A Specific Combination Scheme for Communication Modulation Recognition Based on the Bees Algorithm and Neural Network

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Abstract —Regarding to the problems of low rate of convergence and fault saturation for neural network classifier based on the algorithm of error back propagation during the signal recognition, bee colony algorithm is applied in this paper so as to extract combined feature module of signal and suggest three different algorithms including algorithm with rapidly support, super self-adaption error back propagation and conjugate gradient. These three algorithms are respectively applied in multilayer perception neural network classifier, and help achieve automatic recognition for communication signals and higher recognition rate compared with error back propagation. The simulation result shows that the algorithms put forward in this paper can overcome the drawbacks of error back propagation algorithm. Meanwhile, under the condition that nerve cell has only 20, SNR is 4dB in the hidden layer, the recognition rate of three algorithms are all higher than 95%, the system is easy to implement and has wide range of application prospect in the signal recognition.

Index Terms—Combined feature module, bee colony algorithm, multi-layer perceptron neural network, modulation recognition

I. INTRODUCTION

Modulation identification has been widely used in the military and civil communication, it is foundation of software defined radio, cognitive radio and spectrum sensing. With the emergence of new modulation modes, signal processing becomes increasingly complicated which affect the effectiveness of modulation identification. To achieve the automatic identification technology is still a challenge research topic [1], [2].

Pattern recognition methods adopted in the communication signal automatic recognition is mainly consisted of the extraction of characteristic value and classifier selection. Among them, the current main methods of the characteristic value extraction are: extracting the instantaneous frequency domain eigenvalue, time-domain eigenvalue respectively, and analyzing higher-order origin moments, higher-order cumulants, wavelet transform, spectral correlation, cyclic spectrum correlation, power spectrum, constellation diagram and signal kurtosis etc. [3]-[5]. In order to improve the recognition rate, people tried to use different methods to extract multiple eigenvalues so as to conduct recognition both within and outside, which are all introduced in related journals at home and abroad in recent years [6], [7]. However, in the extraction of multiple eigenvalues, in order to achieve the optimized effect, this paper puts forward the ideas that using the swarm algorithm (Bees algorithm, BA), extracting the signal characters of time domain and frequency domain, the higher-order origin moment and cumulant of the signal and the combination adopting their different number as a combination eigenvalue module, then the signals are automatic recognition through neural network classifier on this basis so as to achieve good results. Among them, the BA algorithm is simple, easy-to-use, accessible, easy-to-implement, and suitable to solve complex optimization problems, especially for solving data clustering and the multi-objective optimization problem [8]. Currently, the main types of classifier are tree classifier, Support Vector Machine (Support Vector Machine, SVM) and neural network classifier etc. Structure of tree classifier is relatively simple, good real-time. But threshold beforehand needs to be determined in advance, the related adaptability is poor, and it is only suitable for classification characteristic parameter to distinguish good signal recognition; The SVM classifier algorithm without having to determine the decision threshold of each feature vector, fully embodies the intelligence of the algorithm, but the algorithm exists faults of slow training speed, complex and processing large in test phase; The neural network classifier has powerful ability of pattern recognition. Meanwhile, it can automatically adapt to environmental changes and can better deal with complex nonlinear problems. It also has better robustness and a potential fault tolerance so as to obtain high recognition rate. But in the neural network classifier, more literatures introduced multilayer perceptron (multi-layer perceptron, MLP) neural network classifier based on error back propagation algorithm (error back-propagation algorithm, BP). BP learning algorithm was first proposed by the scientists headed Rumelhart and Mccelland in 1986. The algorithm is one of the most widely classical neural

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network model and has been widely used in signal recognition technology research. However, some problems presented when taking the BP algorithm into practice may include slow convergence speed; tend to converge to local minimum points; appear false saturation phenomenon, not fully trained paralysis phenomenon and numerical stability is poor; vector, momentum coefficient and parameters such as initial weights are difficult to adjust; cannot meet the requirement of the many online learning; cannot guarantee precision of learning problems [9]-[11]. In this paper, the neural network classifier based on different learning algorithm of Quick Prop (QP), super schemes for adaptation of the error back propagation (super SAB) and Conjugate Gradient (CG) is of significance in the improvement in solving the problems existing in the BP algorithm, and obtained the good recognition when it was firstly applied to the recognition of communication signals.

