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Convolutional Neural Network Analysis for Modulation Classification of Wireless Communication Signal

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Abstract. Modulation classification detects the modulation type of received signals to guarantee that the signals can be correctly demodulated and that the transmitted message can be accurately recovered. For the modulation classification of M-PSK, M-QAM and M-APSK modulated signals with similar constellation maps, we analyze waveform characteristics of the signal in the time domain. Based on the waveform characteristics of the signal, we explore the feasibility of using convolutional neural network (CNN) to identify the modulation classification of the signal. We analyze the data input structure and network model required for modulation classification using CNN. Considering the impairment of the signal by additive white Gaussian noise (AWGN), clock offset and Rician multipath fading, a combined channel is simulated in this paper to obtain the impaired data as dataset. The simulation results show that CNN has great potential for modulation classification.

Keywords. modulation classification, deep learning, CNN, IQ samples

1. Introduction

Modulation recognition of communication signals plays an important role in both military and civil fields. It is widely used in electronic warfare and communication intelligence reconnaissance, communication monitoring and spectrum management, adaptive modulation and software radio, etc [1] [2] [3]. In electronic warfare, if one hopes to recover the message from a piece of intercepted and possibly adversary communication signal, a modulation classifier is needed to determine the modulation type used by the transmitter.

Generally, modulation recognition methods roughly divides into three categories: likelihood-based (LB) methods [4], feature-based (FB) methods [5] and deep learning based methods. The LB methods is based on likelihood function and appropriate decision method to solve the modulation identification problem. The solution provided by the LB methods is optimal in the Bayesian sense. The FB methods are widely used and mainly include two basic steps of feature extraction and pattern recognition. Feature extraction seeks for some handcraft features to distinguish different types of signals, such as high order statistics of instantaneous amplitude, phase and frequency and cyclic stationary characteristics [5] [6]. In the recognition process, the commonly used classifiers include

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decision tree and support vector machine (SVM). In recent years, with the great success of deep neural networks in the fields of image [7] and speech [8] [9], the research on modulation recognition of communication signals is gradually developing towards the direction of deep learning [10] [11]. O'Shea proposed a new method, training convolutional neural networks by baseband IQ data [12]. Mendiset converted signals into images by spectral correlation functions (SCF), and then extracted features from SCF images of receiving signals by using deep belief networks [13]. Wang combined two CNN networks to train data sets [14].

CNN-based classification methods are trained with a large amount of signal sample data to automatically acquire signal features for differentiation. These features can be achieved by signal of original data transformation, can also be converted to images by mapping relations. And a variety of modulation signals are automatically identified and classified through self-learning mechanism of machine learning. In this paper, two CNNs directly train the time-domain data of the signal to obtain the signal features, so as to classify the signal.

2. Dataset Generation

Communication transmits signals from the sender to the receiver through a channel to complete information transmission. In reality, the information must be modulated before entering the channel and demodulated when it is received by the receiver. The data required by the experiment is the unknown modulation data received by the receiver. The experimental dataset is generated through the simulation signal transmission process [15], as shown in figure 1.

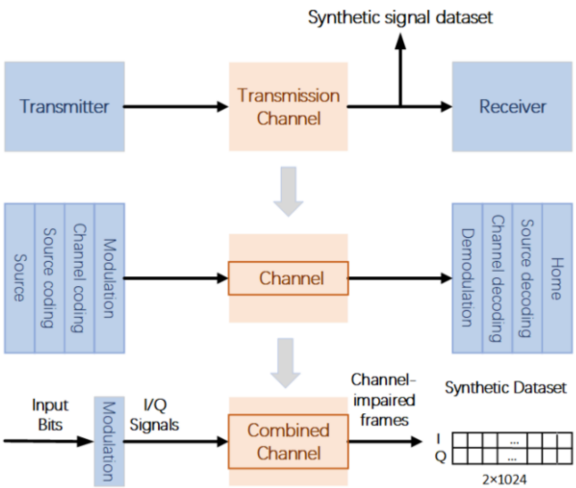

Figure 1. The process of generating modulation data

Generally, I/Q modulation can be expressed by (1), where I is the in-phase component and Q is the quadrature component. Bitstreams obtain I/Q signal data according to (1) mapping in modulation mode. For this, we sample in-phase and quadrature components of a radio signal to obtain a $1 \times N$ complex valued vector.

$$s(t) = I\cos\omega_0 t - Q\sin\omega_0 t \tag{1}$$

The signal channel of communication system is channel based on transmission medium, which usually has uncertain and not completely reversible channel effect. When modeling a wireless channel there are many bad factors that must be considered [16]. We create a combined channel, including Rician multipath fading, AWGN, and clock offset.

