

An Optimized Neural Network Classifier for Automatic Modulation Recognition

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Abstract

Automatic modulation recognition which is one of the key technologies in no-cooperative communications has extensive application prospects in civilian and military fields. The design of classifier played a decisive role in recognition results. The classifier based on back propagation (BP) neural network is better in the existing methods. However, the traditional back propagation neural network (BPNN) has some well-known disadvantages. This study investigates the design of a classifier for recognition of six common digital modulations. This classifier based on BP neural network trained by improved particle swarm optimization (PSO) which is applied as a local search algorithm to find the optimal weights and thresholds of BPNN. The simulation experiment results demonstrate that the proposed classifier has higher recognition accuracy than other classifiers.

Keywords: modulation recognition, particle swarm optimization, inertia weight, neural network

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1. Introduction

Automatic modulation recognition is a technique that automatically reports modulation type of received signals. It has been considered as an intermediate step between signal detection and information recovery. Modulation recognition is extremely important in communication intelligence (COMINT) [1]. In COMINT, one needs to recognize the modulation scheme to demodulate the signal information content. Furthermore, classifying the right modulation type is helpful to choose an appropriate type of jamming to transmit. Automatic modulation recognition plays an important role in a variety of military and commercial applications and has received more and more significant scientific attentions in recent years. Signal modulation recognition is an interdisciplinary composed of signal extraction, signal processing, signal analysis, pattern recognition and so on. As the complex nature of the received signals, there are still many problems to be solved urgently-feature extraction and modulation classifier, for example.

Neural networks (NNs) have been successfully applied to a variety of classification tasks in industry, business and science [2]. Application includes product inspection, bankruptcy prediction, medical diagnosis, handwritten character recognition, modulation classification, etc. A large number of studies have been devoted to using multilayer perceptron (MLP) neural network as signal modulation recognizer. Nandi and Azzouz [3] first proposed MLP-based modulation neural network recognizer for digital modulation recognition. For the single hidden layer back propagation neural network recognizer, all types of six common digital modulations have been correctly classified with more than 93% success rate at the SNR of 10dB. However, as SNRs decreased below 10dB, the classification performance suffered. In [4, 5], both documents introduced Levenberg-Marquardt (L-M) algorithm to substitute BP algorithm in order to obtain a faster convergence speed. In [6], Chen mei et al. introduced a resilient back propagation algorithm to improve the speed of convergence and the performance of modulation recognition. Zhang songhua et al. [7] enhanced the recognition ability at low SNR by the combined classifier of genetic algorithm and back propagation neural network. Since genetic algorithm has three fundamental operations, the arithmetic of this combined classifier is complicated and consumes lots of time. BP neural network adopts gradient descent technology which affects the the global optimization ability and the modulation recognition rate.

This paper suggests a global search algorithm such as the particle swarm optimization algorithm to overcome the limitations of the gradient search technique. We demonstrate through this new modulation classifier optimized by improved particle swarm optimization (IPSO) to identify signal types of 2ASK, 4ASK, 2FSK, 4FSK, BPSK and QPSK. PSO has fast convergence and strong robustness and global search ability. The weights and thresholds of neural network are optimized by IPSO which can raise ANN's convergent efficiency and learning ability. Several experiments have been taken to compare the successful recognition rate of IPSO-BPNN classifier and SPSO-BPNN classifier. The simulation results showed a noticeable improvement. On the average, this classification accuracy exceeded 97.58% at signal to noise ratios ranging from 0dB to 20dB.

The overall structure of this paper is as follows. After the introduction, we present essential concept of back propagation neural network in Section 2. Section 3 describes PSO algorithm, including the standard particle swarm optimization (SPSO) and the improved particle swarm optimization (IPSO). A novel automatic modulation classifier of BP neural network trained by IPSO is presented in Section 4. Section 5 provides application of this new classifier in signal modulation recognition as well as simulation results and analysis of it. Finally, Section 6 concludes the paper.

2. The Proposed Algorithm of Optimized BPNN Based on IPSO

2.1. Back Propagation Neural Network

The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data [8]. Back propagation is currently the most widely used search technique for training NNs [9]. BP neural network relies on a gradient algorithm to obtain the weights of the model and uses back propagation algorithm to minimize the objective function. BPNN typically consists of three layers: an input layer, a hidden layer and an output layer. Figure 1 shows the architecture of a three-layer back propagation neural network.

