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Particle Swarm Optimization-Based Deep Neural Network for Digital Modulation Recognition

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ABSTRACT Modulation recognition is a major task in many wireless communication systems including cognitive radio and signal reconnaissance. The diversification of modulation schemes and the increased complexity of the channel environment put higher requirements on the correct identification of modulated signals. Deep learning (DL) is considered as a potential solution to solve these problems due to the superior big data processing and classification capabilities. This paper proposes an efficient digital modulation recognition method based on deep neural network (DNN) model. Furthermore, we present the particle swarm optimization (PSO) algorithm to optimize the number of hidden layer nodes of the DNN so as to solve the problem that the traditional DNN is trapped in local minimum values and the number of hidden layer nodes needs selecting manually. In this paper, we utilize the proposed PSO-DNN method to learn characteristics extracted from the modulated signal added by additive white Gaussian noise (AWGN) and to train the network, which can improve the performance of recognition under the condition of low signal-to-noise ratio (SNR). The experimental results demonstrate that the recognition rate on this algorithm has improved by 9.4% and 8.8% compared with methods that adopt conventional DNN and support vector machine (SVM) when SNR equals 0 and 1 dB, respectively. Besides, another experiment compared with the genetic algorithm (GA) also proves that our proposed algorithm is more effective in optimizing the DNN. The proposed method is easy to be implemented so that it has a broad development prospect in modulation recognition.

INDEX TERMS Additive white Gaussian noise, deep neural network, digital modulation recognition, particle swarm optimization algorithm.

I. INTRODUCTION

In wireless communications, modulation recognition is a kind of technology which can realize smart reception, processing, and classification of modulated signals. It plays an important role in intelligent control for civilian purpose and signals monitoring for military purpose under the scenario that the receiver does not know the modulation format the sender used [1], [2]. Besides, it is also a basic problem for spectrum sensing in cognitive radios [3]. As the interference of multiple noises complicates the channel conditions and the number of the transmitted signals are becoming much bigger, precise recognition of various modulations at low SNR becomes more challenging.

The traditional solution to recognize the digital modulation patterns is feature based (FB) method, since its theoretical basis is simple and the near-optimal performance can be achieved when designed properly [4]. The FB technique extracts certain features from the modulated signals and a decision is made based on the separation of the received characteristics by the classifier. Guo *et al.* [5] proposed to identify a variety of modulation modes based on the high-order cumulants feature of the signal, which can suppress Gaussian white noise well. Bing [6] adopted the idea of a combination of wavelet and RBF neural network to recognize 4 kinds of digital signals and the experimental results realized high accuracy for each modulation method. Another

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recognition method based on instantaneous statistical characteristics of modulated signals and the SVM classifier can distinguish 8 traditional types of modulation [7]. Although the FB solution has low complexity and easy to implement, it is less effective with the increase of the modulation types. Therefore, the researchers have made great efforts to seek a robust and useful method to improve the performance of classification.

The Deep Learning (DL) method has developed rapidly in recent years because of the superior capability of big data processing and classification, which has certain applications in the field of communication [8], including modulation recognition. DL can combine with the initial simple features to discover more complex features automatically through multiple nonlinear transformations. Research in [9] presented the method based on the combination of FB method and DNN and brought dramatic performance improvement for Doppler fading channels. In [10] and [11], a variety of modulated signals were converted into constellation forms or waveforms and used as the input of the CNN classifier without further features extraction procedure, which also obtained good classification results. The authors in [12] studied feature learning and automatic modulation classification (AMC) under different DL models and concluded that the DNN model with double hidden layers performs best and has 3.2% promotion compared with other algorithms. However, the problem of low recognition rate of the above methods at low SNR has not been effectively solved and the parameters of the DL model require to be determined artificially to find the optimal result. In view of this, integrating feature fusion with model optimization can provide a new idea for modulation recognition.

In this research, we propose a novel method in the scenario of multiple modulation signal recognition in wireless communications, which applied the technique of signal preprocessing and the improved DNN model. Our method can identify 6 kinds of modulated signals which include Phase Shift Keying (BPSK, QPSK, 8PSK) and higher-level Quadrature Amplitude Modulation (16QAM, 64QAM, 256QAM). In our proposed scheme, various features extracted from the modulation signals are learned through the training of DNN so that the modulation modes can be classified more accurately. Moreover, PSO algorithm is utilized to correct the defects in the DNN structure effectively. The main contributions of this paper are summarized in three parts as follows.

