Modulation Recognition Based on Neural Network Ensembles

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Abstract. This paper studies the modulation recognition of digital communication signals based on neural networks. The BP neural network ensembles method is put forward, which is a linear composition of the BP neural networks. The recognition accuracy of ten different modulation formats is given according to the model above in feature extraction. The approach presented is superior to a neural network algorithm in existing articles. The result shows that the method proposed can recognize complex signal modulation formats availably. The overall recognition accuracy is basically up to 100% in the sample data of this paper when the SNR is more than 8 dB.

Keywords: Non-cooperative communication · Modulation recognition · Neural network ensembles · Feature extraction

1 Introduction

Nowadays, communication is the primary way for humans contact to obtain information. Modulation formats are various and sophisticated, no matter whether they are communication countermeasures and electronic warfare in the military or mobile communication in public life. Digital communication signal modulation is thus increasingly complex because of a higher communication accuracy and transmission rate, which brings real difficulties for signal demodulation. Modulation recognition is a process between reception and demodulation [14] and lays a foundation for signal demodulation, monitoring, interference, etc. It aims to identify the modulation format of the modulated signal with noise after receiving the message. There are two kinds of modulation recognition algorithms [7]: maximum likelihood estimation (MLE) hypothesis test based on decision theory and pattern recognition based on feature extraction in the published papers

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on modulation recognition [4]. The advantage of MLE is that, theoretically, the classification is optimal under the Bayes tiniest miscalculation cost criterion [25]. But it needs a lot of prior knowledge, and big calculation due to the complex expressions of statistics caused by unknown parameters [18], which is difficult to process in real-time [22]. Instead, pattern recognition based on attributes and classifiers selected to classification training is relatively less complicated than MLE, in which the accuracy of classifiers can test classification performance [5].

Thus this paper takes advantage of the neural network algorithm for modulation recognition based on the pattern recognition of feature extraction. However, there are always more or less different flaws in the existing articles by the neural network algorithms. The paper studies modulation recognition based on the combined feature parameter and modified probabilistic neural network [26]. But the accuracy of the model is not pretty during low SNR. The paper specializes in modulation recognition based on the combined feature parameter and modified probabilistic neural network [27]. However, the method is challenging to apply because of complex feature parameters and a large amount of calculation. Although the paper [24] adopts a tree-structured neural network to modulation recognition, the approach has no comparison between the layers of different neural networks, and the astringency of the method is inadequate.

This paper digs into research on the above issues, and the approach offered performs well in the excellent accuracy of recognition, simple feature extraction, and small calculation. The contribution of this paper is as follows.

i. This paper develops a new model of neural network ensembles by a combination of the BP neural networks.
ii. The model presented is trained by a dataset of the novel and simple feature extraction of this paper.
iii. The model performance assessed by the testing set is impressive.

The rest of the paper is organized as follows. The feature extraction is clearly stated in Sect. 2. A brief overview of the neural network ensembles and algorithm flow is clarified in Sect. 3. Section 4 analysis results of the experiment simulation. Conclusions and the value of engineering are presented in Sect. 5.

2 Features Extraction

The method based on higher-order cumulant [6] has better adaptability to noise among all kinds of modulation recognition algorithms. The higher-order statistics of the modulation signal have batter anti-fading characteristics. At present, researches have been published in the succession of higher-order cumulant [8,15,19,28]. High-order cumulants, as the stable characteristics for modulation recognition, of all kinds of features are significant [9,13,21,29]. Based on the fourth-order cumulant, the identification of BPSK, QPSK, 4PAM, and 16QAM is carried out, and the effects of SNR and sample number on the recognition performance are discussed [19]. BPSK, 4PSK, and 8PSK are identified based on fourth-order cumulants, and unknown parameters of signals are estimated [29].