This paper firstly summarizes the common eigenvalue extraction method in signal recognition in the same field at home and abroad, the advantages and disadvantages of various classifier algorithm, especially the BP algorithm, which leads to the necessity of extracting combination eigenvalue module through BA algorithm and using neural network classifier through three algorithms of QP, Super SAB, CG. The second part introduces a combination eigenvalue module; The third part present the research on a combination eigenvalue module extract by the BA algorithm; The fourth part introduces the MLP neural network classifier and puts forward a classifier by using different algorithms; The fifth part is analyzing the signal modulation recognition simulation and performance; The end of this paper is the conclusion.

II. Combination Eigenvalue Module

The combination eigenvalue module extraction by BA includes $\gamma_{\max}$, σ_{of}, σ_{op}, high-order original moment, high-order cumulant and their various numbers of combination. When intercepting the signal, $\gamma_{\max}$ is the maximum of the center the instantaneous amplitude power spectrum density, σ_{of} is the standard deviation of the normalized instantaneous frequency absolute value and σ_{op} is the standard deviation of the normalized instantaneous phase nonlinear component absolute value in the period of not weak signals.

A. High-Order Original Moment

A random variable $\boldsymbol{s}$ in the i order original moment can be defined as:

$$\mu_i = \int_{-\infty}^{\infty} s^i f(s) ds \tag{1}$$

If mean value of signal is 0, the i order original moment when the length is N can be presented as:

$$\mu_i = \sum_{k=1}^{N} s_k^i f(s_k) \tag{2}$$

The autocorrelative original moment of random variable $\boldsymbol{s}$ is defined as:

$$M_{pq} = E[\boldsymbol{s}^{p-q}(\boldsymbol{s}^*)^q] \tag{3}$$

p is the order of original moment, $\boldsymbol{s}^*$ is the complex conjugate of random variable $\boldsymbol{s}$. Set 0 mean value baseband sequence as: $\boldsymbol{s}_k = a_k + jb_k$ .According to the definition of autocorrelative original moment with different orders, the original moment with different orders can be calculated as:

$$\begin{aligned} M_{84} = E[\boldsymbol{s}^4(\boldsymbol{s}^*)^4] = a^8 + 10a^6b^2 + \\ 16a^4b^4 - 16a^2b^6 + 21a^4b^4 - 12a^2b^2 + b^8 \end{aligned} \tag{4}$$

Among (4), these higher order origin moment eigenvalues of 2PSK, 16QAM, 64QAM which are applied in simulation experiment are shown in Table I

TABLE I: EIGENVALUES OF HIGHER ORDER ORIGIN MOMENT

Eigenvalues	M_{41}	M_{61}	M_{84}
2PSK	1	1	1
16QAM	0	-1.32	3.13
64QAM	0	-1.3	3.9

B. High-Order Cumulant

The random variable $\boldsymbol{s}$ under condition that the mean value is set as 0, the eigenfunction is $\hat{f}(t)$, expand it as the Taylor Series and is represented as:

$$\log \hat{f}(t) = k_1(jt) + ... + \frac{k_r(jt)^r}{r!} + ... \tag{5}$$

Among (5), k_r is called the cumulant of the random variable $\boldsymbol{s}$. The formula under the p order cumulant is similar to the formula under the p order original moment, and they are showed as:

$$C_{pq} = Cum[\boldsymbol{s}....\boldsymbol{s}, \boldsymbol{s}^*, ...\boldsymbol{s}^*] \tag{6}$$

Among (6), $\boldsymbol{s}\ldots\boldsymbol{s}$ has $p-q$ number, $\boldsymbol{s}^*\ldots\ldots\boldsymbol{s}^*$ has q number. For example:

$$\boldsymbol{C}_{84} = Cum = (\boldsymbol{s}, \boldsymbol{s}, \boldsymbol{s}, \boldsymbol{s}, \boldsymbol{s}^*, \boldsymbol{s}^*, \boldsymbol{s}^*, \boldsymbol{s}^*)$$