- We introduce a novel PSO optimization scheme to improve the structure of DNN to obtain the global optimal number of hidden layer nodes, thus obtaining the optimal accuracy under the condition of low SNR in a modulation recognition system. To the best of our knowledge, this is the first attempt to apply PSO-DNN algorithm to the field of digital modulation recognition, which is a crucial application either in civil or military fields.
- The performance of the proposed method is evaluated in this paper. Simulation results demonstrate that the recognition rate versus different SNR is greatly improved by our scheme compared with the other two conventional recognition methods. In addition, we conduct comparative simulations that utilize another optimization method to optimize DNN. Simulations also prove that our proposed method has a faster convergence speed. Therefore we confirm that the PSO-DNN recognition algorithm is robust and effective.
- We conduct the detailed and extensive experiments and comparative analyses that contain the overall recognition rate comparison and the verification of the effect of particle number on recognition rate. The parameters that provide the best performance are then used in the proposed design.

The rest of this article is arranged as follows: Section II outlines the preprocessing step including the digital modulation and the features engineering used in our system. In Section III the principles of optimizing DNN by using PSO is to be submitted. After that, the proposed PSO-DNN, the conventional DNN and the SVM method are tested versus SNR in Section IV, followed by simulation results and comparative analyses. Finally, the conclusion is given in Section V.

II. DATA PREPROCESSING

The basic content and processing of various digital modulated signals are firstly researched in this paper, which is depicted in Fig. 1. This framework mainly consists of two parts which are digital signal modulation and features engineering component, and the overall framework is described in detail below.

In the first part, our selection of the digital modulation schemes for recognition in this paper is based on the existing communication technologies. The OFDM systems and the wireless LAN standard use a variety of different PSKs depending on the data rate required [12]. In order to achieve higher spectrum utilization, the communication systems employ high dense MQAM constellations which provide better transmission performance. Thus, we choose the following schemes to modulate the raw data: BPSK, QPSK, 8PSK, 16QAM, 64QAM, and 256QAM.

The second part is crucial because the extracted features can provide more accurate signal information for DNN to improve the recognition accuracy of various modulation modes. Each modulated signal sample with added noise first undergoes dimensionality reduction, which is the process of 12 features extraction, to decrease the time cost and maintain the same length of each sample. Then we need to normalize the eigenvectors according to the input criterion of DNN. After the above preprocessing, the data will be sorted on the basis of different recognition labels.

A. DIGITAL MODULATION MODEL

The receiver always receives the signal polluted by noise in practice, so the expression of the complex baseband signal is

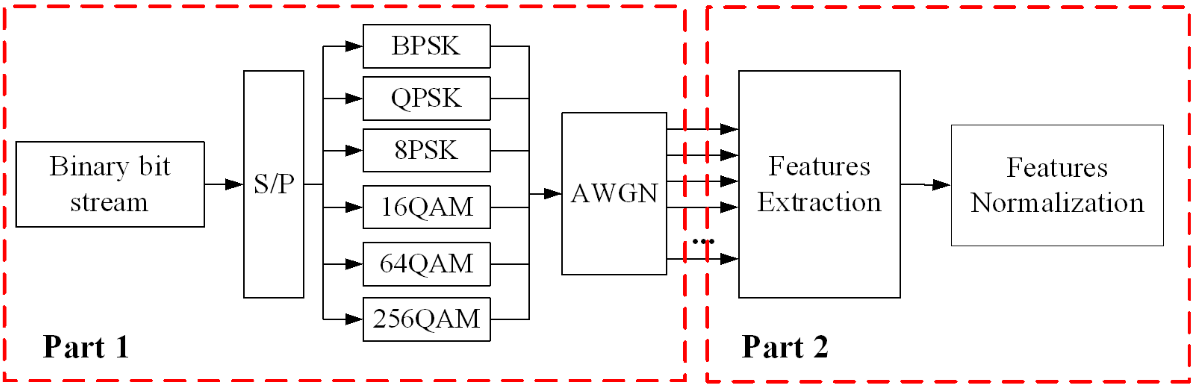

FIGURE 1. The framework of data preprocessing.

