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## Modulation Recognition of Digital Signals Based on Deep Belief Network

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# Modulation Recognition of Digital Signals Based on Deep Belief Network

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**Abstract.** A modulation pattern recognition method for digital modulation signals, 4ASK, BPSK, QPSK, 2FSK and 4FSK digital modulation signals, which is based on deep learning model of deep belief network is proposed. The modulation signal is pre-processed and its high order cumulants are calculated as input training features. Solutions to the problem that the same high Modulation signals are generated in different SNR environments. Using the semi-supervised learning characteristics of deep confidence network, data sets are obtained to train the parameters of deep Confidence network layer by layer for feature extraction and recognition of modulation modes. The simulation results show that the recognition rate of this method is ideal.

## 1. Introduction

The communication environment is increasingly complex, and multiple modulation methods are required for different communication signals in order to increase the frequency band utilization. The diversification of signal modulation methods has led to the continuous development of modulation and recognition technology. For the received signals, further analysis and processing can be carried out under the premise of successfully identifying the modulation mode. Therefore, its importance is self-evident in both military and civilian fields.

The modulation recognition of communication signals is mainly divided into two methods: modulation classification recognition method based on decision theory and modulation classification recognition method based on statistical pattern recognition. The former method is simple, but the a priori information of the signal is required to be high. At the same time, the performance of the method is limited by the artificial decision threshold. The key technology of the latter method lies in feature extraction and classifier selection, which requires a lower priori information and is widely used at present. Nowadays, with the rapid development of artificial intelligence, modulation recognition technology has also been fully reflected. The classifier in the classification method of modulation recognition based on statistical pattern recognition applies the related content of machine learning.

There are many models in machine learning. Decision tree model has been widely used in the early stage. The model can enter the next level by comparing and discriminating the threshold values of each level. The algorithm is relatively simple, and it can make feasible and effective results for large data sources in relatively short time [1,2]. Support Vector Machine (SVM) has a complete theoretical basis and good practical effect, which makes SVM-based modulation recognition methods emerge endlessly. By using cyclic cumulant [3], high-order cumulant [4], and wavelet transform [5] of communication signals as classification feature vectors, SVM achieves automatic recognition of



multi-class digital modulation signals. In view of the problems of SVM modulation types, more features needed to be extracted, more computation and slower speed, the researchers adopted the idea of grading, and achieved good results[6]. The researchers used a random forest model to overcome the over-fitting problem of low-order digital modulation signal decision tree method with low signal-to-noise ratio (SNR), and achieved good recognition results.[7]. The most representative model in machine learning is neural network. E.E.Azzouz et al. choose instantaneous value of communication signal as feature, and use artificial neural network as classifier to realize modulation recognition of a variety of analog digital signals[8,9,10]. Most of the above machine learning models are shallow network models. With Professor Hinton [11] putting forward the deep belief network for the first time in 2006, deep learning began.

As a rapidly developing field of machine learning in recent years, deep learning has shown its unique technical advantages in many fields, such as speech recognition, image recognition, natural language processing, and has many applications in modulation recognition of communication signals. The modulation mode classification algorithm based on deep learning has achieved good classification performance [12,13,14]. This paper proposes a modulation recognition method based on deep belief network (DBN), which uses the performance of semi-supervised learning to input training sets of high-order cumulant features of five digitally modulated signals of 4ASK, BPSK, QPSK, 2FSK, and 4FSK. The network was trained and tested on the network. The test results showed that the recognition of the five signals was more than 93% under different conditions.

## 2. Related theory

### 2.1 High order cumulant

For the complex stationary random signal  $X^{(t)}$ , its high order moment is:

$$M_{(p+q)(p)} = E[X^p (X^*)^q] \quad (1)$$

Where \* denotes conjugate. The high order cumulant of the complex stationary random signal can be expressed as:

$$C_{(p+q)(q)} = cum[X, \dots, X, X^*, \dots, X^*] \quad (2)$$

Where, the number of  $X$  is  $p$  and the number of  $X^*$  is  $q$ . Then the expression of each order cumulant is:

1) second-order cumulants

$$C_{20} = cum(X, X) = M_{20} \quad (3)$$

$$C_{21} = cum(X, X^*) = M_{21} \quad (4)$$

2) fourth-order cumulants

$$C_{40} = cum(X, X, X, X) = M_{40} - 3M_{20}^2 \quad (5)$$

$$C_{42} = cum(X, X, X^*, X^*) = M_{42} - |M_{20}|^2 - 2M_{21}^2 \quad (6)$$

3) sixth-order cumulants

$$C_{60} = cum(X, X, X, X, X, X) = M_{60} - 15M_{20}M_{40} + 30M_{20}^2 \quad (7)$$

$$C_{63} = cum(X, X, X, X^*, X^*, X^*) = M_{63} - 6M_{41}M_{20} - 9M_{42}M_{21} + 18(M_{20})^2M_{21} + 12M_{21}^3 \quad (8)$$

4) eighth-order cumulant

$$C_{80} = cum(X, X, X, X, X, X, X, X) = M_{80} - 28M_{60}M_{20} - 35M_{40}^2 + 42M_{40}M_{20}^2 - 630M_{20}^4 \quad (9)$$

Suppose that the energy of the signal is expressed by  $E$ , the high order cumulant theoretical values of different signals can be seen from table 1. The computational complexity for high order cumulants is lower, so the complexity of pre-processing work is relatively low when selected as a pre-training set. It can be seen from Table 1 that 2FSK and 4FSK cannot be distinguished. For this problem, multiplying the 2FSK and 4FSK complex signals by the carrier required for demodulation and

then calculating the high order cumulant can be obtained (in Table 2) . The processed MFSK signal has obvious features.

Table 1. Theoretical values of high order cumulants for modulating signals

	C20	C21	C40	C42	C60	C63	C80
4ASK	E	E	$-1.36E^2$	$-1.36E^2$	$8.32E^3$	$8.32E^3$	$-111.85E^4$
2FSK	0	E	0	$-E^2$	0	$4E^3$	0
4FSK	0	E	0	$-E^2$	0	$4E^3$	0
BPSK	E	E	$-2E^2$	$-2E^2$	$16E^3$	$16E^3$	$-272E^4$
QPSK	0	E	$E^2$	$-E^2$	0	$4E^3$	$-34E^4$

Table 2. Theoretical values of high order cumulants for MFSK after processing

	C20	C21	C40	C42	C60	C63	C80
2FSK	0.5E	E	$0.36E^2$	$-1.29E^2$	$0.5E^3$	$7.4E^3$	$E^4$
4FSK	0.28E	E	0	$1.08E^2$	$0.1E^3$	$4.9E^3$	$0.3E^4$

## 2.2 Deep belief network

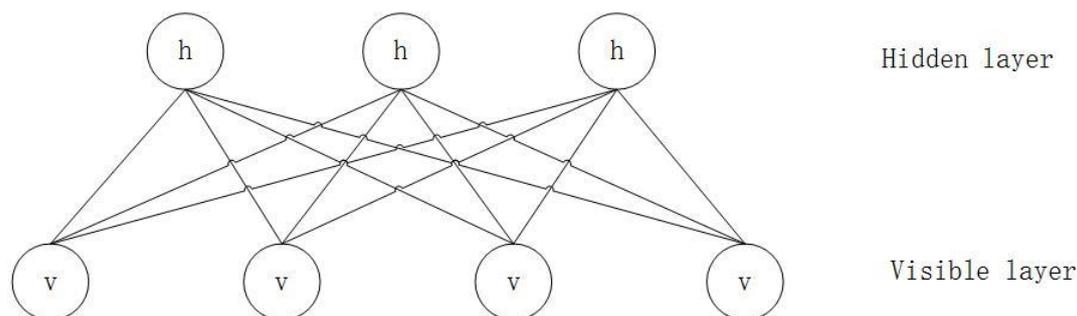


Figure 1. The structure of RBM

Deep belief network (DBN) is a non-convolution model proposed by Hinton in 2006 and successfully applied in Deep learning training. DBN is a deep learning network composed of multi-layered restricted Boltzmann machines (RBM, see Figure 1). RBM is an energy-based model with binary visible and hidden layers. In the model, there is no direct interaction between neurons in any two visible layers or neurons in any two hidden layers, while there is mutual connection between neurons in visible layer and neurons in hidden layer. Several RBMs are connected to form a DBN network. The training process of this network is a layer-by-layer training mode, that is, the hidden layer of the former RBM is the visible layer of the latter RBM.