1. Rician multipath fading: Received signal is the superposition of the complex Gaussian signal and the direct component (i.e. sinusoidal wave plus narrowband Gaussian process), and the probability density function of the envelope obeys the Rice distribution.

2. Additive white Gaussian noise: AWGN is a kind of noise superimposed on the signal, and its amplitude follows the Gaussian distribution. It is the most basic noise and interference, and is usually denoted as n(t).

3. Clock offset: It occurs because of the inaccuracies of internal clock sources of transmitters and receivers, can be expressed as C.

Thus, the general model representation of the channel is shown in (2). By entering data into the combined channel, we get channel-impaired data.

$$r(t) = s(t) * C + n(t) \tag{2}$$

3. Signal Classification Models

3.1. Classification Approach by CNNs

CNN is a kind of feedforward neural networks with convolutional computation and deep structure [17]. It has the ability of representation learning, which can learn the most essential features of dataset, and is widely used in recognition and classification tasks in various fields. Since Alexnet [18], CNN has made leapfrog progress in hierarchical architecture, so its performance has been significantly improved.

Neural network is mainly composed of input layer, convolution layer, pooling layer and full connection layer. These layers use parameter intensive matrix operation and nonlinearity to map the input h_{in} and output h_{out} of each layer, which can be expressed as follows. Where W is weights, b is bias, and max() is an activation function.

$$h_{out} = max(0, h_{in}W + b) \tag{3}$$

Figure 2 illustrates the overall system model of this paper, divided into two phases. In the training phase, the generated data is pre-processed to obtain the required dataset, which is then input the developed CNN to obtain a trained network. In the testing phase, the trained network can classify signals with unknown modulation patterns. Thus, the model completes modulation classification.

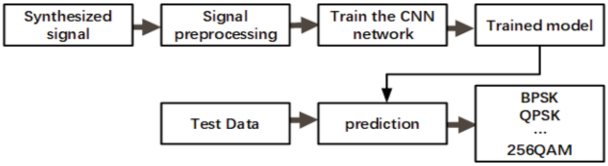

Figure 2. This is the overall system model

3.2. CNN Models

The first model consists of 12 convolution layers, 6 max pooling layers, 2 fully connected layers and 1 softmax layer, as shown in figure 3. Each convolution layer except the last is followed by a BN layer and ReLU activation layer. In the last convolution layer, the max pooling layer is replaced with an average pooling layer. Softmax is used as the classification layer.

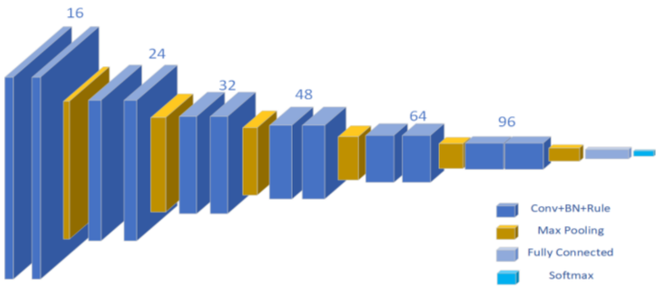

Figure 3. The first CNN layout

The second CNN model adds an inception block, as in figure 4. The Inception model is designed to solve two problems of CNN classification models, one is how to increase the depth of the network while increasing the classification performance of the model; the other is how to ensure that the classification accuracy of the classification network is increased or maintained without decreasing while the computational and memory overhead of the model is reduced sufficiently [19]. Reducing the number of channels by 1x1 convolution aggregates the information, then performing feature extraction and pooling at different scales obtains information at multiple scales, and finally superimposing the features outputs to next layer. The second CNN model has 3 convolution layers and an inception block.