2ASK, 4ASk, 8ASK, 4PSK, and 8PSK are classified based on fourth-order cumulants and support vector machines [21]. It is concluded that the sixth-order cumulant has stronger benefits of anti-interference by comparing the performance of the higher-order cumulants and the cyclic spectrum for MPSK modulation signals of the mixed recognition algorithm [15]. The signal is differentiated, and then the higher-order cumulant is calculated to realize the MFSK signal recognition [13]. BPSK, QPSK, OQPSK, 8PSK, $\pi/4$DPSK, 16APK, 16QAM, and 32QAM are identified based on higher-order cumulants [8]. The theoretical basis of the high-order cumulant of the modulation signal [19] is given mainly including the definition of the high-order moment and high-order cumulant as follows.

2.1 Cumulant of a Random Variable

x is a continuous random variable, $f(x)$ is probability density function, eigenfunction is defined as:

$$\phi(\omega) = \int_{-\infty}^{+\infty} f(x)e^{j\omega x}dx = E[e^{j\omega x}]. \tag{1}$$

the cumulant generating function is defined as:

$$\psi(\omega) = ln(\phi(\omega)). \tag{2}$$

The $k-$moment of random variable x is defined as:

$$m_k = E[k] = \int_{-\infty}^{+\infty} x^k f(x)dx. \tag{3}$$

If $m_k(k = 1, 2, ..., n)$ exists, the relationship between the $k-th$ moment of x and the eigenfunction is:

$$m_k = (-j)d^k \frac{\phi(\omega)}{(d\omega)^k}|_(\omega = 0) = (-j)^k \phi(\omega)^k (k \leq n). \tag{4}$$

The $k-$order cumulant of random variable x is defined as:

$$c_k = (-j)^k \frac{d^k \phi(\omega)}{(d\omega)^k}|_{\omega=0} = (-j)^k \psi^k(0)(k \leq n). \tag{5}$$

2.2 Cumulant of the Random Process

$x(n)$ is the zero mean $k-$order stochastic stationary process, the $k-$order moment of the process is defined as:

$$m_{kx}(\tau_1, \tau_2, ...\tau_{k-1}) = mom(x(n), x(n + \tau_1), ..., x(n + \tau_{k-1})). \tag{6}$$

The $k-$order cumulant of $x(n)$ is:

$$c_{kx}(\tau_1, \tau_2, ...\tau_{k-1}) = cum(x(n), x(n + \tau_1), ..., x(n + \tau_{k-1})). \tag{7}$$

$mom(\cdot), cum(\cdot)$ are united moment and united cumulant respectively.

For stationary complex random sequences $x(n)$, the moment and cumulant are defined as:

$$M_{p+q,q} = E[x^p(n), (x^*(n))^q], \tag{8}$$

$$C_{p+q,q} = cum[x(n), ...x(n), x^*(n), ..., x^*(n)], \tag{9}$$

where the number of $x(n)$ and $x^*(n)$ are p and q respectively.

2.3 High Order Cumulant Characteristic Parameters

The higher-order cumulants of the communication signals with Gaussian white noise are equal to the sum of the higher-order cumulants of the communication signals and Gaussian noise from the properties of higher-order cumulants [28]. The higher-order cumulant (more than 2-order) of Gaussian noise is equal to zero, so the higher-order cumulant has excellent anti-noise performance. In this paper, the second, fourth, sixth, and order cumulants are selected, referring to previous articles.

- the expressions of second order cumulants are:

$$C_{20} = cum(x(n), x(n)) = M_{20}. \tag{10}$$

$$C_{21} = cum(x(n), x*(n)) = M_{21}. \tag{11}$$

- the expressions of fourth order cumulants are:

$$C_{40} = cum(x(n), x(n), x(n), x(n)) = M_{40} - 3{M_{20}}^2. \tag{12}$$

$$C_{41} = cum(x(n), x(n), x(n), x*(n)) = M_{41} - 3M_{20}M_{21}. \tag{13}$$

$$\begin{aligned} C_{42} &= cum(x(n), x(n), x*(n), x*(n)) \\ &= M_{42} - M_{20}M_{21} - 2{M_{21}}^2. \end{aligned} \tag{14}$$