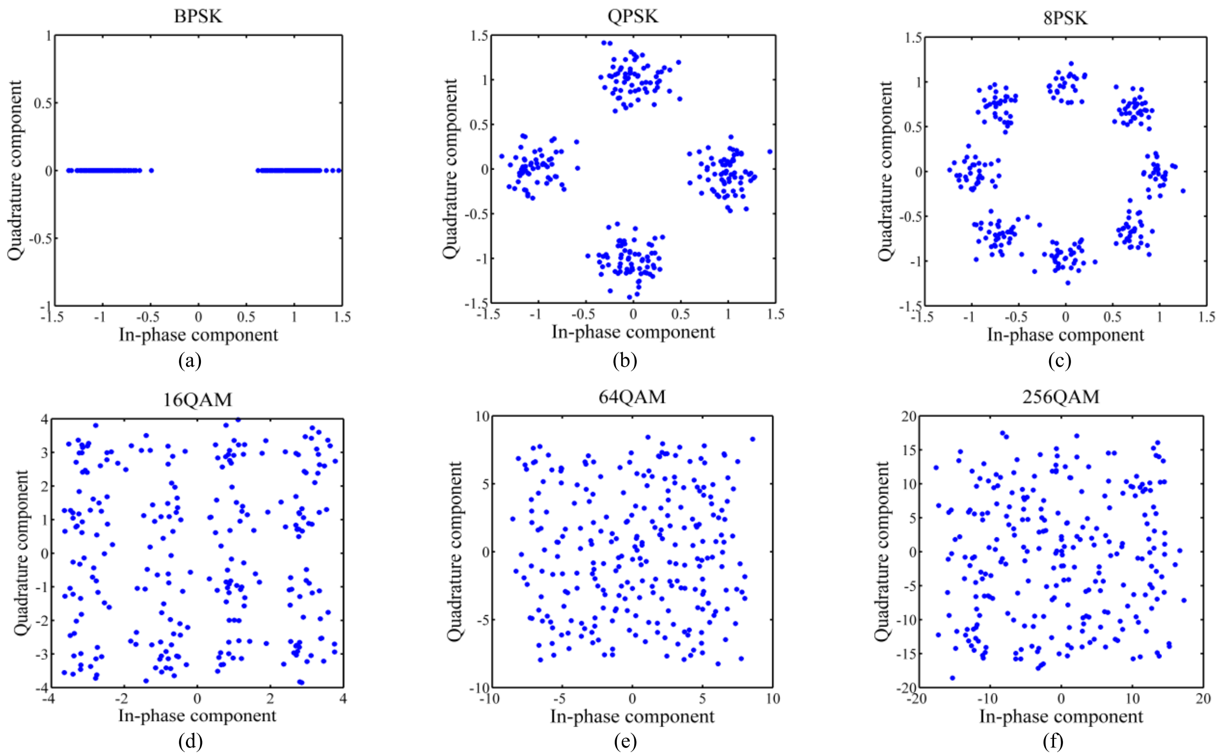

FIGURE 2. The constellation diagram of different modulations at SNR = 10dB. (a) BPSK, (b) QPSK, (c) 8PSK, (d) 16QAM, (e) 64QAM, and (f) 256QAM.

as follows:

$$\begin{aligned} s(t) &= x(t) + n(t) \\ &= \sum_n a_n \sqrt{E} p(t - nT_s) e^{j(2\pi f_c t + \theta_c)} + n(t) \end{aligned} \tag{1}$$

where $s(t)$ is the received modulated signal, $x(t)$ depends on the modulation mode, E maps the energy of the signal and $p(t)$ is the finite energy signal with a T_s duration, $n = 1, 2 \ldots, \mathrm{N}$, N represents the length of the transmitted binary symbol sequence, the carrier frequency and phase are defined as f_c and θ_c respectively, $n(t)$ equals the AWGN with zero means, which is independent of $x(t)$. Meanwhile, the SNR is written as

$$SNR = 10log_{10}\frac{S^2}{N^2} \tag{2}$$

where S and N are corresponding to the effective power of signal and noise. The constellation diagram of the 6 modulated signals is interfered by AWGN at SNR = 10dB as denoted in Fig. 2. In order to make a fair comparison with traditional methods, we assume that the timing error has been recovered at the receiver. According to the principle of digital signal modulation and the mapping relationship of the constellation diagram, the two symbol sequence a_n in the