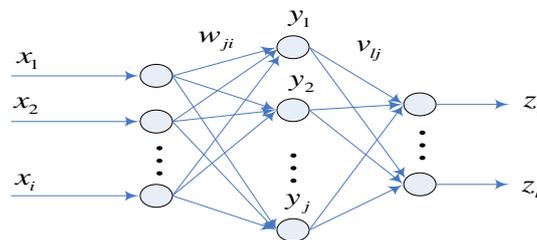


Figure 1. The Architecture of a Three-layer BPNN

The most fundamental processing elements called artificial neurons in BP network simulate the basic biological neurons. The summation function of a neuron will be performed as in Equation (1):

$$b_j = T \left(\sum_i r_{ji} a_i + \delta_j \right) \quad (1)$$

$$y_i = f \left(\sum_i w_{ji} x_i + \theta_j \right) \quad (2)$$

$$z_l = g \left(\sum_j v_{lj} y_i + \phi_l \right) \quad (3)$$

$$E = \frac{1}{2} \sum_i (t_i - z_i)^2 \quad (4)$$

Where b_j is the activation level of neuron j , T is the transfer function, r_{ji} is weight value, δ_j is bias. So the output of hidden layer and output layer described by the following equation (2) and (3). The error of output neuron is given by Equation (4).

Where x_i and z_i are the input and output signals. y_i is the output of the hidden layer. w_{ji} is the weight between input neuron j to hidden neuron i . v_{lj} is the weight between hidden neuron l to output neuron j . θ_j and ϕ_l are the biases for the hidden layer and output layer. f and g are transfer functions for hidden and output layers. t_l is the expected output. E is the error between the expected output and calculated output.

The main limitations of the BP algorithm are its slowness in convergence speed and its inability to escape local optima. Most frequently-used methods to improve upon the original BP focus on adding momentum values, changing learning rate and employing Levenberg-Marquardt algorithm. Because of the gradient nature of BP neural network, those limitations of BP can be eliminated by adopting global search techniques, such as particle swarm optimization.

2.2. Particle Swarm Optimization

Particle swarm optimization based on fish schooling and bird flocking have been introduced by Kennedy and Eberhart in 1995. This approach have highly attracted the interest of researchers and have been applied to solved optimization problems in different areas. Compared with other evolutionary algorithms, PSO has powerful global search strategy [10-11]. This search model is simple and easy to implement. In PSO algorithm, each particle which represents a potential solution dynamically adjusts its velocity and position according to the values of personal best and global best. $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ and $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ are represent the position and velocity of the i th particle. $pbest_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ is the local best parameter of a single particle. $gbest = (g_{11}, g_{12}, \dots, g_{1D})$ is the global best parameter of all the particles. Each particle's velocity and position parameter is updated as in the following Equation (5) and (6):

$$v_{iD}^{k+1} = \omega v_{iD}^k + c_1 r_1 (pbest_i^k - x_{iD}^k) + c_2 r_2 (gbest^k - x_{iD}^k) \quad (5)$$

$$x_{iD}^{k+1} = x_{iD}^k + v_{iD}^{k+1} \quad (6)$$

Where k is number of iteration. ω is the inertia weight. c_1 and c_2 are acceleration coefficients stand for self-learning factor and comparative learning factor. r_1 and r_2 are uniformly distributed random numbers range from 0 and 1. v_{iD}^{k+1} is the mean vector of v_{iD}^k , $pbest_i^k - x_{iD}^k$ and $gbest^k - x_{iD}^k$. Figure 2 shows one particle's movement track in two dimensions for one step.

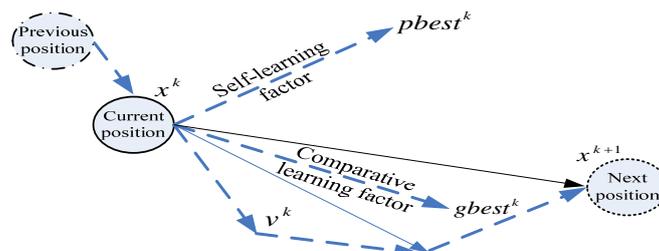


Figure 2. The Diagram of One Particle's Movement in Two Dimensions

In Figure 2, the self-learning factor and comparative learning factor adjusted the attractive force of personal best vector and global best vector towards the individual. Individual particle modify its movement decision by three factors: the inertia weight, the self-learning factor and the comparative learning factor. The particle pulled away from its previous position by the inertia weight. The self-learning factor pulled it toward its personal best position, meanwhile, the comparative learning factor pulled it toward the best position found by any particle in its neighborhood [12]. On average, this particle would move from current position to next position as marked by the black arrow. This algorithm has been successfully and widely applied in many areas such as function optimization, neural network training, task assignment, pattern recognition, fuzzy system control and other fields [13].