- the expression of sixth order cumulants are:

$$\begin{aligned} C_{60} &= cum(x(n), x(n), x(n), x(n), x(n), x(n)) \\ &= M_{60} - 15M_{40}M_{20} + 30{M_{20}}^3. \end{aligned} \tag{15}$$

$$\begin{aligned} C_{61} &= cum(x(n), x(n), x(n), x(n), x(n), x*(n)) \\ &= M_{61} - 5M_{40}M_{21} - 10M_{41}M_{20} + 30M_{21}{M_{20}}^2. \end{aligned} \tag{16}$$

$$\begin{aligned} C_{63} &= cum(x(n), x(n), x(n), x*(n), x*(n), x*(n)) \\ &= M_{63} - 6M_{41}M_{20} - 9M_{42}M_{21} \\ &+ 18M_{21}{M_{20}}^2 + 12{M_{21}}^3. \end{aligned} \tag{17}$$

According to the calculation method of the theoretical value of the higher-order cumulant, the notional value of each digital modulation signal's cumulant is obtained, as shown in Table 1 [15]. The signal energy is E.

Table 1. The theoretical value of the cumulant of different modulations

Modulation	C_20	C_21	C_40	C_42	C_60	C_61	C_63
4ASK	E	E	$-1.36E^2$	$-1.36E^2$	$-8.32E^3$	$8.32E^3$	$8.32E^3$
2FSK	0	E	0	$-E^2$	0	0	$4E^3$
MSK	0	E	$-0.8E^2$	$-E^2$	0	$3.3E^3$	$4E^3$
BPSK	E	E	$-2E^2$	$-2E^2$	$-16E^3$	$16E^3$	$16E^3$
QPSK	0	E	E^2	$-E^2$	0	$4E^3$	$4E^3$
8PSK	0	E	0	$-E^2$	0	$4E^3$	$4E^3$
16QAM	0	E	$-0.68E^2$	$-0.64E^2$	0	$2.08E^3$	$2.08E^3$
32QAM	0	E	$-0.62E^2$	$-0.43E^2$	0	$0.74E^3$	$0.74E^3$
OFDM	–	–	0	0	0	0	0
CPM	0	E	0	$-E^2$	$0.36E^3$	E^3	E^3

2.4 Feature Parameters Selection

Considering that the higher-order cumulant will be affected by many factors such as signal amplitude and reference phase, besides, the cumulant of below the second-order Gaussian noise is not zero, this paper constructs the characteristic parameters are as follows based on the article [15].

$$F_1 = \frac{|C_{40}|}{|C_{42}|}. \tag{18}$$

$$F_2 = \frac{|C_{63}|^2}{|C_{42}|^3}. \tag{19}$$

$$F_3 = \frac{|C_{61}|^2}{|C_{42}|^3}. \tag{20}$$

The value of F_2, F_2, F_3 can be calculated according to the Table 1 and formula (18–20), as shown in Table 2 to Table 4.

Table 2. The value, F_1 of different modulations

Modulation	F_1	Modulation	F_1
CPM	0	2FSK	0
4ASK	1	MSK	0.8
BPSK	1	OFDM	0
QPSK	1	16QAM	1.06
8PSK	0	32QAM	1.49

Table 3. The value, F_2 of different modulations

Modulation	F_2	Modulation	F_2
CPM	1	2FSK	16
4ASK	27.52	MSK	16
BPSK	32	OFDM	0
QPSK	16	16QAM	13.76
8PSK	16	32QAM	6.89

Table 4. The value, F_3 of different modulations

Modulation	F_3	Modulation	F_3
CPM	1	2FSK	0
4ASK	27.52	MSK	10.89
BPSK	32	OFDM	0
QPSK	16	16QAM	13.76
8PSK	16	32QAM	6.89

Signals can be divided seven groups: {OFDM}, {4ASK}, {2FSK, MSK, QPSK, 8PSK}, {CPM}, {BPSK}, {32QAM}, {16QAM} by, F_2, from Table 3. QPSK, 8PSK, 2FSK, and MSK can be classified as {2FSK}, {MSK}, and {QPSK,8PSK} with parameter F_3, from Table 4. Finally, QPSK and 8PSK is recognized by parameter F_1.