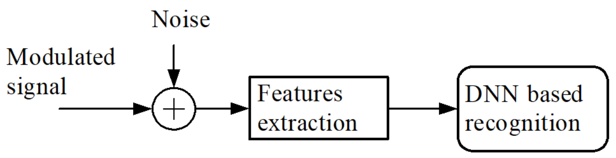

FIGURE 3. Features extraction based recognition framework.

above formula can be expressed as follows:

$$a_{MPSK} = e^{\frac{j2\pi(n-1)}{N}} \tag{3}$$

$$a_{MQAM} = I_n + jQ_n = \sqrt{I_n^2 + Q_n^2} * e^{j\varphi_n} \tag{4}$$

where a_{MPSK} and a_{MQAM} are PSK and QAM modulated symbol sequence respectively, I_n and Q_n map the value of in-phase component and quadrature component respectively, φ_n is the phase of the complex data in the polar coordinate system, i.e. $arctan(Q_n/I_n)$.

B. FEATURE ENGINEERING

Feature engineering is the process of extracting, combining and manipulating features by using a number of expert knowledge to obtain representative information of the signals in the field of communication [13]. The FB recognition framework is comprised of two subsystems which are features extraction and recognition system, as shown in Fig. 3.

For simple computations, the distinct features are exhibiting as sufficient separation of each modulation class at different SNR as possible on the one hand, and as better noise suppression as possible on the other hand. The high-order cumulant features greater than the second-order remains zero for any zero-mean Gaussian stochastic process, thus utilizing these features to reduce the influence of noise on the signal and dimensionality of the data. Furthermore, among many features available, we append four signal characteristics to the basis of high-order cumulant values. These four features sufficiently exhibit good separation of each modulation method and successfully train the DNN structure to achieve higher recognition accuracy versus different SNR.

The first feature is the ratio of in-phase component and quadrature component signal power [9]

$$\beta = \frac{\sum_m a_Q^2(m)}{\sum_m a_I^2(m)} \tag{5}$$

where $a_I(m)$ and $a_Q(m)$ are the in-phase and quadrature component for the complex baseband signal. The second feature is the standard deviation of the absolute value of normalized signal amplitude in (6), as shown at the bottom of this page, where $a(m)$ is the complex point formed after the signal is modulated, i.e. $a_I(m) + ja_Q(m)$, and M is the number of sampling points for $a_v(m)$. The main value of the signal magnitude χ is defined as

$$\chi = \frac{1}{M}\sum_{m=1}^{M} |a(m)| \tag{7}$$

Similarly, the normalized square root value of amplitude summation of signal χ_2 can be written as

$$\chi_2 = \frac{1}{M}\sqrt{\sum_{m=1}^{M} |a(m)|} \tag{8}$$

The next feature is hybrid order moments v_{20}, which can be expressed as

$$v_{20} = \frac{M_{4,2}(y)}{M_{2,1}^2(y)} = \frac{E[|a(n)|^4]}{E[|a(n)|^2]} \tag{9}$$

where $M_{\mathrm{p+q,p}}(y)$ denotes $E[a(m)^p a(m)^{*q}]$, $a(m)$ and $a(m)^*$ are mutually conjugated. The remaining features are the high-order cumulants of the modulated signal with the equations below:

$$C_{20} = \mathrm{Cum}\,(a(m), a(m)) = E[a(m)^2] \tag{10}$$

$$C_{21} = Cum\left(a(m), a(m)^*\right) = E[|a(m)|^2] \tag{11}$$

$$C_{40} = Cum\,(a(n), a(n), a(n), a(n)) = M_{40} - 3M_{20}{}^2 \tag{12}$$

$$C_{41} = \mathrm{Cum}\left(a(m), a(m), a(m), a(m)^*\right) = M_{41} - 3M_{20}M_{21} \tag{13}$$

$$C_{42} = M_{42} - |M_{20}|^2 - 2M_{21}{}^2 \tag{14}$$

$$C_{63} = M_{63} + 18M_{20}{}^2 M_{21} - 6M_{20}M_{40} - 9M_{42}M_{21} + 12M_{21}{}^3 \tag{15}$$

$$C_{80} = M_{80} - 35M_{40}{}^2 - 28M_{60}M_{20} + 420M_{40} - 630M_{20}{}^4 \tag{16}$$