The cumulant under the n order is the function of the original moment whose order accumulates to n. According to the definition of accumulates, this original moment can be showed as:

$$M[\boldsymbol{s}_1, \cdots, \boldsymbol{s}_n] = \sum_{\forall p} Cum[(\boldsymbol{s}_j)_{j e v_1} \cdots Cum[(\boldsymbol{s}_j)_{j \in v_q} \tag{7}$$

According to the definition of the original moment, the cumulant can also be showed as:

$$\begin{aligned} Cum[\boldsymbol{s}_1, \cdots, \boldsymbol{s}_n] = \sum_{\forall v} (-1)^{q-1}(q-1)! \times \\ E[\prod_{j \in v_1} \boldsymbol{s}_j] \cdots E[\prod_{j \in v_p} \boldsymbol{s}_j] \end{aligned} \tag{8}$$

Among (8), each component $v = (v_1, \cdots, v_q)$ related to the index （1,2, , , , , , n ） is accumulated. If the high

order cumulant under the order 2, order 4, order 6, order 8 can be calculated respectively, 14 types of high-order cumulant including $\boldsymbol{C}_{20}$, $\boldsymbol{C}_{21}$, $\boldsymbol{C}_{40}$, $\boldsymbol{C}_{41}$, $\boldsymbol{C}_{42}$, $\boldsymbol{C}_{60}$, $\boldsymbol{C}_{61}$, $\boldsymbol{C}_{62}$, $\boldsymbol{C}_{63}$, $\boldsymbol{C}_{80}$, $\boldsymbol{C}_{81}$, $\boldsymbol{C}_{82}$, $\boldsymbol{C}_{83}$, and $\boldsymbol{C}_{84}$ are regarded as the characteristic of the signal [12], [13]. Three input signals higher order cumulant eigenvalues of 2PSK, 16QAM, 64QAM which are applied in simulation experiment are shown in Table II.

TABLE II: EIGENVALUES OF HIGHER ORDER CUMULANT

Eigenvalues	$\boldsymbol{C}_{61}$	$\boldsymbol{C}_{80}$	$\boldsymbol{C}_{84}$
2PSK	16	-244	-244
16QAM	2.08	-13.99	17.38
64QAM	1.797	-11.5	0

III. THE EXTRACTION OF COMBINATION EIGENVALUE MODULE THROUGH BA

The principle of extracting the combination eigenvalue through BA is based on the model of bee colony's nature secret behavior. The optimal solution can be found through the implementation of global search strategy and the algorithm of the strategy of the local neighborhood search. The principle is:

The first process is random initialization. n worker bees reconnoiter and the worker bees will search continuously for the whole solution space in this algorithm. Therefore, the updated formula is:

$$x_i = \min + rand(0,1)(\max - \min)$$
$$i \in (m+1, m+2, \cdots, n) \tag{9}$$

Among (9), min is the next value of solution space and max is the previous value of the solution space.

In the iterative process of finding the optimal solution, m better worker bees are firstly selected. After the selection, these better worker bees in the flowers should be reinforced respectively. The worker bees reinforced will be generated by the following formula:

$$v = (x_i - ngh) + 2 \times ngh \times rand(0,1)$$
$$i \in (m+1, m+2, \cdots, n) \tag{10}$$

Among (10), ngh is the radius of flowers and presents the neighbourhood search area.

Selecting the best worker bees v_{best} in these worker bees reinforced. If v_{best} is better than current worker bees x_j, x_j will be replaced by v_{best}.

After each iteration, m most optimal worker bees are retained and other $n-m$ worse worker bees are updated iterated based on (9). Only when a satisfactory combination eigenvalue module is obtained (also called the extraction of the satisfactory combination eigenvalue module), the optimization process finish. Otherwise, return, continuously iterated, and update so as to find the optimal combination eigenvalue module [14].