3 Model of the Neural Network Ensembles

The researches show some problems with the prediction model for a neural network to digital communication signals modulation recognition [1–3, 20, 23]. First, the number of hidden layer nodes in a neural network will increase greatly on complex modulation signals, which will lead to training difficulties on account of difficulties of parameter setting and fast multiplication of training time [20]. Second, a neural network will cause an "overfitting" phenomenon due to the excessive pursuit of training accuracy [2]. Third, the defects of weak robustness and generalization in a neural network perform significant differences in the prediction of unknown data, which can not guarantee the accuracy of modulation recognition of digital communication signals [1]. But the neural network ensemble can improve performances by making the most of the information in multiple independent networks [3].

The neural network ensemble (NNE) [2] refers to the combination of multiple neural networks to complete the same training task. The output of each neural network determines the production of ensembles in the input samples.

This paper proposes a model named BP neural network ensembles (BPNNE) based on the BP neural network [11]. The mode is divided into two levels: the first level consists of T neural networks, and the second level is composed of S NNE. The individuals on the first level are trained by the feature parameters F_2, F_2, and F_3 extracted from different modulation signals. The output of the NNE on the last level is a linear combination of the output of the first level. Weight distribution is a typical optimization problem solved by a quantum immune algorithm [10]. Assuming that the last output of input x is y, there is a functional expression, g, between x and y. Based on a testing set, $V(x_i, y_i)(i = 1, 2, \cdots, N)$, and training set, $D_i(i = 1, 2, \cdots, T)$, T neural networks are trained independently to form a set, $H = h_t(t = 1, 2, \cdots, T)$. Each element h_t of H is an approximation of function g. The purpose of optimization is to improve the generalization ability of the neural network ensemble, which is to reduce the generalization error. That is, the neural network ensemble with a smaller generalization error is better than others. The generalization error can be expressed as the expected risk of ensemble optimization. The mean square error of the neural network ensemble on a given data set can be used as an estimation of generalization error. According to the criteria of minimum mean square error of neural network ensembles, the objective function of weight optimization is the mean squared error:

$$f_{2min}(\omega) = \sum_{i=1}^{N}[y_i - \sum_{s=1}^{S} NNE_s(x_i)/S]^2/N, \tag{21}$$

$$NNE_s(x_i) = \sum_{t=1}^{T} \omega_{st} h_t(x_i), \tag{22}$$

where $\omega = \omega_s t(s = 1, 2, \cdots, S; t = 1, 2, \cdots, T)$, $\omega_s t$ is the weight of the s-th ensemble with the $t-$th independent neural network, y_i is theoretical output of the $i-$th NNE, $NNE_s(x_i)$ is the $s-$th ensemble output, x_i is the $i-$th input. In the process of weight optimization, the value range of weight is usually limited to $[0, 1]$, and the sum of weight is set to 1, to reduce the influence of collinearity and noise [16]. The specific structure is shown in Fig. 1.

Figure 1 The structure partitioning policies: *S ensembles* and *1 ensemble*. *S ensembles* indicates the first ensemble, *1 ensemble* manifests the last ensemble.