2.2.1. Standard Particle Swarm Optimization

When the inertia weight ω is large, the algorithm emphasizes global search, otherwise emphasizes local search. For the sake of balancing the global and local exploration abilities of PSO algorithm, Shi and Eberhart [14] proposed a linearly varying inertia weight ω . This ω is called Linearly decreasing weight (LDW). The varying scheme is described by the following Equation (7):

$$\omega = \omega_{\min} + \frac{(\omega_{\max} - \omega_{\min})t}{G} \quad (7)$$

Where ω_{\min} and ω_{\max} are minimal and maximal values of the inertia weight. t and G are the current iteration and maximum iteration number. The empirical studies in [12] indicated that the optimal solution can be improved by varying the value of ω from 0.9 at the beginning of the evolutionary process to 0.4 at the end of the evolutionary process for most problem. This inertia weight which varies with iteration can significantly heighten PSO's ability of approaching an optimal solution for a problem. This algorithm is generally called standard particle swarm optimization (SPSO).

2.2.2. Improved Particle Swarm Optimization

PSO algorithm adopted LDW often leads to the occurrence of two problems: the linear decreasing method reduces the speed of convergence in the early search stage; As ω decreasing linearly the algorithm is easy to fall into local optima in the later stage. In this research, we refer to [15]. The decreasing inertia weight which based on Gaussian function can heighten the PSO's ability of global search. The inertia weight performed as in Equation (8):

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \exp\left[-\frac{t^2}{(c \times G)^2}\right] \quad (8)$$

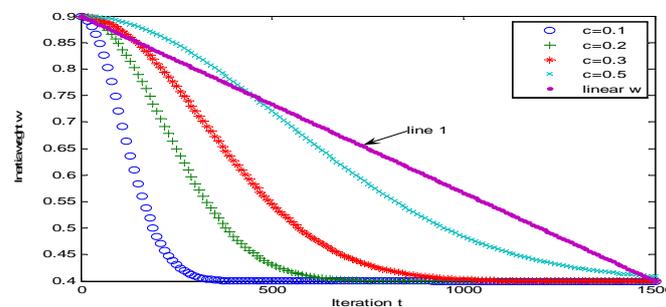


Figure 3. The Inertia Weight

Where c is a constant coefficient which can change variance ratio of ω . This modified PSO algorithm which obtained better search ability, convergence rate and computation efficiency than the SPSO utilized the distribution and locality property of Gaussian function to

adjust the inertia weight. As shown in Figure 3, line 1 stands for the linearly varying inertia weight and other lines represent the inertia weight based on Gaussian function when c is set as 0.1, 0.2, 0.3 and 0.5. In addition, the value of ω_{\min} and ω_{\max} is 0.4 and 0.9.

2.3. Optimized BPNN Based on IPSO

As a new evolutionary computation technique, particle swarm optimization is a non-gradient approach and is a very promising approach for training ANNs. Owing to the efficiency and adaptability of combination PSO and ANN, we explore a novel means of designing back propagation neural network trained with this IPSO algorithm. It has been proved that BPNN strongly lies on the choice of initial connection weights. So we use IPSO algorithm to determine BPNN's the weights and biases which were represented by each particle's position vector. Individual is evaluated by its fitness value in per iteration. And at last the best particle is considered to be the optimal solution to the weights. In the training process, the appropriate network connection weights and biases are adjusted by fitness evaluation as in Equation (9):

$$J = \frac{1}{2N} \sum_{i=1}^N \sum_{j=1}^C (Y_{ji} - y_{ji})^2 \quad (9)$$

Where C is the number of neurons in output layer. N is the number of training samples. y_{ji} is the output of in BPNN. Y_{ji} is the target output of BPNN.

The position vector of individual particle is shown in Figure 4. This position vector contains the weights and bases of BP neural network. w is the weights between input layer and hidden layer. v is the values of weight between hidden layer and output layer. θ and ϕ are the bases of hidden layer and output layer.