For three kinds of modulating signal of 2PSK, 16QAM, 64QAM which are applied in simulation experiment, corresponding parameter values of combination eigen-value module extraction by BA are shown in Table III.

TABLE III: CORRESPONDING PARAMETER VALUES OF COMBINATION EIGENVALUE MODULE EXTRACTION BY BA ALGORITHM

n	m	e	ngh	min	max
30	8	2	0.1	4	15

IV. MLP NEURAL NETWORK CLASSIFIER AND DIFFERENT APPLIED ALGORITHMS IN CLASSIFIER

A. MLP Neural Network Classifier

There are different types of MLP, feedforward network, for example, three layers including the input layer, hidden layer and output layer. Each input in the input layer is feed to hidden layer, the output of each cell from hidden layer is connected to every nerve cells the next layer of it (the output layer), as a feedforward network, generally it can have any number of hidden layer [15]. But in dealing with most of the problem, a hidden layer is usually enough. In addition, the number of cellular neural network can be completely arbitrary, actually each layer can have any number of nerve cells, which all depends on the complexity of the problem to be solved. But the more nerve cells, the lower the work of network speed is. So the scale of the network is always requested not to be as small as possible [16].

B. Different Algorithms Used in the Classifier

The most commonly used algorithm in MLP is BP algorithm [17]. Apart from the BP algorithm, this paper puts forward QP, Super SAB, and CG algorithm to learn and train MLP so as to be used for communication signal modulation classification recognition. The theoretical analysis and comparison of the algorithm are as following respectively:

- BP algorithm

The basic idea of BP algorithm is, the learning process includes the positive signal propagation and error back propagation, through the output error being in back propagation, the error will be spread to all the units in each layer, so as to get error signal of each unit, and then fixed weights of each unit.

The rules of change weight in BP algorithm are as follows:

$$x_{ij}(t+1) = x_{ij}(t) + a_{ij}\boldsymbol{g}_{ij}(t) \tag{11}$$

Among them, $x_{ij}(t)$ represent weights from cells i to j at t moment, $x_{ij}(t+1)$ represent weights from cells i to j at $t+1$ moment, $\boldsymbol{g}_{ij}(t)$ represent the gradient of weight change from cells i to j at t moment, while a_{ij} represent the learning rate from cells i to j.

BP algorithm is easy to form a local minimum; appear false saturation phenomenon and cannot get the global optimal; make the learning efficiency is low because numbers of training should be conducted and a lot of computation are needed to do; have slow convergence speed and exist the phenomenon that paralysis is not fully trained and numerical stability, vector, momentum

coefficient and the parameters such as initial weights are difficult to be adjusted.

- QP algorithm

The weights of QP algorithm are updated by using the quasi-newton method to reduce the weight error range. The main ideas of the algorithm proposed are based on two major assumptions:

1) Error weighting curve is a convex parabola;

2) The change of the slope associated with a weight error curve is not subject to any other influence of changing weights at the same time.

Quick support weights update rules are as follows:

$$x_{ij}(t+1) = x_{ij}(t) + \Delta x_{ij}(t) \tag{12}$$

$$\Delta x_{ij}(t) = \frac{\boldsymbol{g}_{ij}(t)}{\boldsymbol{g}_{ij}(t-1) - \boldsymbol{g}_{ij}(t)} \Delta x_{ij}(t-1) \tag{13}$$

$$\boldsymbol{g}_{ij}(t) = \frac{\partial E}{\partial x_{ij}} \tag{14}$$

$\Delta x_{ij}(t)$ represent weights are revised from cells i to j at t moment, $\Delta x_{ij}(t-1)$ represent weights are revised from cells i to j at $t-1$ moment, E represents error function, $\boldsymbol{g}_{ij}(t)$ represents gradient of the weight change from cells i to j at t moment.

For QP algorithm, applying the quasi-newton algorithm can quickly reduce weight error range and create less number of iterations, the high efficiency of searching, and the fastest learning rate.