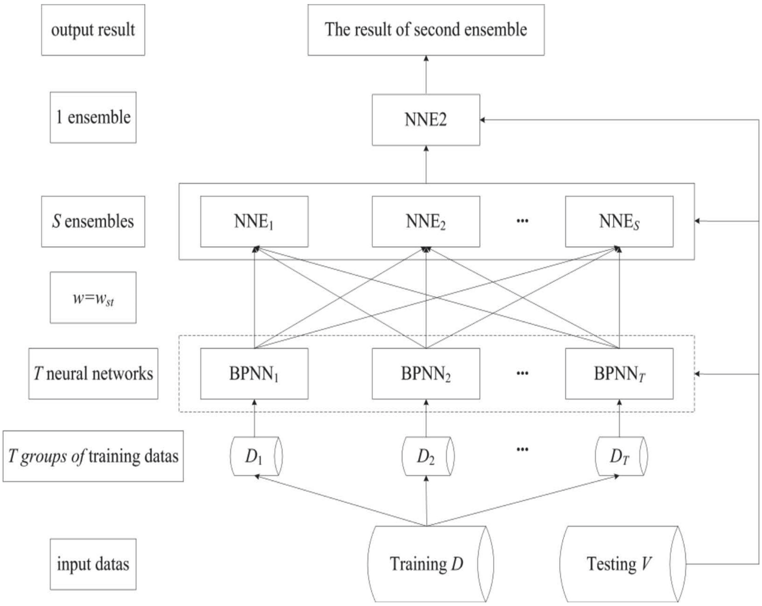

Fig. 1. Structure of BPNNE.

3.1 Algorithm Flows

The algorithm exploits neural network ensemble to optimize performance, and the implementation steps are as follows:

Step 1: The input dataset of the model offered is formed by extracting feature parameters.

Step 2: Divide the input dataset into a training set, D, and testing set, V, according to the proportion, and divide training set, D, into T groups randomly and equally, that is, $D_i(i = 1, 2, \cdots, T)$.

Step 3: According to the training data , $D_i(i = 1, 2, \cdots, T)$, of neural network sets, $P_j(j = 1, 2, \cdots, T)$ neural networks are trained independently by changing the number of hidden layers and nodes. And, the first level neural network set, $H = h_t(t = 1, 2, \cdots, T)$, consists of the neural networks selected in each set, P_j, with the best performance based on MSE.

$$f_{1min} = \sum_{i=1}^{N}[y_i - \sum_{p=1}^{P} h_p(x_i)/P]^2/N, \tag{23}$$

where h_p is the training output of neural network set $H = h_t(t = 1, 2, \cdots, T)$.

Step 4: The secondary neural networks are obtained by the weighted sum of the set, $H = h_t(t = 1, 2, \cdots, T)$, referring to formula (22). The weights of the secondary neural networks are optimized according to the MSE minimum principle. The optimization employs the quantum immune algorithm [12] which makes weights, $\omega = \omega_{st}(s = 1, 2, \cdots, S; t = 1, 2, \cdots, T)$, map to quantum code, $p = \{\alpha_{\mathbf{st}}, \beta_{\mathbf{st}}\}^{\mathrm{T}}$, where, α_{st}, and, β_{st}, are quantum probability amplitudes, T represents transposition.

Step 5: The output of secondary neural network ensemble is obtained by a simple average, that is $\bar{y} = \sum_{s=1}^{S} NNE_s(x_i)/S$.

4 Experiment Simulation and Result Analysis

The modulation signals used in this paper are generated by simulation on MATLAB [17]. The modulated signals include 2FSK, MSK, BPSK, QPSK, 8PSK, 4ASK, 16QAM, 32QAM, OFDM, and CPM, totaling ten formats. SNR of the simulation signal varies from 0 dB to 15 dB. The noise added is Gaussian white noise. The carrier frequency is three GHz. The symbol rate is one GB/S. The sampling frequency is sixteen GHz. The roll off coefficient of the pulse shaping filter is 0.25, and the initial phase is randomly selected in the range of $[0, 2\pi]$. MATLAB randomly generates signal symbols. The amount of data generated is two thousand samples every 1 dB, two hundred samples for each modulation format. One hundred samples are used to train the network model, and the others are used to test the model. Therefore, there are sixteen thousand samples of training data and sixteen thousand samples of test data, and each sample contains one thousand and two hundred symbols. The algorithm is implemented on MATLAB [11]. Each BP neural network contains the input layer, the hidden layer, and the output layer. The number of nodes in the input layer and the output layer is 3 and 10, respectively. And the number of the hidden layer's nodes is denoted by M, which can be obtained according to the empirical formula given by the paper [23], $M = \sqrt{I + O} + K$, where I, O, and L are the number of input nodes, output nodes, and hidden layers, while K is an integer between 1 and 10. The maximum of neural network ensembles epochs is 500. The value of the neural network set P_j, on the first level is set to ten. And the model proposed is trained by the different parameters above. The results of the experiments are shown in the following figures.