Normalization transforms the eigenvalues of data samples into the same dimension, which maps the data between 0 and 1. Meanwhile, normalizing the data can make the weight of each feature dimension consistent with the objective function and improve the convergence speed of the iterative solution. Therefore, the maximum and minimum normalization method is applied to scale the features vector equally and can be calculated by:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{17}$$

$$\begin{aligned} \sigma_v &= \sqrt{\frac{1}{M}\sum_{m=1}^{M} a_v^2(m) - \frac{1}{M}(\sum_{m=1}^{M} |a_v(m)|)^2} \\ &= \sqrt{\frac{1}{M}\sum_{m=1}^{M}(\sqrt{\frac{a(m)}{var(a(m))}} - 1)^2 - \frac{1}{M}(\sum_{m=1}^{M}|\sqrt{\frac{a(m)}{var(a(m))}} - 1|)^2} \end{aligned} \tag{6}$$

where X_{norm} is the normalized data, X maps the original feature value, X_{max} and X_{min} are the maximum and minimum values of each feature vector, respectively. It is also worthwhile to mention here that these characteristics possess good drop resistance performance, so this technique can be applied to the case of channel fading and noise interference in practice.

III. PROPOSED PSO-DNN MODEL FOR MODULATION RECOGNITION

Inspired by using PSO to optimize the parameters of DL model [14] and improve the performance of CNN [15], this section presents a deep neural network based on PSO for modulation recognition application in future wireless communications, which are expected to handle the existing problems of DNN and low recognition rate in the increasingly complex channel environments with dynamic changes. At first, we briefly introduce the basic content of the PSO algorithm. Then the training progress of DNN is described. The last part presents the specified steps of our proposed method, which is the most important part of the whole article.

A. ALGORITHM OF PARTICLE SWARM OPTIMIZATION

The PSO algorithm, also known as the flock foraging algorithm, is an evolutionary method developed by J. Kennedy and R. C. Eberhart [16]. It first generates a random solution and then finds the optimal solution with the best fitness value iteratively. This kind of algorithm has been widely applied to the Back Propagation (BP) neural network because of the advantages of easy implementation, high precision and fast convergence. Moreover, it has demonstrated superiority in solving practical problems [17], [18] and been initially applied in the field of DL [14], [15], [19].

The basic form of the PSO algorithm consists of a group of particles which communicate with each other to reach the best place repeatedly. To optimize the problem, the method updates the position, velocity and fitness value of each particle that are determined by mathematical equations. Particles' position represents the candidate solution to the problem sought and is recorded as the individual best solution p_{ibest}. The changing of position is influenced by its individual best fitness value p_{fit}, which is the smallest reached value in previous iterations, and guided toward global best position g_{best} corresponding to the global fitness value g_{fit} among all results in the entire space.

The PSO algorithm can be expressed as the following equations:

$$V_i[k+1] = wV_i[k] + c_1 rand_1 (p_{ibest} - P_i(k)) + c_2 rand_2 (g_{best} - P_i(k)) \quad (18)$$

$$P_i(k+1) = P_i(k) + V_i[k+1] \quad (19)$$

where w is the inertia weight that helps the particles move through the interior to a better position, c_i represent the constants and $rand_i$ are the uniform random value, the position vector and velocity vector of the i-th particle are $P_i(k)$ and $V_i(k)$ respectively at the k-th iteration and the $P_i(k)$ is updated by $V_i(k+1)$.

B. DEEP NEURAL NETWORK MODEL

DL is the foundation of many modern Artificial Intelligence (AI) applications, which consists of multiple hidden layers and neural nodes. At present, it has been wildly utilized in image recognition [20]–[22], voice processing [23], [24], etc., and some progress in communication has been achieved [25]–[27].