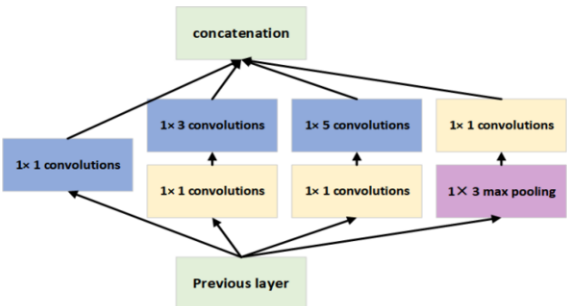

Figure 4. Inception model

4. Simulation Results

4.1 Dataset

There are 9 digital modulation methods, including BPSK, QPSK, 8PSK, 16APSK, 32APSK, 64APSK, 16QAM, 32QAM, 64QAM. The DVB-S2 standard adds APSK modulation to improve spectral efficiency. The difference between APSK modulation and traditional QAM signal modulation is that APSK modulation well avoids the nonlinear effect of communication RF amplifiers. The constellation diagrams of the 9 digital modulation look very similar, as in figure 5.

The center frequency of generated data is 900 MHz. Each modulation method generates 10,000 frames of data. Each frame has 1024 samples. Generated data is divided into training set, validation set and testing set by 8:1:1. For each frame in the synthetic dataset, we independently draw a random value for each variables shown in channel. This leads to a new and uncorrelated random channel initialization for each frame.

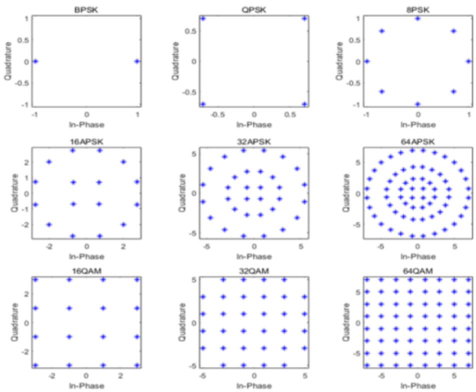

Figure 5. Constellation diagrams of M-PSK, M-APSK, M-QAM

4.2 Implementation

The experiment is implemented by pytorch framework. We first load the generated dataset, and then pre-process it to match the network input format. SGD was used as the optimal algorithm to optimize the model. In addition, We measure the performance of our model classification by the Cross-Entropy Loss function to adjust weights and calculate the difference between the output and the label of dataset. We train for 50 epochs and batch size of 64.

4.3 Results

According to the experimental process described in this paper, the sample set is sent to the proposed network model for training, then the test data set containing 9,000 frames are used to verify the accuracy of the generated network to identify signals modulation. Figure 6 shows the training process of the first CNN model, figure 7 shows the training process of the second CNN model, blue broken line represents training set, red broken line represents verification set. The accuracy curve and the loss curve show that both networks are well trained. The training accuracy of the first CNN model is 87.66%, and that of the second model is 90.53%. The total training parameters of the first network are 131,815 , and the second network are 125,145. And the training time of the second network is less than half of the first network. Thus, the CNN network with inception block has better classification ability for time-domain I/Q data with fewer parameters and faster training.

As can be seen from the confusion matrix, the recognition rate of the model in out-of-class modulation mode is higher than that in in-class modulation mode. The recognition rate in M-QAM is only 80.00% and 80.17%, the lowest of the 3 categories. In general, in-class modulation recognition is more challenging than out-of-class modulation recognition.

5. Conclusion

In this paper, the modulation classification method of communication signal based on CNN is proposed. The CNN network directly extracts the features of the original data sequence for classification without manual feature selection. DL method has great potential to improve the sensitivity and accuracy of radio signal identification.

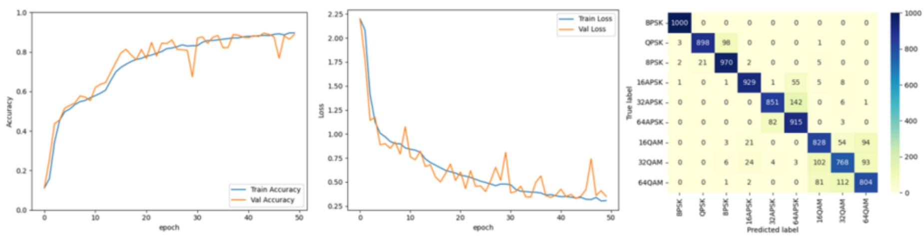

Figure 6. The results of the first CNN model

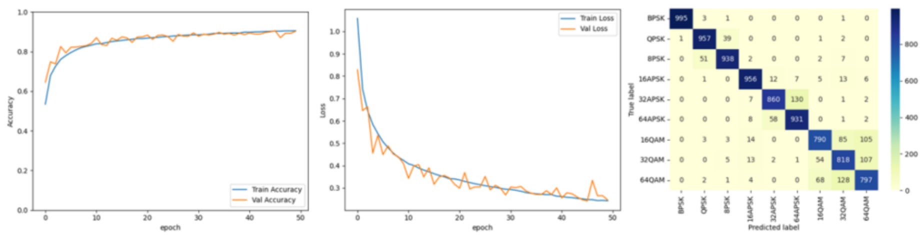

Figure 7. The results of the second CNN model

References

[1] X.Li, F. Dong, S.Zhang, W.Guo, “A Survey on Deep Learning Techniques in Wireless Signal Recognition,” Wireless Communications and Mobile Computing, vol. 2019, Article ID 5629572, 12 pages, 2019