Figure 2 The above figure is the recognition accuracy curves of 10 modulation formats under different SNR of the BPNNE.

Figure 2 shows the curves of recognition accuracy of ten different modulation formats mentioned above with different SNR when the hidden layer's nodes is ten, and epochs are eighty. The probability of the correct recognition of ten formats is over 94% when SNR is 5 dB from Fig. 2. The BPNNE model proposed can recognize the ten modulated signals infallibly when SNR is 8 dB during the sample sets of the paper. However, the performance of the BPNNE model is inadequate near 0 dB.

Figure 3 The above figure is the recognition accuracy curves of 10 modulation formats with different hidden layer's nodes of the best BP neural network.

Figure 4 The above figure is the recognition accuracy curves of 10 modulation formats with different hidden layer's nodes of the best BP neural network.

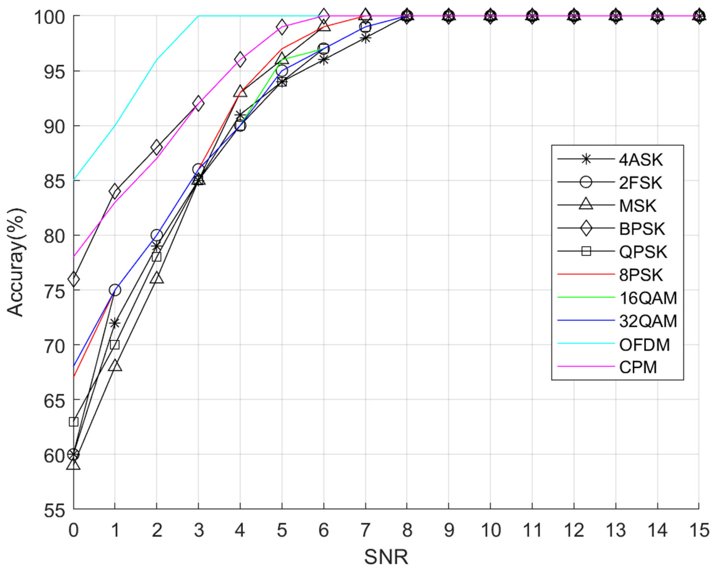

Fig. 2. Curves of accuracy with SNR.

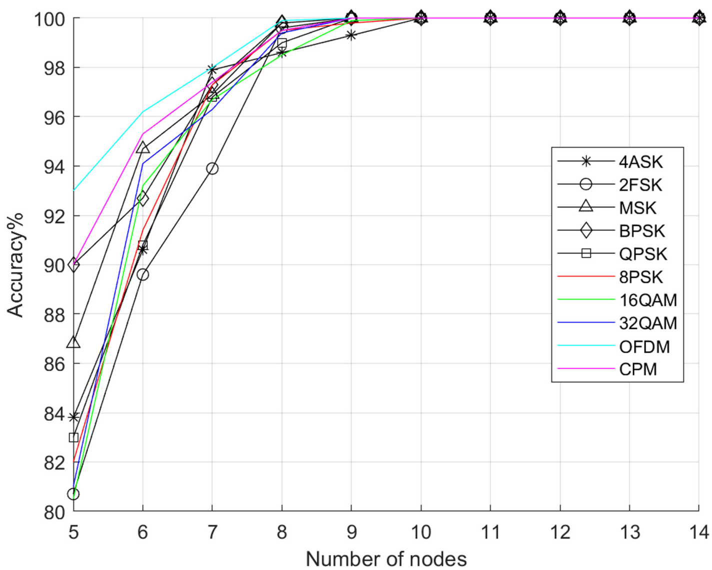

Fig. 3. Curves of accuracy with different nodes of the hidden layer.

