

Automatic Signal Modulation Recognition based on Deep Convolutional Neural Network

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Abstract. Deep learning (DL) shows great vitality in all areas, but it rarely involves wireless communication. This paper proposes an automatic signal modulation recognition method based on deep convolutional neural network to solve common problems in wireless communication. The algorithm automatically extracts various feature details of the image through the deep convolutional neural network of deep learning, instead of the huge engineering of manual design features to achieve accurate recognition of signal and noise under various signal-to-noise ratio conditions. The method uses the image processing GPU to build VGGNet to automatically recognize 10 kinds of modulated signals in MPSK and MQAM under the deep learning architecture TensorFlow. The simulation results show that the minimum recognition accuracy of various signals is 96.7% when the signal-to-noise ratio is 5dB. Compared with other methods, the proposed method is better.

Keywords: deep learning (DL); neural network; modulation; wireless communication.

1. Introduction

With the rapid development of communication technology and the rapid growth of people's demand for information, the wireless communication environment becomes increasingly dense, and the wireless communication system and modulation pattern become complex and diverse. Communication signals transmitted in space are distributed in a limited bandwidth with a certain frequency. Only by accurately determining the modulation type of communication signals can interference suppression or demodulation be performed on the communication signals. This technique is called Automatic Modulation Classification (AMC) [1]. Generally, modulation recognition is divided into two categories: maximum likelihood signal recognition based on hypothesis testing [2] and statistical pattern signal recognition based on feature extraction [3].

The constellation diagram is a common method of digital modulation signal analysis, and its shape reflects the amplitude and phase distribution of the modulation signal [4]. The modulation signal of each modulation mode can be converted into a unique constellation diagram, so the modulation identification problem can be converted into a pattern identification problem, which avoids complex signal analysis and processing. Mobasser first proposed based on the constellation diagram such as the classification of signal modulation mode, the most basic modulation recognition based on the constellation diagram study is by restoring the constellation diagram clustering algorithm, and then through the rule of maximum likelihood classification criterion, Common algorithms for constellation restoration include Fuzzy c-means (FCM) clustering algorithm[5], subtraction clustering algorithm[6], etc.

2. The System Model

The model of automatic modulation recognition system based on convolutional neural network proposed in this paper is shown in the following Fig 1:

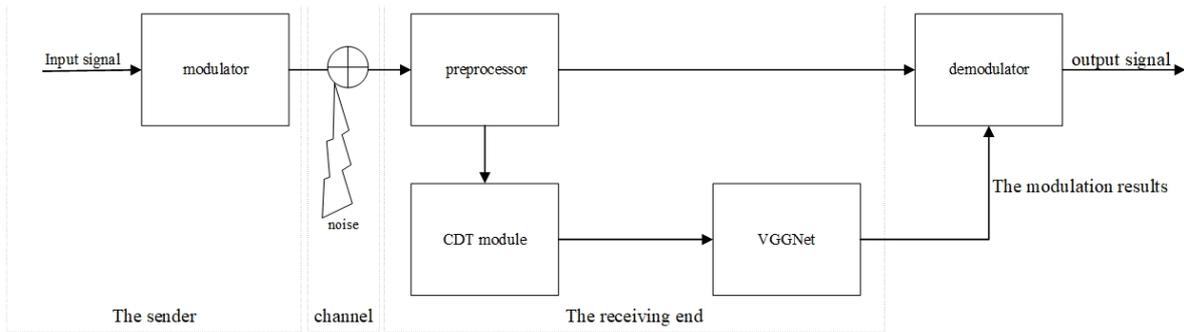


Fig. 1 System model diagram

The input signal passes through the sending end of the system, gets the modulated signal through the demodulator, and passes through the channel (additive white gaussian noise channel) to the receiving end of the system. The signal passes through the preprocessor at the receiving end of the system, the constellation diagram transform (CDT) module, and the VGGNet recognition module to identify the modulation mode of the signal. The demodulator receives the modulation signal and the modulation information of the signal to complete the demodulation of the signal and restore the original signal. VGGnet of the system module is the innovation of the article, this article focuses on this part

2.1 VGG Module.

Convolutional neural network (CNN) is a multi-layer forward feedback neural network, which is generally composed of convolution, sampling layer and fully connection layer [7]. CNN is a kind of deep learning framework, which can extract features from data through multi-layer linear transformation. It has strong learning ability and expression ability, and reduces the requirement of data preprocessing. It is mostly applied in the field of pattern recognition. Here, we select the VGG-16 network for training.

3. Analysis of Simulation Results

3.1 Data Set Preparation.

In order to obtain the neural network model for the classification of communication signal modulation mode, it is necessary to obtain a large number of constellation images as the sample data of supervised training. In the neural network model of the constellation, the training samples and the test samples are the constellation images marked in different modulation modes and in different signal-to-noise ratio environments. In this paper, used Matalab to generate a signal source and modulate it in 10 typical digital modulation modes: QPSK, 4QAM, 8PSK, 8QAM, 16PSK,16 QAM,32QAM, 64QAM, 128QAMand 256QAM. The signal preprocessed by gaussian noise is added to the constellation map to obtain the training set and test set, which are expanded by rotation, scaling and translation. In the training set of each modulation mode, 100 constellations are selected as test sets every 5db in the range of 0-20db.