## 3. Modulation recognition based on DBN

### 3.1 Algorithmic process

The modulation recognition algorithm based on the deep belief network selects the high order cumulant features of 4ASK, BPSK, QPSK and 2FSK digital modulation signals as the training set and the test set for sample preprocessing. On the basis of constructing the deep belief network, the training and learning are carried out and the test samples are tested on the network. The algorithm flow is shown in the figure 2.

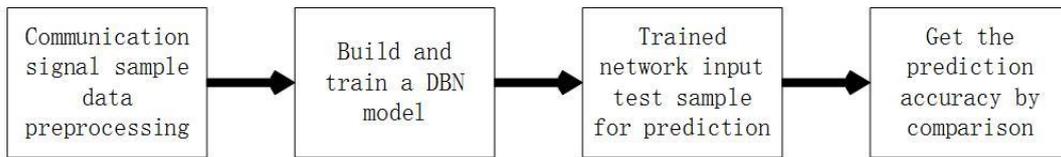


Figure 2. Flow chart of modulation recognition algorithm based on DBN

Each kind of signal randomly generates signals with signal-to-noise ratio of 0db, 10db and 20db respectively. Under the background condition of AWGN, the high order cumulant is calculated to get samples and labels are generated at the same time. Since the input data range of the first RBM of the deep belief network is 0 to 1, it can be seen from table 1 and table 2 that the theoretical values of each order cumulant of each signal are greatly different from each other, so it is necessary to carry out normalization processing. The function of normalization is to summarize the statistical distribution of samples. For different high order cumulants, the column vectors that generate samples are normalized to meet the input data range of RBM and retain their characteristics.

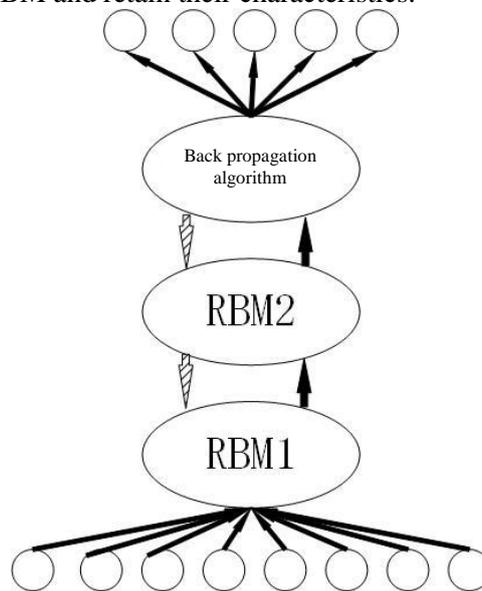


Figure 3. DBN networks

3.2 Algorithm simulation and result analysis

Table.3 Recognition Rate of 0dB SNR Data Set

	0dB	10dB	20dB
4ASK	96.3%	99.8%	100%
2FSK	94.5%	98.7%	100%
4FSK	94%	98.4%	100%
BPSK	100%	100%	100%
QPSK	99%	100%	100%

Table.4 Recognition Rate of 10dB SNR Data Set

	0dB	10dB	20dB
4ASK	93.6%	96.5%	100%
2FSK	93.1%	95%	99.7%
4FSK	92.4%	95.3%	100%
BPSK	96.4%	98.3%	100%
QPSK	95%	100%	100%

The network training and testing were carried out in the MATLAB environment. Five kinds of signals were simulated and randomly generated with 0dB, 10dB and 20dB signals at different signal-to-noise ratios, using 0dB data (Table 3) and 10dB (Table 4) data respectively. The network is trained to obtain the modulation signal recognition rate under different SNR. It can be seen from the results that when the signals with different signal-to-noise ratios are used as the training set, the network recognition rate of the training set with low signal-to-noise ratio is higher, and the test result is good under the 0dB SNR, and the recognition rate is above 94%.

#### 4. Conclusion

Based on the pre-training samples, the deep belief network performs semi-supervised training on the network, and performs modulation pattern recognition on the digital modulation signals of 4ASK, BPSK, QPSK, 2FSK and 4FSK in the communication signal. In the different signal-to-noise ratio environments after adding different Gaussian white noise to different modulated signals, the high order cumulant is calculated, and the problem that MFSK has the same high order cumulant under the same calculation method is solved. The input samples are further optimized. The experimental results show that the training data training network with low SNR can obtain higher classification recognition accuracy. In the future, research will be conducted on whether more signals are suitable for deep confidence network identification.

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