A new scheme of automatic modulation classification using Convolutional Neural Network with constellation diagram

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Abstract: Automatic Modulation Classification (AMC) of the transmitted signals remains a challenging area in modern intelligent communication systems such as cognitive radio system. In this research, we propose a new system for AMC using Convolutional Neural Network (CNN) with constellation diagrams in Additive White Gaussian Noise channel and use the trained model to recognize five digital modulation methods: BPSK, QPSK, 8PSK, 16QAM and 64QAM with constellation diagrams. We have achieved high efficiency and high precision recognition of modulation methods by using new CNN models, improved input image size, number of dropout layers and simulation hyperparameters.

Keywords: Automatic Modulation Classification, Convolutional Neural Network, Constellation Diagram

Classification: Wireless communication technologies

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1 Introduction

Automatic modulation classification (AMC) can be applied to recognize the modulation methods of transmitted signals usually corrupted by noise, and plays a key role in cognitive radio system. In the IEEE 802.22 standard, the typical variable of detection probability in spectrum sensing for cognitive radio system is 90%. As a technology in cognitive radio system, it is also necessary that the recognition accuracies are higher than 90% for AMC. It has been studied for traditional classification systems since a long time ago, but there are some problems such as low efficiency and low accuracy [1]. According to conventional method, when the $E_b/N_0 \geq 0$dB, the automatic modulation recognition accuracy is above 90% with using Artificial Neural Networks (ANN) [2]. However, when the $E_b/N_0 \leq 0$dB, the above method is almost impossible to recognize the modulation method.

In recent years, there are extensive applications on field of image recognition for the Convolutional Neural Network (CNN), and they have achieved great recognition results [3]. Therefore, we propose a new system for AMC using CNN with constellation diagrams in Additive White Gaussian Noise (AWGN) channel. And then we have achieved high efficiency and high precision recognition of modulation methods by using new CNN models, improved input image size, number of dropout layers and simulation hyperparameters.

2 Digital communication system model

![Digital communication system model](image)

**Fig. 1.** A digital communication system.

We use the digital communication system model that can be seen in Fig. 1. First, we generate random signals with the equal probability distribution of 0 and 1. Second, we generate signal modulated by different methods. Third, we use the
Square Root Raised Cosine filter (SRRC) filter at the sending end and the Matched filter at the receiving end. Fourth, we use the AWGN channel to add the Gaussian white noise in the original signal. Here the parameter of AWGN is $E_s/N_0$. Finally, we use the sampled signal to generate constellation diagrams.

3 Convolutional Neural Network model

We use two different CNN models in this research, CNN model 1 is the same CNN model as previous research [5], however we improve input image size and number of dropout layers in the model. CNN model 2 is the CNN model based on Google Inception-ResNet-v2 model [4].

3.1 CNN model 1

CNN model 1 is the same CNN model as previous research, however we change input image size of input layer from $299 \times 299 \times 3$ pixels to $199 \times 199 \times 3$ pixels. The following is the particular structure of CNN model 1. There are one Stem layer, four Inception-A layers, one Reduction-A layer, seven Inception-B layers, one Reduction-B layer, three Inception-C layers, one Average Pooling layer, two Fully Connected layers and two Dropout layers in the model, finally the output layer outputs results according to five modulation methods.

3.2 CNN model 2

We use the CNN model based on Google Inception-ResNet-v2 model and set the size of input layer to $299 \times 299 \times 3$ pixels. The following is the particular structure of CNN model 2. There are one Stem layer, five Inception-resnet-A layers, one Reduction-A layer, ten Inception-resnet-B layers, one Reduction-B layer, five Inception-resnet-C layers, one Average Pooling layer, two Fully Connected layers and two Dropout layers in the model, finally the output layer outputs results according to five classification methods.

4 Simulation and results

For the two models in this research, we used the same data set, and different hyperparameters to simulate.

First we set simulation parameters for digital communication system model, in addition we used to $E_s/N_0$ represent the value of signal energy per bit to background noise power spectrum destiny ratio, and chose the range of $E_s/N_0$ from -20dB to 5dB. And then we used five digital modulation methods: BPSK, QPSK, 8PSK, 16QAM and 64QAM. For the carrier frequency and the sampling frequency, we set to 2kHz and 8kHz. The sampling point was set to 1024. We superposed AWGN channel on signal processing, and generated constellation diagrams.

