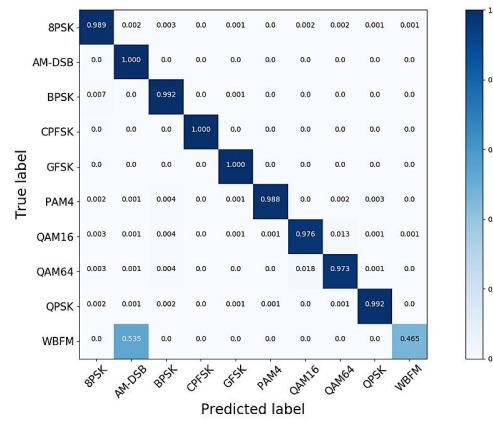


Figure 7 The confusion matrix of the proposed model at SNR=16 dB

The recognition accuracies of 10 modulation modes in this paper under different SNRs are shown in Fig. 8. Besides 8PSK, the recognition accuracies of the other 9 modulation modes are positively correlated with SNR. When SNR=0dB, except for WBFM, the recognition accuracies of the other 9 modulation modes is above 93%. Especially, when

SNR>=4dB, the recognition accuracy of these 9 modulation methods is higher than 97%, among them, the recognition accuracies CPFSK and GFSK have reached 100%. Although the recognition accuracy of WBFM is positively correlated with the SNR, the overall recognition accuracy is less than 50%.

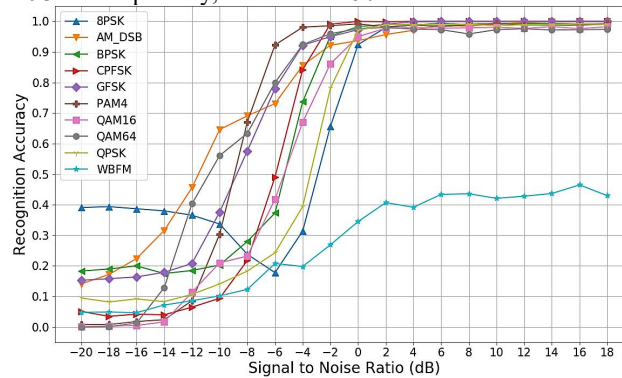


Figure 8 The recognition accuracy of 10 modulation modes

In this paper, floating-point operations (FLOPs) and parameters of the neural network model are used as the criteria to measure the complexity of the model. The computational complexity of the model proposed in this paper and the four models mentioned in [4] are shown in Fig.

9 (a) and (b). The number of FLOPs and parameters in the proposed model are significantly lower than the other four models, which shows the efficiency and simplicity of the proposed model.

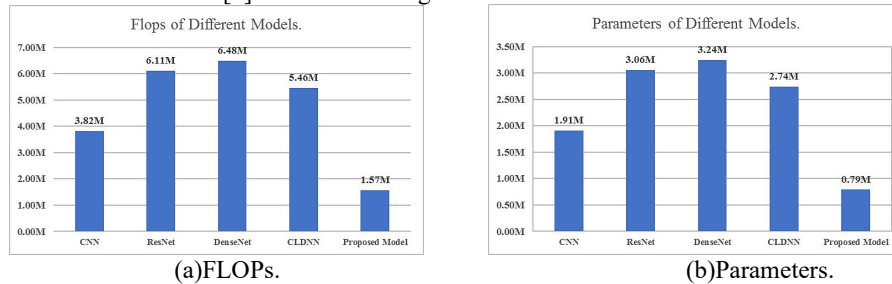


Figure 9 The histograms of FLOPs and parameters for different models

5. CONCLUSION

In this paper, a blind recognition model of signal modulation mode based on the one-dimensional convolutional neural network is proposed. The proposed model fully uses the idea of ResNet's identity mapping and DenseNet's dense connection to enhance the ability of feature extraction and reduce the computational complexity. Compared with the

existing models based on the two-dimensional convolution neural network, the proposed model has better performance. The experimental results show that the recognition accuracy of the proposed model can reach 93.7% at high SNR, which is a blind modulation recognition model with superior robustness and low computational complexity.

ACKNOWLEDGMENT

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