Figure 4. The Structure of Particle's Position Vector

The procedures for connection weights and biases which trained via the IPSO algorithm can be summarized as follows:

Step 1: Fix the topology structure of BP neural network and initialize parameters of PSO including the number of particles, inertia weight, acceleration constants and maximum velocity, etc;

Step 2: Set random location and velocity of individual particle. Each particle's position contains the weights and bases of BPNN;

Step 3: Calculate the fitness of individuals by training samples in Equation (9);

Step 4: For each particle compare the calculated fitness value with each particle's personal best. If current fitness is better, then update the personal best. Further, if current fitness is better than the global best, then reset it immediately;

Step 5: Update the position and velocity and inertia weight of each particle by Equation (5), (6) and (8);

Step 6: If sufficiently good fitness or predefined maximum number of generation is not satisfied, go to Step 3. Otherwise, the training ends. Then the best individual from particle swarm is chosen. Output a set of best connection weights and biases for BP neural network.

3. Research Method of Application in Automatic Modulation Recognition

3.1. Application Background

New classes of modulation recognition algorithms have been published in the literatures, since mid-1980s. Until now there are two main methods of the automatic modulation recognition. One is the decision theoretic approach and the other is the statistical pattern

recognition. The decision theoretic approach requires an optimal threshold for each selected feature. The selected features and the order of modulation recognition will directly affect the recognition rate. Therefore, there are some restrictions on the application of the decision theoretic approaches. The statistical pattern recognition system can be divided into three subsystems: the data preprocessing subsystem, the feature extraction subsystem and the classifier design subsystem. The first subsystem is to get data sampling, recovery of complex envelop through Hilbert transform, etc. The function of the second subsystem is to extract features which represent typical modulation characteristics from the intercepted signal. The function of the third subsystem is indicate the modulation pattern according to the extracted features. The modulation classifier can be implemented in many ways, e.g. artificial network, Fuzzy clustering, support vector machine, etc. After identified the modulation schemes, data demodulation, information extraction and signal exploitation can be followed at once. This paper advanced a new method of automatic modulation recognition based on the statistical pattern recognition

3.2. Recognition Model

The complete process of the proposed IPSO-BPNN modulation classifier is shown in Figure 5. The automatic modulation recognition includes two phases: the training phase and the testing phase. In the training phase, the weights and biases are updated once every training epoch by a batch training input and target output. When the fitness value is suitable, the BPNN's weights are calculated by the improved SPO algorithm as the initial value for the testing phase of BPNN.

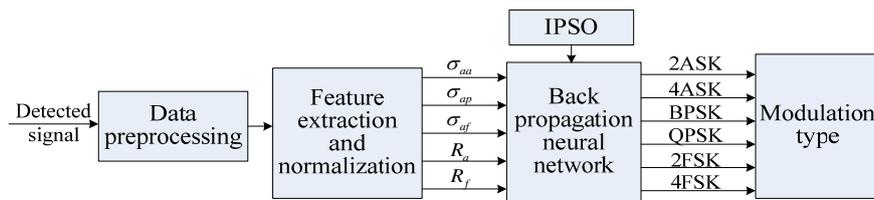


Figure 5. Proposed IPSO-BPNN Modulation Classifier

In Figure 5, data preprocessing includes data sampling, estimation of carrier frequency and recovery of complex envelope through Hilbert transform. There are five features taken into account in the process of feature extraction and normalization. Those features are extracted from the instantaneous amplitude, phase and frequency of the intercepted signal. They are σ_{aa} , σ_{ap} , σ_{af} , R_a and R_f . First three key features were used in [16], and the other is referred to [17]. According to these five kinds of selected features, six commonly used digital signals can be classified by the following decision tree as in Figure 6:

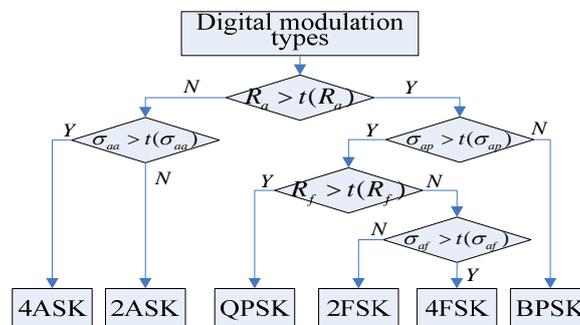


Figure 6. Decision Tree for Modulation Recognition

After the input features are chosen, we need to normalize the extracted features before feeding them into the BP recognizer for training and testing. The features are normalized to ensure that they are zero mean and unit variance [18]. Equation (10) shows the normalization of the features:

$$f_i' = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}} \quad (10)$$

Where f_i is i th feature. f_i' is the normalized feature of f_i . f_{\max} and f_{\min} are the maximum and minimum values of f_i . The five key features extracted from the incoming signal are normalized and rescaled in a range between [0,1]. This preprocessing is done to make the training of network more efficient and improve the performance of neural network classifier [19]

2. Experimental Results and Discussion

The recognition performance of this proposed classifier is investigated with six digital modulation schemes. The carrier frequency, symbol rate and sampling frequency are respectively 150KHz, 10kbit/s and 1200KHz. The noise environment is AWGN, and the range of SNR is chosen from 0 to 20dB with 5dB interval. In [20], an adaptive optimization of wavelet threshold de-noising method is represented to eliminate the noises in signals' instantaneous information. This method is also used in our study to enhance the recognition rate.

The IPSO-BPNN classifier has five input nodes and six output nodes corresponding to the five normalized features and six schemes of digital signals to recognize. We need to determine the number of neurons in hidden layer manually at this stage. The structure of BPNN which is 5-10-6 based on structure given in [3]. This article demonstrated that this structure performed better than other various structures at different SNRs. We use tan-sigmoid activation function in hidden layer and log-sigmoid activation function in output layer. The parameters of the IPSO algorithm need to be defined before the experiments. The population size is 30, the minimum and maximum inertia weight is 0.4 and 0.9. The number of iterations equal to 1500.

The constant coefficient c is 0.2, c_1 and c_2 equal to 2. This IPSO-BPNN classifier was trained using 400 samples for each of six modulation types. A separate set of 400 samples were used as testing set for each digital schemes.

4.1. Experimental Results

Six modulation types have been simulated at 5dB and 10dB in Table1 and Table 2. Each of modulation type at each SNR was simulated 400 times. From Table 1, at 5dB SNR, the IPSO-BPNN recognizer can show up to 99.25% accuracy, except the recognition of 2FSK and 4FSK. The correct classification rate of 2FSK and 4FSK is lower but is still above 96.75%. It can be observed from Table 2 that six modulation types have been correctly classified with more than 97.5% success rate at 10 dB SNR.

Table 3 is shown an accuracy comparison between SPSO-BPNN recognizer and IPSO-BPNN recognizer through training and testing performance with different SNRs. Under the same conditions and configuration, the performances of SPOS-BPNN classifier and IPSO-BPNN classifier are generally good even with low SNR values.

Table 1. The Performance of IPSO-BPNN Recognizer at SNR=5dB

Simulated modulation type	Deduced modulation type					
	2ASK	4ASK	BPSK	QPSK	2FSK	4FSK
2ASK	99.25%	0.75%				
4ASK	1%	99%				
BPSK			100%			
QPSK				100%		
2FSK					98%	2%
4FSK					3.25%	96.75%

But the IPSO-BPNN recognizer performs better in the training and testing processes. For example at 0dB SNR, the testing performance of IPSO-BPNN is over 97.85%, while the testing performance of SPSO-BPNN is over 96.88%.

Table 2. The Performance of IPSO-BPNN Recognizer at SNR=10dB

Simulated modulation type	Deduced modulation type					
	2ASK	4ASK	BPSK	QPSK	2FSK	4FSK
2ASK	99.5%	0.5%				
4ASK	0.25%	99.75%				
BPSK			100%			
QPSK				100%		
2FSK					99.75%	0.25%
4FSK					2.5%	97.5%

Table 3. The Performance of IPSO-BPNN and SPOS-BPNN at Different SNR Values

SNR (dB)	SPSO-BPNN recognizer		IPSO-BPNN recognizer	
	Training perf. (%)	Testing perf. (%)	Training perf. (%)	Testing perf. (%)
0	97.5%	96.88%	97.92%	97.58%
5	98.83%	98.46%	99.17%	98.83%
10	99.46%	99.21%	99.58%	99.42%
15	99.79%	99.71%	99.88%	99.92%
20	99.83%	99.88%	100%	99.96%

The results shown in Figure 7 illustrate the correct recognition of six modulation types by IPSO-BPNN classifier. It is clear that the correct recognition rate has increased with SNRs increasing. At the SNR of 15dB and 20dB, five of these six modulation types have been successfully classified every time and the classification accuracy is 100%. Excluding 4FSK, the identification of this modulation type is a bit lower than other signal types at various SNRs. The average recognition rate is 97.58% for signal-to-noise ratio of 0dB. This indicated that the use of the IPSO-BPNN recognizer to classify six modulation types achieves satisfactory performance and is feasible.

