Research on signal modulation based on machine learning intelligent algorithm and computer automatic identification

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Abstract. In the process of communication, modulation signal recognition and classification are an important part of non-cooperative communication. Automatic modulation recognition technology of communication signals based on feature extraction and pattern recognition is a key research object in the radio field. The use of neural network can achieve automatic recognition of a variety of modulation signals and achieve good results. In this method, the received signal is preprocessed to obtain the complex baseband signal including in-phase component and orthogonal component. As the data set of the input convolution neural network model, the signal further optimizes the traditional method of manual extraction of expert features for communication signal recognition, which has great limitations and low accuracy under low signal-to-noise ratio, and the simulation results are verified. The results show that the proposed method has stronger feature representation ability and competitiveness in automatic modulation recognition, and is helpful to promote the application of deep learning in the field of automatic modulation recognition.

Keywords: Modulation signal, Automatic identification, Machine learning, Residual error.

1. Introduction
The basic purpose of communication signal modulation recognition is to provide a basis for selecting a suitable signal demodulator; automatic modulation recognition has certain significance and value in both military and civilian fields. It is the process of obtaining the modulation mode of the received signal after a series of signal processing, and it has always been the focus of research. Automatic modulation recognition is the key technology of non-cooperative communication, which plays an important role in both civil and military fields [1]. In the civil field, it is widely used in intelligent wireless systems and software radio [2]. In the military field, the correct identification of modulated signals is a prerequisite for intercepting and interfering with enemy communications. As a wireless communication method, automatic modulation recognition has attracted more and more attention in recent years.

The modulation mode of the signal is the basis of obtaining the content of the communication signal, and as a technology between signal detection and signal demodulation, the main purpose of modulation recognition is to determine the modulation mode of the signal to be tested, and it is also a decisive prerequisite for subsequent estimation of the parameters of the signal to be tested. Modulation recognition and parameter estimation of communication signals are widely used in civil and military
fields. After identifying the modulation mode of the digital signal and reasonably estimating the parameters of the signal, the signal can be demodulated correctly. In the part of parameter estimation, the main estimated parameters are the carrier frequency and symbol rate of the signal. In the process of communication between the two parties, if the interferer wants to obtain the information from the sender from the signal to be tested, it needs to reasonably estimate the carrier frequency of the signal, demodulate the signal through the carrier frequency, and then estimate the symbol rate, and then obtain the important information carried in the signal. For this reason, this paper uses the depth learning method to identify the modulation mode of the digital signal and estimate the parameters of the signal.

The typical automatic modulation process is divided into signal preprocessing and signal classification. Signal preprocessing mainly includes signal parameter estimation and channel noise processing. There are mainly two kinds of signal classification algorithms: maximum likelihood method based on hypothesis test [3] and pattern recognition method based on feature extraction [4]. The method based on likelihood function can reduce the probability of misclassification and need to store a lot of data to find the decision threshold [5], so the computational complexity is very large and requires a lot of computing time. The manual extraction of expert features in the feature-based method is suboptimal, and it is difficult to extract the deep features of the signal completely [6]. The calculation of the two methods is tedious and easy to be affected by environmental changes, so it is difficult to implement in the real wireless communication system.

2. Dataset and generation

There are three basic digital modulation methods: multi frequency shift keying, multi amplitude keying and multi-phase shift keying. By using the signal obtained by digital down conversion, the complex baseband signal is obtained, which includes in-phase component and quadrature component. The general expression is as follows:

\[ M(n) = H(n)\sin(\omega_n n + n\omega(n) + \phi_n + \phi_0) \]
\[ P(n) = H(n)\cos(\omega_n n + n\omega(n) + \phi_n + \phi_0) \]

\( M(n) \) represents the in-phase component of the modulated signal, and \( P(n) \) represents the quadrature component of the modulated signal. After passing through the channel, the received signal \( y(n) \) can be described as:

\[ y(n) = \sum_{i=1}^{N} C_i e^{-j2\pi f_i (n-k_i)} \cdot (M(n-k_i) + P(n-k_i)) + v(n) \]

Modulation recognition is to classify the modulation types of received communication signals, which is an n-class decision-making problem. After passing the root raised cosine filter, a \( 2 \times N \) two-dimensional vector matrix is obtained as the input data set, in which the first row of the matrix is the co-directional component of the complex baseband signal, and the second row is the orthogonal component of the complex baseband signal. The process is:

![Figure 1. Generate data sets](image-url)
3. Convolution neural network structure

3.1. Principle
Recognition using machine learning belongs to a recognition algorithm based on feature extraction [7] [8], which can train a large number of collected signals supervised or unsupervised for automatic modulation. The input modulation signal can be the original sampled signal or the pre-processed transform domain signal features, so as to extract the complex features in the signal, and then use these features for recognition and classification. The signal information can be better extracted and classified by using convolution network [9]. The neural network with convolution layer is convolution neural network, the input of convolution neural network is a two-dimensional image, and the result of classification is the probability value of each category. CNN is completely different from the fully connected network, on the contrary, it has its own unique characteristics, such as local connection and weight sharing.

![Automatic identification of modulation signal process](image)

**Figure 2.** Automatic identification of modulation signal process

3.2. Structure
First of all, several kinds of preprocessed modulation signals are processed into training set and test set respectively, and then the CNN model is trained through the training set, and the super parameters of CNN model are fine-tuned. After training, the CNN model is tested by input test set, and finally the digital communication signals are identified and classified.