Next we generated training sets, validation sets and test sets for CNN model. For a start, we generated 125 constellation diagrams for each 1dB, and there were 3250 constellation diagrams for each modulation method under the range of $E_s/N_0$ from -20dB to 5dB. In that way, there were 16250 constellation diagrams as original data. In addition we chose 80% of original data as training sets, 10% of original data as validation sets, and 10% of original data as test sets. For training sets, we used four ways of data augmentation, such as Random Brightness, Random Crop,
Random Flip and Random 90 degrees rotate. Especially for Random Crop, which was different from previous research [5], we changed random crop size from 150×150×3 pixels to 10×10×3 pixels. Therefore there were a total of 65000 constellation diagrams as training sets.

In this research, training times of CNN models 1 and 2 can be seen in Fig. 2. We calculated the training time by using prepared training sets to train with the CNN model. When the CNN model training reaches perfection, the accuracy curves of training sets and validation sets will converge. We found that the training time of each epoch of CNN model 1 is faster than that of CNN model 2 in Fig. 2(a), but the training of CNN model 1 requires more training epochs than CNN model 2 when accuracy curves of two sets converging. Therefore in Fig. 2(b), total training time of CNN model 1 was 417 minutes and total training time of CNN model 2 was 406 minutes. We knew that when the training time was practically the same, the recognition accuracy curves of the verification sets for the two models converged and the recognition accuracies were practically equal.

![Fig. 2. Training times of CNN models 1 and 2.](image)

And then for the two trained models, we used two test methods to evaluate model performance. The first method is to test sets according to five digital modulation
methods, and test recognition performance of the two trained models for each of five modulation methods as $E_b/N_0$ changing. The second method is to use all test sets to test recognition performance of the two trained models for each of five modulation methods with $E_b/N_0$ from -20dB to -5dB. Then we used recognition accuracy as results of this research.

For the first test method, recognition accuracies of CNN models 1 and 2 for each of five digital modulation methods can be seen in Fig. 3. In Fig. 3(a), compared with results of previous research [5], when the $E_b/N_0 = -5$dB, we increased the lowest recognition accuracy for each of five modulation methods from 90% to 94% in this research. Therefore when the $E_b/N_0 \geq -5$dB, recognition accuracies for each of five modulation methods were higher than 94%. In Fig. 3(b), compared with results of previous research, when the $E_b/N_0 = -5$dB, we increased the lowest recognition accuracy for each of five modulation methods from 90% to 92% in this research. In other words when the $E_b/N_0 \geq -5$dB, recognition accuracies for each of five modulation methods were higher than 92%. In that case we knew that there were stronger recognition performance for each of five modulation methods on CNN model 1 when the $E_b/N_0 \geq -5$dB.

For the second test method, we obtained that recognition accuracies of the CNN model 1 in five digital modulation methods: BPSK, QPSK, 8PSK, 16QAM and
64QAM were 92.6%, 55.1%, 72.7%, 26.1%, and 62.5% in turn. We also obtained that recognition accuracies of the CNN model 2 in five digital modulation methods were 98.9%, 63.6%, 73.9%, 37.5%, and 45.5% in turn. Therefore we found that there were stronger average recognition performance on BPSK, QPSK, 8PSK and 16QAM methods with $E_s/N_0$ from -20dB to -5dB on CNN model 2, in addition there were stronger average recognition performance on 64QAM method with $E_s/N_0$ from -20dB to -5dB on CNN model 1.

In the field of computer vision, the recognition performance of Google Inception-ResNet-v2 model is stronger than Google Inception-v4 model, but in the work of AMC, this is not the case through the two test methods. For that reason, based on the principle of Occam's razor, we knew that

- When the $E_s/N_0 \geq -5$dB, the two models satisfied the IEEE 802.22 standard for AMC systems and CNN model 1 was the best choice for AMC in the two models at almost the same training time.
- When the $E_s/N_0$ was from -20dB to -5dB, in the two models, CNN model 1 was the best choice on 64QAM method for AMC, in addition CNN model 2 was the best choice on BPSK, QPSK, 8PSK, and 16QAM methods for AMC.

5 Conclusion

In this research, we used two CNN models to test methods and increased recognition performance of CNN model for five modulation methods by using new CNN model, improving input image size, number of dropout layers and simulation parameters. For that reason we knew that when the $E_s/N_0 \geq -5$dB, the two models satisfied the IEEE 802.22 standard for AMC systems and CNN model 1 was the best choice for AMC at almost the same training time, and when the $E_s/N_0$ was from -20dB to -5dB, CNN model 1 was the best choice on 64QAM method, in addition CNN model 2 was the best choice on BPSK, QPSK, 8PSK and 16QAM methods for AMC. Future research includes comparing this research with the conventional methods such as the cyclostationary detection and the energy detection.

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