[2] S. A. Ghunaim, Q. Nasir and M. A. Talib, “Deep Learning Techniques for Automatic Modulation Classification: A Systematic Literature Review,” 2020 14th International Conference on Innovations in Information Technology (IIT), 2020, pp. 108-113

[3] Z. Zhang, C. Wang, C. Gan, S. Sun and M. Wang, “Automatic Modulation Classification Using Convolutional Neural Network With Features Fusion of SPWVD and BJD,” IEEE Transactions on Signal and Information Processing over Networks, vol. 5, no. 3, pp. 469-478, Sept. 2019

[4] J. Sills, “Maximum-Likelihood modulation classification for PSK/QAM,” in Proc.IEEE Communication Conf., vol. 5, 1999

[5] L. Pei-Hua, Z. Hong-Xin, W. Xu-Ying, X. Nan, and X. Yuan-Yuan, “Modulation recognition of communication signals based on high order cumulants and support vector machine,” Elsevier Signal Processing, vol. 19, pp. 61-65, June 2012

[6] G. J. Phukan and P. K. Bora, “An algorithm for blind symbol rate estimation using second order cyclostationarity,” 2014 International Conference on Signal Processing and Communications (SPCOM), 2014, pp. 1-6

[7] A. El Housseini, A. Toumi and A. Khenchaf, “Deep Learning for target recognition from SAR images,” 2017 Seminar on Detection Systems Architectures and Technologies (DAT), Algiers, Algeria, pp. 1-5, 2017

[8] G. E. Dahl, D. Yu, L. Deng, and A. Acero, “Context-dependent pretrained deep neural networks for large-vocabulary speech recognition,” Audio, Speech, and Language Processing, IEEE Transactions on, vol. 20, no. 1, pp. 30-42, 2012

[9] N. Jaitly, P. Nguyen, A. W. Senior, and V. Vanhoucke, “Application of pretrained deep neural networks to large vocabulary speech recognition.,” in INTERSPEECH, pp. 2578-2581, 2012

[10] J. H. Lee, K. Kim and Y. Shin, “Feature Image-Based Automatic Modulation Classification Method Using CNN Algorithm,” 2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), 2019, pp. 1-4

[11] S. Peng, S. Sun and Y. -D. Yao, “A Survey of Modulation Classification Using Deep Learning: Signal Representation and Data Preprocessing,” in IEEE Transactions on Neural Networks and Learning Systems, doi: 10.1109/TNNLS.2021.3085433, early access

[12] T. J. O’Shea, J. Corgan, and T. C. Clancy, “Convolutional radio modulation recognition networks,” in Proc. Int. Conf. Eng. Appl. Neural Netw., 2016, pp. 213-226

[13] G. J. Mendis, J. Wei and A. Madanayake, “Deep learning-based automated modulation classification for cognitive radio,” in Proc. IEEE Int. Conf. Commun. Syst., Dect.2016, pp. 1-6

[14] Y. Wang, M. Liu, J. Yang and G. Gui, “Data-Driven Deep Learning for Automatic Modulation Recognition in Cognitive Radios,” in IEEE Transactions on Vehicular Technology, vol. 68, no. 4, pp. 4074-4077, April 2019

[15] T. J. O’ Shea and N. West, “Radio machine learning dataset generation with GNU radio,” in Proc. GNU Radio Conf., 2016, vol. 1, no. 1

[16] T. J. O’ Shea, T. Roy and T. C. Clancy, “Over-the-Air Deep Learning Based Radio Signal Classification,” in IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 168-179, Feb. 2018

[17] Goodfellow, I., Bengio, Y., Courville, A.Deep learning (Vol. 1). Cam- bridge: MIT press, 2016: 326-366

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proc. Adv. Neural Inf. Process. Syst., 2012, pp. 1097-1105

[19] C. Szegedy et al., “Going deeper with convolutions,” 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 1-9