The inner product of n input vectors \([x_1, x_2, ..., x_n]\) and their corresponding weight vectors \([w_1, w, ..., w_n]\), and bias b, is used as inner product, and then the output f is obtained through the nonlinear activation function \(h(\sum_i w_i x_i + b)\) to obtain the output \(f(x; w, b)\). Convolution neural network has the characteristics of local perception and weight sharing, which can reduce the number of training parameters and reduce the computational complexity.
4. Convolution Neural Network Model for self-Modulation recognition

4.1. Establishment of signal Modulation Model based on residual Neural Network

The input parameters are represented by $x_i$, the input set is represented by $M$, the weight convolution kernel is represented by $w_{ij}$, the corresponding offset is represented by $b_j$, the activation function is represented by $f$, and the feature mapping result of the output is represented by $y_j$, then the output after convolution calculation is:

$$y_j = f\left(\sum_{i \in M} x_i \times w_{ij} + b_j \right) \tag{3}$$

By convolution achieve a before and after the layer connection. Hypothesis through each layer after the convolution function $F(x)$, then after k residual unit output formula:

$$x_{k+1} = \text{ReLU}\left( F\left(x_k\right) + x_k \right) \tag{4}$$

4.2. Modulation signal

For single signal modulation recognition application scenarios under AWGN channel, built SNR environment ideally different modulation mode data set. A mathematical model of the received signal under AWGN channel:

$$y(t) = s(t) + n(t) \tag{5}$$

Thus, in the first layer, one-dimensional convolution layer is used to convolution the input one-dimensional eigenvector. Passing parameter. After the optimization, the convolution kernel of size 1 to 1 is adopted, the number of filters is set to 64, the step size is set to 1 padding, and the same is set, which gradually slips through the original input data, multiplies the value of the convolution kernel with the value of the corresponding position in the input eigenvector, and then uses a non-linear activation function ReLU to improve the representation ability of the network model. The specific formula is as follows.
The second layer uses one-dimensional convolution layer to convolution the eigenvector of the output of the first layer again. Operation. Gradually slide over the input data 1x, multiply its value by the value of the corresponding position, and then pass a non-linear activation function ReLU.

Local correlation can also be established by using convolution, and the range of receptive field can be expanded by increasing the number of network layers. For this reason, the paper uses multi-layer perceptron and convolution neural network for automatic modulation recognition, and further proposes a deep residual convolution network for modulation recognition.

![Network Model](image)

**Figure 5.** Network Model

A residual network structure model is designed for modulation recognition. In the last layer, the average pool and full connection are used to classify the final output. Multi-classification cross entropy and Adam optimizer are used to optimize the model during training.

5. Simulation and result analysis

5.1. Simulation result

According to the above analysis and calculation results, the cross-entropy loss function is selected to check the change of the loss value in the training process. After each update of the parameters, the learning rate becomes 0, and the updated exponential decay rate is β 1-0.9 and β 2-0.99, respectively. During the training process, the Batch_size=1000 and the number of iterations are Epochs=1000. After
each Epoch, the training data are disturbed again, and when the training loss value is reached for 10 consecutive iterations, it does not decrease.

Cross entropy for:

\[
L(y, \hat{y}) = - \sum_i y_i \log \hat{y}_i
\]

(7)

5.2. Comparison of results

The learning rate starts from 0.001. When the loss value of the test set is greater than the maximum loss value at this time, the learning rate is multiplied by 0.01 to modify the learning rate. A total of 100 rounds of training were conducted in the experiment, and the time of each round was about 20 seconds. Figure 4 shows the curve of training loss and verification loss and training rounds. With the increase of the number of rounds, the training loss and verification loss values decreased rapidly, and the two curves gradually tended to be the same, indicating that there was no fitting phenomenon in this experimental model.
The trained model is verified by the test set of communication signals, and the results show that the average recognition accuracy of several signals increases with the increase of SNR. When the signal-to-noise ratio is -4db, the recognition rates of BPSK, 2FSK and 4FSK are all more than 99%.

6. Analysis and discussion
Among the parameters of the modulated signal, the accuracy of the estimation of carrier frequency and symbol rate is evaluated. It is an important basis for the performance of wireless communication system. After determining the modulation mode of the digital signal, the accurate estimation of the carrier frequency of the signal is beneficial to the correct demodulation of the signal, and the accurate estimation of the symbol rate is helpful to obtain the important information carried in the original signal. The estimation of these parameters under non-cooperative conditions is also very important.

![Figure 8. Two methods under different SNR signal average recognition accuracy](image)

This method improves the accuracy by about 25.41%. When the signal-to-noise ratio is equal to 0dB, the average accuracy of this paper is 94.61%, while the average accuracy of the traditional method is 72.13%. When the signal-to-noise ratio is 18db, the accuracy of this method is 98.85%, while that of the literature method is 95.32%. Compared with the traditional methods, the accuracy of CNN-IQ is greatly improved at low signal-to-noise ratio and to a certain extent when the signal-to-noise ratio is high.

7. Conclusion
Aiming at the communication signal modulation technology, this paper proposes an improved convolution neural network modulation method. First, the data is preprocessed, and then the convolution neural network is trained by using the generated data set. The improved residual neural network extracts richer signal features by superimposing a certain number of residual blocks in each flow. The improved residual network is used to simulate eight kinds of modulation signals generated by simulation. This method not only increases the width, but also enriches the extracted signal feature types. The over-fitting phenomenon caused by depth deepening is avoided, and the recognition accuracy is also very high. Therefore, this method also has higher recognition accuracy and better feature representation ability. In the future, the method of model compression can be further considered to ensure the accuracy and improve the computational efficiency at the same time.
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