Finally, a comparison was made with recognition results gained with BP, SPSO-BP, IPSO-BP neural network and decision tree (DT) recognizer using the same extracted features for classifying six digital modulation types. The DT classifier which was shown in Fig. 6 requires the optimal threshold values. As in Figure 8, we can see that the IPSO-BPNN recognizer consistently outperforms the other three recognizers for all SNRs. Even as low as at SNR of 0dB, the average recognition rate of this new classifier is over 97.58%.

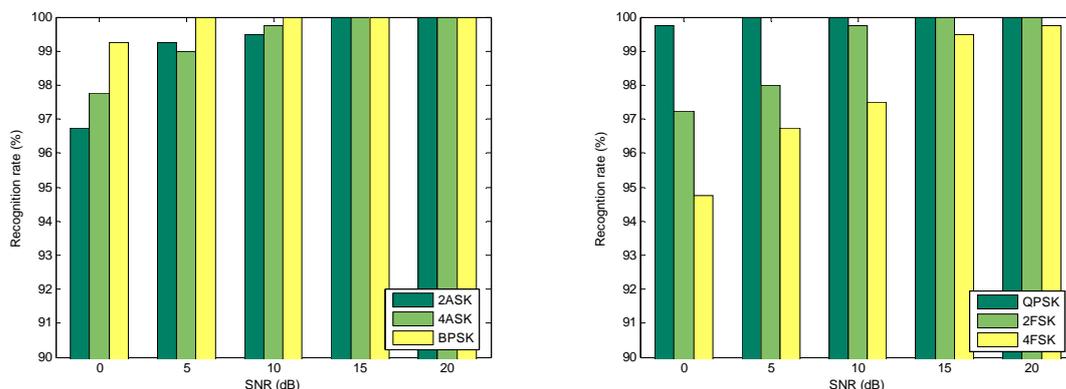


Figure 7. The Correct Recognition of 2ASK,4ASK, BPSK, QPSK, 2FSK and 4FSK at Various SNR Values

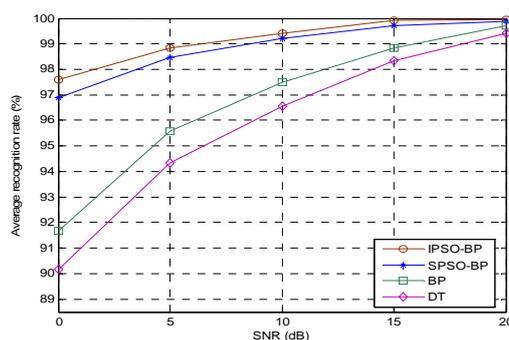


Figure 8. Performance Comparison of Average Recognition Rate

4.2. Discussion

Because the directed comparison with other works is difficult in modulation classifier [18]. First, there are no standard digital modulation database. Second, the parameters of each digital modulation is not exactly the same in various literature. Third, different extraction of features will lead to different performance of identification. In [3], Azzouz report over 93% correct recognition rate of over 10dB. But if SNR is less than 10dB, the performance of BP-based classifier drops. In [7], the GA-BP classifier achieves 97%, 96% and 99% accuracy for 2ASK, 2FSK and 2PSK at 5dB. However the GA-BP classifier is more complicated and consumes more training time than IPSO-BP classifier. The IPSO-BP classifier proposed in this work shows a higher recognition rate with SNR ranging from 0dB to 20dB. And the average recognition rate is about 99.17%. From the comparison, it is obvious that IPSO-BP classifier is capable of identifying six digital modulation types with low SNR values.