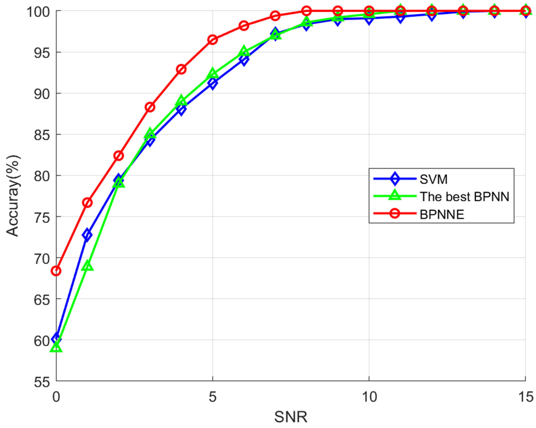

Fig. 4. Performance of different methods.

Figure 3 depicts the recognition accuracy curves of 10 modulation formats with different hidden layer's nodes of the optimal BP neural network when SNR is 15 dB. We can obtain that the accuracy is best of 10 nodes. The picture above also indicates property of the correct recognition is not improved any more. In other words, the hidden layer's nodes are not the more the better. Besides the figure exhibits The best BP neural network is inferior to the BPNNE model.

Figure 4 compares the recognition accuracy of support vector machine (SVM), the single optimal BP neural network and the BPNNE model in different SNR. In the sample set of this paper, the performance of the single neural network and SVM is almost the same, while the counterparts of BPNNE model is significantly improved compared with other algorithms. When the recognition

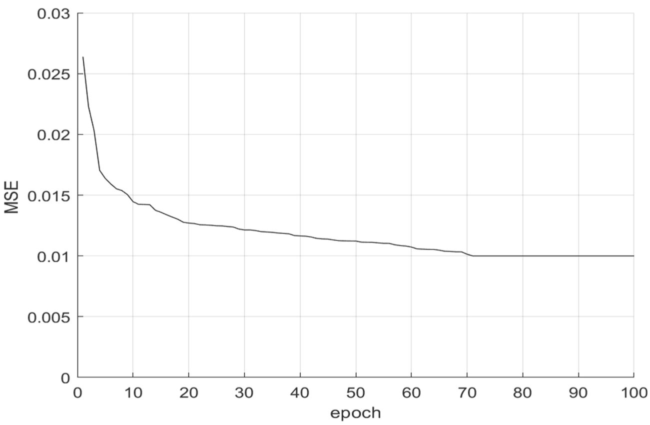

Fig. 5. MSE of BPNNE with Epochs.

accuracy is 98%, BPNNE model is 2 dB better than SVM and the single neural network.

Figure 5 The above figure diplays the minimum mean square error (MSE) of the BPNNE model with epochs when the SNR is 5 dB, and the nodes of the hidden layer are 10.

Figure 5 is mainly used to characterize the generalization performance of the BPNNE model. It can be seen from the above picture that MSE converges to 0.01 when epoch is 70, which indicates that the generalization error of the model can reach 10^{-2}, showing good generalization ability.

5 Conclusions

In this paper, a method of modulation recognition based on neural network ensembles is proposed on the foundation of the BP neural network. The characteristic parameters are simulated and verified by BP neural network ensembles. The experimental results manifest ten modulation formats are identified efficiently, including the complex modulation signals such as OFDM and CPM. The algorithm presented has high accuracy, and the extracting features are simple, which is not complicated for engineering applications.

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