- Super SAB algorithm

Super SAB algorithm is the modified algorithm based on the BP algorithm and is the algorithm of error feedback learning rate based on the locality with adaptively adjusting the strategy error. The algorithm can independently adjust the network learning step based on the continuous gradient error energy function. Compared with standard BP algorithm through using global adjustment strategy, it is more advantageous to avoid network into a local minimum point so as to improve the convergence performance. Its basic idea is that learning rate can make automatic adjustment with the changing range of error. The scope of its weights is updated according to the following rules:

$$\Delta x_{ij}(t+1) = -\eta_{ij}(t)\frac{\partial E}{\partial x_{ij}}(t) + a_{ij}\Delta x_{ij}(t-1) \tag{15}$$

$$\frac{\partial E}{\partial x_{ij}}(t-1)\frac{\partial E}{\partial x_{ij}}(t) \succ 0$$

$$\eta_{ij}(t) = \eta^{+}\eta_{ij}(t-1)$$

$$\frac{\partial E}{\partial x_{ij}}(t-1)\frac{\partial E}{\partial x_{ij}}(t) \prec 0$$

$$\eta_{ij}(t) = \eta^{-}\eta_{ij}(t-1)$$

η^{+} and η^{-} are increment and decrement factor respectively. For Super SAB algorithm, as using super learning rate adaptive algorithm, and constantly adjust the search step length and coefficient of gain matrix, accelerate the iterative convergence process, improve the efficiency of the signal processing, thus learning rate is faster than BP algorithm.

- CG algorithm

CG algorithm is an optimization algorithm using the theory of error function of second order differential, When the error function is the quadratic function, the algorithm can be used to reach the minimum after N steps search, each of these weights update is the conjugate gradient of original weight, and linear search is asked to calculate the length and weight falling direction search vector, finally find the minimum point. Weight updating rules are as follows:

$$\begin{aligned} \Delta x(t+1) &= -\eta(t)d(t) \\ d(t) &= -g(t) + \beta(t-1)d(t-1) \end{aligned} \tag{16}$$

According to Polak–Ribiere law, the function is as following:

$$\beta(t-1) = \frac{g(t)\left[g(t) - g(t-1)\right]}{g(t-1)^2} \tag{17}$$

CG algorithm with using conjugate gradient algorithm, is algorithm of unconstrained optimization to solve problems. The most important feature of this algorithm is small storage capacity. Regarding to the convergence speed, although this algorithm cannot compare with the quasi Newton method and learning rate adaptive algorithm, but in general situation such as when the number of network node (hidden layer) is not large, convergence speed is still faster than BP algorithm. But when the number of hidden layer is asked to be increased, and the information to be storage is increased, the convergence speed is restricted due to less memory in its algorithm [18].

V. Modulation Recognition Simulation of System and Performance Analysis

BA algorithm is used in system to extract different number of combination eigenvalue modules, and then the extracts are entered into the classifier as input characteristic parameter vector of MLP neural network, then training the MLP classifier respectively through QP, Super SAB, CG algorithms etc, so as to reach the comparison between input signal modulation recognition of 2 PSK and 16 QAM and 64 QAM and BP algorithm, simulation parameters and conditions are: using random sequence as a modulation signal, the symbol rate is R_S=12kb/s, the signals to be modulated and recognized are 2PSK,16QAM,64QAM. Its carrier frequency is 200kHz, three layers feedforward network is used in the neural network, as the total number of modulation type to identify is 3 kinds, the number of neurons in output layer is 3, the number of neurons in hidden layer are 20 and 40 respectively. Transfer function among the input layer, hidden layer and output layer is the hyperbolic tangent S

function. The rate of square error is 10^{-6}, the channel is white Gaussian noise channel, the signal-to-noise ratio is range of -4 dB ~12 dB, and the training sample is 2000. The simulation results are shown in Fig. 1-Fig. 5:

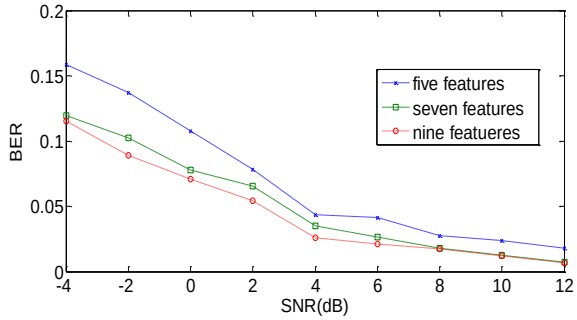

Fig. 1. The results of modulation recognition simulation on different number of combination eigenvalue module extracted by BA algorithm

Fig. 1 shows the relationship between modulation average error recognition rate (BER) of 2PSK, 16QAM, 64QAM three kinds of signal and the SNR through the way that the QP algorithm learn and train MLP classifier under condition of that the numbers of neurons is 20 in hidden layer, the different number of combination eigenvalue module parameters of the input neural network extracted by BA algorithm is ($\gamma_{\max}$ σ_{of} σ_{op} M_{41} C_{61}), ($\gamma_{\max}$ σ_{of} σ_{op} M_{41} M_{61} C_{61} C_{80}), ($\gamma_{\max}$ σ_{of} σ_{op} M_{41} M_{61} M_{84} C_{61} C_{84} C_{80}) respectively. Three curves represent three of simulation results respectively under the condition of three kinds of different combination eigenvalue modules, with the increasing number of combination module eigenvalue, system modulation average recognition rate significantly increased, As shown in Fig. 1, when the module combination characteristic value number increases from five to seven or nine, the modulation average recognition rate is relatively bigger, particularly in low signal-to-noise ratio (less than 0 dB), when the number of the eigenvalue in combination modules achieve a certain extent, such as more than seven, the acceleration of system modulation average recognition rate slows down, So it is foreseeable that system modulation recognition is not no longer increased when the number of combination characteristic values achieve a certain degree because the optimization of combination eigenvalue module extracted by BA algorithm has reached its limit state.

Fig. 2 and Fig. 3 respectively represent the results of simulation test and classifier learning through four different algorithms of BP, Super SAB, CG and QP when the numbers of neurons in hidden layer is 20, 40. In this part, the aim of test is to observe correct recognition performance of MLP classifier on the sample in different conditions. From Fig. 2, MLP classifier is carried out identification training and test on the sample through three kinds of algorithm of Super SAB, CG, QP. The average recognition rate is higher than that by the common BP algorithm, especially in the low signal-to-noise ratio (SNR<6dB), the situation is particularly obvious. Comparing the Fig. 2 and Fig. 3, in the condition of the same SNR, even when the numbers of neurons is 20 in hidden layer, the average correct recognition rate in the recognition training and testing of MLP classifier through three algorithms of Super SAB, CG and QP is better than the corresponding part through BP algorithm under the condition that the number of neurons is 40 in hidden layer, the main reason is the of BP algorithm has some drawbacks such as slow convergence speed, tend to converge to local minimum points, appear false saturation phenomenon, not fully trained paralysis phenomenon etc, but Super SAB, CG, QP three algorithms can avoid the defects of BP algorithm.

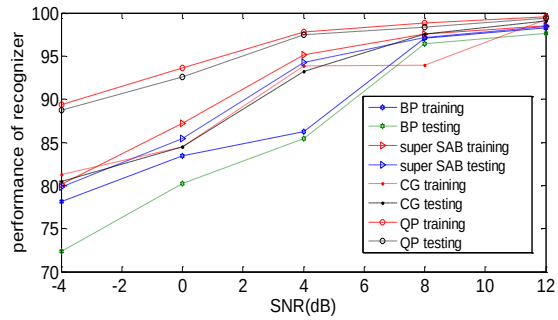

Fig. 2. The results of simulation test and classifier learning, through four different algorithms of BP, Super SAB, CG, QP when hidden layer cell number is 20