5. Conclusion

In recent years, automatic modulation recognition has been widely used in military and commercial applications. This technique is one of the most promising research area and has received much interest. In this research, a novel automatic modulation recognizer which identified six digital signals with five input features by training back propagation neural network with improved particle swarm optimization is proposed. Simulations and the experimental tests show that the proposed recognizer achieves about 94.75% recognition performance at the SNR of 0dB. Compared with other three classifiers, we proved that the performance of the proposed classifier is superior to those classifiers at signal to noise ratios ranging from 0dB to 20dB. So, this recognizer is found to be effective in separating the commonly used digital signals. And this classifier algorithm is computationally simple. Further work is needed to separate more groups of analog and digital signals with appropriate features. How to extend this method with signals corrupted by different noise and by the channel distortion is another interesting aspect.

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References

- [1] Nandi AK, Azzouz EE. Automatic analogue modulation recognition. *Signal Processing*. 1995; 46(2): 211-222.
- [2] Guo Qiang, Peter Zhang. Neural networks for classification: a survey. *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Application and Reviews*. 2000; 30(4): 451-462.
- [3] Azzouz EE, Nandi AK. Automatic modulation recognition of communication signals. The Netherlands: Kluwer Academic Publishers. 1996: 147-148.
- [4] Zhao zhijing, Zhuang chanfei, Gan Li. Classifier of Modulation types using BP neural network. *Modern Rader*. 2003; 25(10): 22-24.

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- [5] Li junjun, Lu mingquan, Feng zhenming. Modified automatic digital modulation recognition algorithm. *Systems Engineering and Electronics*. 2005; 27(12): 2023-2024.
- [6] Chen mei, Zhu qi. Research on automatic recognition based on improved neural network. *Journal of Chongqing University of Post and Telecommunications (natural science edition)*. 2009; 21(6): 764-770.
- [7] Zhang Songhua, He yigang. Research on modulation classification methods of RFID at low SNR. *Application of Electronic Technique*. 2010; 4: 111-114.
- [8] Anil K Jain, Robert PW. Duijn, Jiangchang Mao. Statistical pattern recognition: A review. *IEEE transaction on pattern analysis and machine intelligence*. 2000; 22(1): 4-37.
- [9] Randall S Sexton, Robert E Dorsey. Reliable classification using neural networks: a genetic algorithm and backpropagation comparison. *Decision Support Systems*. 2000; 30(1): 11-22.
- [10] Reza Firsandaya Malik, Tharek Abdul Rahman, Razali Ngah, Siti Zaiton Mohd. Hashim. The new multipoint relays selection in OLSR using particle swarm optimization. *TELKOMNIKA*. 2012; 10(2):343-352.
- [11] Andi Muhammad Ilyas, M Natsir Rahman. Economic dispatch thermal generator using modified improved particle swarm optimization. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(3): 459-470.
- [12] M Conforth, Y Meng. Reinforcement learning using swarm intelligence-trained neural networks. *Journal of Experimental & Theoretical Artificial Intelligence*. 2010; 22(3): 197-218.
- [13] Jianxia Chang, Xiaoyuan Xu. *Applying neural network with particle swarm optimization for energy requirement prediction*. Proceedings of the 7th World Congress on Intelligent Control and Automation. Chongqing. 2008: 6161-6163.
- [14] Y Shi, RC Eberhart. *Empirical study of particle swarm optimization*. Proceedings of IEEE Congress on Evolutionary Computation. Washington. 1999: 101-106.
- [15] Zhang Xun, Wang Pin, Xing Jianchun, Yang qiliang. *Particle swarm optimization algorithms with decreasing inertia weight based on Gaussian function*. Application Research of Computers. 2012; 29(10): 3710-3712.
- [16] EE Azzouz, AK Nandi. *Automatic identification of digital modulation types*. Signal Processing. 1995; 47(1): 55-69.
- [17] Tan xiaoheng, Liu juan, Hu youqiang. New algorithm for digital modulation recognition under low SNR. *Systems Engineering and Electronics*. 2009; 31(6): 1520-1524.
- [18] MLD Wong, AK Nandi. *Automatic digital modulation recognition using artificial neural network and genetic algorithm*. Signal processing. 2004; 84(2): 351-365.
- [19] Ganesh Arulampalam, Vis Ramakonar. *Classification of digital modulation schemes using neural networks*. Proceedings of the 5th International Symposium on Signal Processing and its Applications. Brisbane. 1999: 649-652.
- [20] T Yujing, Z Hongwei. Optimization threshold algorithm of wavelet de-noising. *Technical Acoustic*. 2009; 28(4): 503-506.