3.2 Model Training and Identification.

In this paper, the VGG-16 network should be built through the most widely used TensorFlow framework. We slightly changed the three layers of the VGG-16 network, changed the output layer 1000 of the network to the number 8 consistent with the signal modulation type, and reduced the number of neurons in the 17th and 8th layers of the full connection layer to 512, because the original 4096 neurons in the actual training always led to the difficulty of convergence. In addition to changing the basic structure, some network parameters are optimized for signal modulation in this paper. The number of training samples is 2000, the number of test samples is 400, and the SNR range is 0-20db. In this simulation, gaussian white noise channel is adopted. The prepared constellation map training

set was used to train the VGG-16 network, initial learning rate $\alpha = 0.01$, and the gradient descent optimization algorithm used Adam momentum optimization algorithm, and the training results were shown in the Table 1. It can be seen that modulation signals of MPSK class can achieve 96% accuracy when the SNR is above 5db by this method, while modulation signals of MQAM class can achieve 91% accuracy when the SNR is 0db by this method, 97% identification accuracy when the SNR is 5db, and 99% accuracy when the SNR is 20db. By analyzing the recognition results of the table 1, it can be found that, under the same SNR condition, the recognition accuracy decreases slightly with the increase of the adjusted order. With the increase of SNR, the accuracy of the six modulation methods is significantly improved. When the SNR is greater than 5, the recognition accuracy of these modulation methods is above 96%.

Table 1. The recognition accuracy of different SNR under VGG-16

Type	0db	5db	15db	20db
QPSK	91.7%	98.4%	99.6%	99.9%
8PSK	87.3%	98.2%	99.3%	99.9%
16PSK	80.8%	96.7%	99.0%	99.6%
4QAM	92.3%	98.3%	99.7%	100%
8QAM	92.9%	97.9%	99.3%	99.9%
16QAM	92.5%	97.5%	99.5%	99.9%
32QAM	91.8%	97.5%	99.5%	99.9%
64QAM	91.7%	97.4%	99.4%	99.8%
128QAM	91.4%	97.2%	99.3%	99.9%
256QAM	91.5%	97.3%	99.4%	99.9%

In order to demonstrate the superiority of this algorithm in recognition accuracy, The proposed method is used together with the Recognition of radar emitter signals based on SVD and AF main ridge (SVD-AF) method[8], radar signal Recognition based on ambiguity function features and cloud model similarity (AF_CMS)[9], and radar signal Echo based on ambiguity function features and cloud model similarity (MWC_STFT) [10]and AlexNet model were used for comparison. We select 16PSk and 16QAM signals for modulation identification by the above methods.

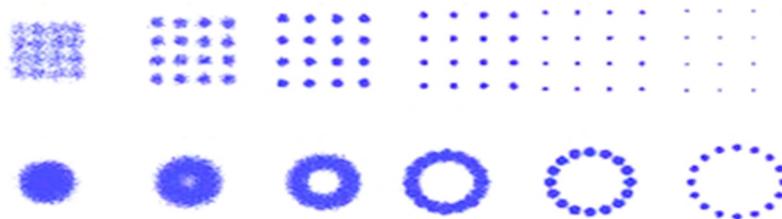


Fig 2. The constellation diagram of 16PSK and 16QAM signal at different SNR

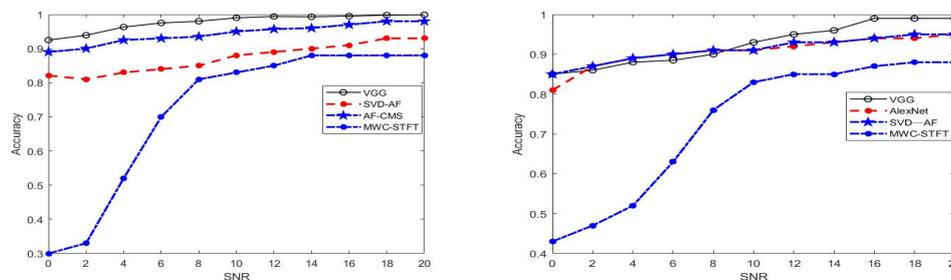


Fig 3. The accuracy of 16QAM and 16PSK signal in different recognition methods

As shown in the Fig 3, the overall recognition rate of 16PSK signal using the VGG-16 network model used in this paper at 0db is respectively 80.8% and 92.5%, and the recognition accuracy rate at 20db is 99.6% and 99.9%.

The recognition rate of 16PSK signal in SVD-AF, AF-CMS and MWC-STFT is 82.3%, 88.7% and 30% respectively. When the SNR is 20 dB, the recognition rate of SVD-AF, AlexNet and MMWC-STFT is 91.3%, 98.4% and 83.3% respectively. The recognition rate of 16QAM signal under the signal-to-noise ratio of SVD-AF, AlexNet and MMWC-STFT is 81.9%, 85.4% and 42.3%, respectively, while the recognition accuracy is 95.1%, 95.1% and 88% under the signal-to-noise ratio of 20db.

Through the above comparison, it can be seen that the above methods have limited extraction of signal features and are sensitive to noise, which is not as good as the full extraction of signal features and good anti-noise performance of the method VGGNet in this paper.

4. Summary

As an important characteristic to distinguish communication signals of different systems, modulation mode is a basic task of modulation recognition of communication signals, which has important research significance. In this paper, the signal modulation automatic recognition technology based on deep convolutional neural network avoids the problem of feature extraction and selection in traditional algorithms, and realizes the self-learning of classification features and modulation style recognition. The simulation results show the effectiveness and feasibility of the algorithm proposed in this paper, and also show that there are some problems in the performance stability of the algorithm in the case of low SNR, as well as the difference in the recognition ability of different modulation modes, which is the research focus of the next step.

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