Modulation Type Recognition Algorithm Based on Modulation Instantaneous Structure Difference and Deep Learning

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Abstract. In order to solve the problems of signal modulation recognition in non-cooperative communication, this paper proposes a modulation type recognition algorithm based on instantaneous difference by neural network. Firstly, the method uses the structural difference of modulation parameters in time domain of modulation signal, and displays the difference in the form of image, so as to transform the modulation recognition problem into image recognition problem; secondly, it uses the advantage of convolution neural network to automatically extract features, and it classify different modulation signals; finally, a hierarchical neural network structure is formed to identify the unknown modulation signals.

Keywords: Modulation recognition, characteristic parameters, classification, Convolution Neural Network; layered neural network.

1. Introduction

Wireless signal modulation type recognition plays an important role on radio, electronic countermeasures, information security management and intelligent radio, but because of the complexity of the electromagnetic space, how to realize the wireless signal modulation type identification with high precision in the absence of a priori information and the presence of electromagnetic interference still has difficulties.

At present, main research on modulation recognition are divided into expert feature recognition method and deep learning method [1]. Expert feature recognition method based on the differences of characteristics when modulation type changes, such as amplitude differences of characteristics, phase differences of characteristics and the characteristics of frequency difference [2][3]. This kind of technology needs to obtain the value space of each feature and establish the corresponding threshold value. However, due to the influence of noise and channel fading, the range will change dynamically, and the feature cannot fully represent the difference of the signal, and misjudgment will occur [4]. Therefore, it is necessary to modify the decision threshold for signals in different scenarios in practical application. The other is based on deep learning, which builds a neural network and trains and learns the difference of the original data [5]. This method does not need to extract features and set a fixed threshold value, and can adapt to the influence of channel on the signal [6], but it needs a large number of sample data, and is prone to over-fitting, resulting in performance degradation.
In this paper, a modulation type recognition algorithm based on deep learning of signal difference of modulation parameters is proposed. The basic idea is to extract the modulation parameters from the original signal data, remove the invalid information components in the sample, maximize the difference, and construct the image of the specific difference structure, and use the CNN model to identify the image. This kind of technology combines the technical advantages of feature extraction and deep learning to avoid the influence of over-fitting and invalid samples on the model. The differences of modulation methods can be fully characterized through structured images, which requires fewer samples and has high recognition accuracy in the presence of interference. Through the overall structure of the image, it can still maintain high accuracy and has the function of anti-interference. Moreover, in order to train and optimize the recognition of the neural network in this paper, a layered neural network architecture is established, which can accurately backtrack the process of modulation recognition, and locate and optimize the problems of the local network.

2. Signal acquisition and recognition model

2.1. Signal receiving model
This paper based on the non-cooperative receive scene and construct a signal acquisition and recognition model. First, the antenna receives wireless signal, and then send the signal through low noise amplifier and low pass filter. After the intermediate frequency signal sampling, the signal is divided into two road further mixing respectively, finally obtain baseband sample I and Q. Due to the lack of prior information, errors exist in the collection process. In the absence of channel and symbol information, the received signal exists frequency offset, inter-symbol interference, amplitude random fading and so on.

2.2. Time-frequency structure extraction of modulation parameters
Whether it is analog or digital modulation, there are usually three basic modulation methods: AM, FM and phase modulation.

Let the baseband signal be \(m(t)\) and the carrier signal be \(c(t) = A_c \cos(2\pi f_c t + \phi_c)\).

- Amplitude modulation is a method to use the baseband signal to control the amplitude of the carrier, so that the amplitude of the carrier changes with the baseband signal. Therefore, the modulated wave formed after modulation can be expressed as:

\[
s_{am}(t) = (A_c + k_{am} m(t)) \cos(2\pi f_c t + \phi_c)
\]

\(k_{am}\) is the amplitude modulation coefficient.

- Frequency modulation is to control the frequency of the carrier with the baseband signal, so that the frequency of the carrier changes with the rule of the baseband signal. Therefore, the modulated wave formed after modulation can be expressed as:

\[
s_{fm}(t) = A_c \cos[(2\pi f_c + k_{fm} m(t))t + \phi_c]
\]

\(k_{fm}\) is the frequency modulation coefficient.