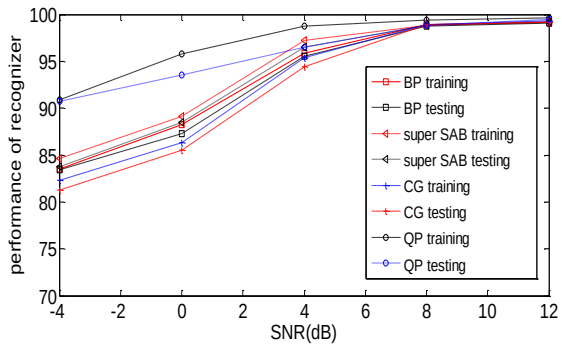

Fig. 3. The results of simulation test and classifier learning, through four different algorithms of BP, Super SAB, CG, QP when hidden layer cell number is 40

When the number of neurons is 40 in hidden layer as shown in Fig. 3, compared with the condition that the number of neurons are 20 in hidden layer, when MLP classifier is carried out training and testing, the recognition rate under only using Super SAB, QP algorithm is higher than that through the common BP algorithm while the result of using CG algorithm is lower than that through using BP algorithm. The main reason is that when the number of neurons in hidden layer reaches a certain number, the amount of information storage become greater in two-way transmission of each node. Due to the smaller storage capacity of CG algorithm, the learning speed is affected so the simulation result is consistent with theoretical analysis.

From Fig. 2 and Fig. 3, despite the number of neurons is 20 or 40 in hidden layer, the average correct

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recognition rate is the highest when MLP classifier is carried out training and testing through the QP algorithm because the learning speed of QP algorithm is the fastest in four kinds of algorithm, then Super SAB algorithm ranks second.

Fig. 4 shows the relationship between modulation average error recognition rate (BER) of 2PSK, 16QAM, 64QAM three kinds of signal and the different SNR through the way that the BP, Super SAB, CG, QP algorithm learn and train MLP classifier under condition of that the numbers of neurons is 20 in hidden layer and the combination characteristic parameters module of the input neural network extracted by BA algorithm is（$\gamma_{\max}$ σ_{of} σ_{op} M_{41} M_{61} M_{84} C_{61} C_{84} C_{80}）, This part is signal modulation recognition performance testing through the whole system. From Fig. 4, based on extracting combination eigenvalue module by BA algorithm, when using four different algorithms of QP, Super SAB, CG, BP respectively to train MLP neural network classifier, realize signal automatic identification, the recognition rate by QP algorithm is the highest, the recognition performance of Super SAB and CG algorithm is similar but they are less than the QP algorithm, but when the number of neurons in hidden layer is not very big, the number of neurons as shown in Fig. 4 is only 20, and the recognition rate of QP, Super SAB, CG three algorithms is higher than that of the conventional BP algorithm. When the number of neurons is larger such as 40, recognition rate through CG algorithm is slightly less than that through BP algorithm, especially under the condition of low signal-to-noise ratio. The analysis of the reason is same to that in Fig. 3.

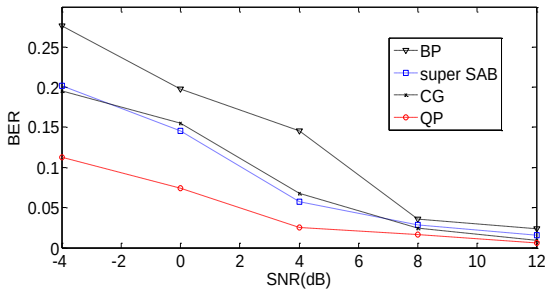

Fig. 4. Performance of modulation recognition through four algorithms

VI. Conclusion

In this paper, the extraction based on BP algorithm includes $\gamma_{\max}$, σ_{of}, σ_{op} and a combination eigenvalue module consisted of different numbers of high-order origin moment and high-order cumulants. On this basis, it is the first time that MLP neural network classifier is trained by three different algorithms of QP, Super SAB, and CG, which achieve the modulation recognition of the communication signals. Compared with the conventional BP algorithm, the simulation result presents that the modulation recognition rate of communication signals through MLP neural network classifier trained by three different algorithms of QP, Super SAB, CG is higher than that by conventional BP algorithm. When the number of neurons in hidden layer is 20 and the SNR is lower (e.g. 4dB), the average recognition rate through using these three algorithms is higher than 95%.

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