- Phase modulation is to control the phase of carrier with baseband signal, so that the phase of carrier changes with the rule of baseband signal. Therefore, the modulated wave formed after modulation can be expressed as:

\[
s_{pm}(t) = A_c \cos(2\pi f_c t + k_{pm} m(t) + \phi_c)
\]

\(k_{pm}\) is the phase modulation coefficient.
2.3. Extraction of differences of modulation parameters

According to the theoretical analysis of signal modulation principle, one or two characteristics of the modulated signal carry the basic information, which is also the part that can best reflect the difference of modulation types. For example, the modulation characteristics of the AM signal are only reflected in the amplitude of the modulated signal. The amplitude of the modulated signal changes regularly in time according to the change of the baseband signal, while the amplitude of the non-AM signal changes disorderly in time. We call this phenomenon as the Instantaneous difference of modulation parameters.

2.3.1. Analysis of Instantaneous differences of modulation parameters of various types of signals. Let the expression of the signal to be recognized received by the receiver end be:

\[r(t) = A(t)\cos[2\pi f(t)t + \varphi(t)]\]  

(4)

The time-domain Instantaneous differences of modulation parameters of AM, FM and phase-modulated signals are shown in the table below:

|                | Amplitude modulation signal | Frequency modulation signal | Phrase modulation signal |
|----------------|-----------------------------|-----------------------------|--------------------------|
| Amplitude \(A(t)\) | \(A_c + k_{am}m(t)\)       | \(A_c\)                     | \(A_c\)                  |
| Frequency \(f(t)\)   | \(f_c\)                    | \(f_c + k_{fm}m(t)\)       | \(f_c\)                  |
| Phase \(\varphi(t)\) | \(\varphi_c\)             | \(\varphi_c\)              | \(\varphi_c + k_{pm}m(t)\) |

From the above analysis, it can be seen that the extraction of time-domain structural differences of signal modulation parameters with different modulation styles depends on different degrees of processing of received signals.

2.4. Image conversion

It is mentioned in the introduction that the characteristic parameters in the modulation identification method based on expert features will constantly change the selection threshold due to the influence of multipath fading, low signal-to-noise ratio, interference of various noises, time-frequency overlap and so on. In order to avoid such optimal decision threshold based on specific experimental environment, we converted the extracted time-domain structural differences of modulation parameters into two-dimensional images, as shown in the figure below:

![Figure 1. Time domain difference diagram of modulation parameters of signal in Amplitude (a), Frequency(b), and Phase(c) structure](image-url)
After the time-domain structural differences of modulation parameters are transformed into images, firstly, the influence of manual threshold set by traditional methods can be eliminated, and only the structural features of the feature map need to be recognized. In addition, when the convolutional neural network algorithm is used for image recognition, it can ensure that the extracted features are the features related to the difference of modulation types, rather than the features of the experimental environment, which has a certain universality.

3. Recognition architecture based on layered convolutional neural network

In this paper, the convolutional neural network is used to learn the time-frequency structure characteristics of modulation parameters, and the layered neural network architecture is constructed based on the differences of different parameters.

3.1. The CNN framework

![Figure 2. Convolutional neural network structure](image)

As shown in Figure. 2, for the time-domain structural difference of each modulation parameter of the signal, the CNN network structure in the figure above was adopted for classification. There are 11 hidden layers (8 convolution layers and 3 full connection layers) in the whole network.

The structure of CNN network is designed on the basis of VGG network. The improvement of VGG network is that several consecutive 3x3 convolution kernels are used to replace the larger convolution kernels, and the maximum pooling size is set as 2x2 uniformly. For a given receptive field, the stacked small convolution kernel is better than the large convolution kernel, because the multi-layer convolution layer can increase the network depth to ensure the learning of more complex patterns, stronger feature learning ability, and the cost is relatively small (fewer parameters), and the small pooled kernel can bring more detailed information capture. VGG model has a deeper network structure, smaller convolution kernel and pooling sampling domain, which makes it possible to control the number of parameters while acquiring more image features, and avoid excessive computation and complex structure.

3.2. Layered neural network architecture

Based on the difference analysis of the time-domain structure of modulation parameters of various types of signals in Section 2.3.1, we can determine the relatively optimal recognition hierarchy and sequence according to the uniqueness and co-ownership of the differences. For the co-existence of differences, theoretically speaking, the instantaneous phase of the AM signal is a straight line that changes linearly with time, while the instantaneous phase of the FM signal is a line segment with different slopes that changes linearly with time. For the uniqueness of the difference, the difference of
amplitude modulation signal's time-domain structure, the difference of frequency modulation signal's time-domain structure, and the difference of phase modulation signal's time-domain structure can represent the essence of this kind of modulation signal.

Based on the common property of modulation parameters, we classify the signals between classes as the first layer of the layered neural network. After the intra-class signals of each class are obtained, the intra-class signals are classified as the second layer of the layered neural network by using the uniqueness of the temporal structural differences of modulation parameters. The algorithm flow chart of modulation mode recognition based on layered neural network is shown below.

Among them, each branch of the whole algorithm adopts the convolutional neural network structure as shown in Figure 2.

4. Experimental simulation and results

4.1. Signal acquisition and processing
In this paper, the experiment in the scene to simulate the actual non-cooperative communication scenarios, using SMW200A vector signal generator to generate different modulation type of signal in the experiments, the use of the antenna signal emission in the air, the last on the computer side with IQ acquisition toolbox of signal sampling, and in the form of IQ sample data stored in the suffix called mat files.

We generated images of amplitude A(t) for AM and 2ASK signal IQ samples, images of frequency F(t) were generated by 2FSK, 4FSK and FM, and constellation images were generated by BPSK, QPSK, 8PSK, 16QAM, 32QAM and 64QAM, which were used for intra-class inter-class recognition. In each image, the length of IQ data used is 5000 sample points, the sampling frequency is 62500Hz, and the image size is 150×150 pixels.

4.2. CNN model training for in-class recognition
For the training of CNN model, this paper uses API Keras in the TensorFlow framework, which supports fast experiments and can quickly turn ideas into results.

After using Keras to build the CNN framework shown in Figure 2, the loss function in this paper uses the categorical crossentropy function during model compilation, which is used for multivariate classification problems. Adaptive momentum estimation ADAM is used to update the weight parameters. This algorithm is not easy to fall into local advantages, it is faster, and the learning effect is more effective.

After the data of the test set were predicted, the prediction accuracy and confusion matrix of each type of signal were obtained according to the prediction results, as shown below:
4.3. **Hierarchical neural network algorithm simulation**

For signal IQ samples with unknown modulation types, the modulation parameter differences of the signal, instantaneous phase, frequency and amplitude, were saved as corresponding pictures, and the hierarchical neural network simulation diagram in Figure. 4 was used for classification. The specific operation process is as follows: firstly, the signals are classified according to the instantaneous phase, and the signals related to amplitude, frequency and phase modulation are classified; Then, according to the classification results of this layer, the classification of the next layer is carried out, and the more specific classification is made by using the difference of intra-class modulation parameters of each type of signal.

**Figure 4.** CNN test set predicted the results of the confusion matrix.

![Confusion Matrix](image1)

![Confusion Matrix](image2)

![Confusion Matrix](image3)

**Figure 5** Recognition results of 7 signals
Using the idea of stratification, we completed the classification of signals shown in Figure 5 by loading the CNN model trained in class as shown above. The ratio of the samples with correct predicted results to the input samples was taken as the standard to measure the performance of each layer of the model. The time-frequency feature picture proposed in this paper is composed of the time-frequency structure features of each sampling point, making full use of the signals, and the extreme outlier values in the signals will not affect the overall structure of time-frequency features, so it has advantaged that traditional feature recognition methods do not have.

5. Conclusions
Modulation type recognition of communication signals is affected by channel noise, interference and frequency offset, etc. In this paper, a modulation signal type recognition method based on time-frequency difference of modulation parameters combined with deep learning is proposed. This method effectively solves the influence of interference factors such as noise and frequency offset on the recognition results. In this paper, based on the idea of layered neural network, a modulation signal recognition architecture is built according to various time-frequency structure images and CNN classifier, which can effectively realize the recognition of modulation signal types. In the experiments, based on the non-cooperative communication of the received signal model of the prototype experiment scene decorate, seven kinds of modulation signal of receiving recognition, in the presence of noise deviation, layered neural network recognition results can remain above 85% with.

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