Modulation recognition of digital signals has gradually changed from the traditional method to DNN method with the rapid development of DL. This new method can also be regarded as a learning concept from "learning the system model" to "learning the signal features". In fact, the process of treating DNN as a classifier can be seen as a combination of signal features and Machine Learning (ML). The input of DNN, also named as the training example, is a multidimensional data vector presented in the visible layer. Then each hidden layers perform a series of non-linear transformations that can be defined as follows:

$$Y = sig(W * A + b) \quad (20)$$

where A is the input of each neural node, W and b equal the encoding weight matrices and bias vector respectively, sig is denoted as sigmoid activation function, i.e. $1/(1+e^{-x})$. We have adopted the Stochastic Gradient Descent (SGD) method for training the hidden layers and used Mean Square Error (MSE) function to calculate the output error that is given as follows:

$$E_{out} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\sum\nolimits_{j=1}^{J}(A'_{ji} - A_{ji})^2 + \lambda * \Omega_{weight} \quad (21)$$

where A'_{ji} is the actual output after a series of operations, λ maps the coefficient for the L_2 regularization and Ω_{weight} is applied to the weights of the cost function and can be written as:

$$\Omega_{weight} = \frac{1}{2}\sum\nolimits_{k}^{L}\sum\nolimits_{j}^{Z}\sum\nolimits_{i}^{M}(W_{ji}^{(k)})^2 \quad (22)$$

where L and M are the number of hidden layers and the number of input variables respectively. After training the DNN model, the test data will be fed into this model for prediction and converted to the recognition accuracy at the output.

Nevertheless, the DNN model is a black box that cannot be observed how it works and the characteristics it learns cannot be observed neither, which leads to a series of problems. Therefore, we use PSO algorithm as the solution to the problem that the DNN is easy to fall into the local minimum value and the number of hidden layer nodes is not fixed, thereby improving the accuracy of modulation recognition.

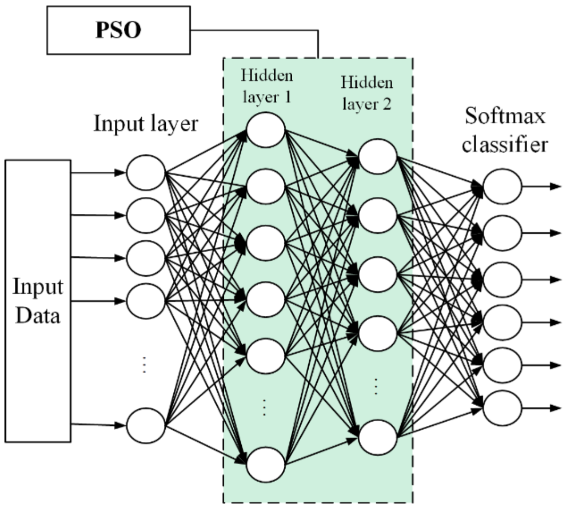

FIGURE 4. The proposed PSO-DNN model.

C. MODULATION RECOGNITION BASED ON PSO-DNN

After training the DNN, the modulation recognition is executed by using a combination of PSO algorithm and DNN architecture in our proposed method, as shown in Fig. 4. The normalized feature vector is utilized as the input of the network model. Then, the number of double hidden layer nodes of the DNN is automatically tuned by using the global optimization capability of the PSO algorithm to obtain the optimal number of nodes and to improve recognition accuracy, based on observing the MSE achieved. In order to have a better observation of the recognition results, we add Softmax function to normalize the output layer to get the final recognition rate $\hat{y}$ of each output node that can be expressed as:

$$\hat{y}^i = \mathrm{P}(\mathrm{y} = \mathrm{i}|\mathrm{out}) = \frac{e^{out^i}}{\sum_{i=1}^{6} e^{out^i}} \tag{23}$$

where $\hat{y} = [\hat{y}^1, \hat{y}^2, \hat{y}^3, \hat{y}^4, \hat{y}^5, \hat{y}^6]^T$, which equal BPSK, QPSK, 8PSK, 16QAM, 64QAM and 256QAM respectively, out^i represents the i-th element of the output vector out. Finally, the modulation modes are classified, which are corresponding to the maximum $\hat{y}$, based on the distinction of features by using the PSO-DNN algorithm.

Here, we generate α sets of data, which are the number of particles in a swarm. The individual best fitness value p_{fit} and global best fitness value g_{fit} represent the minimum recognition error corresponding to the optimal number of nodes in i.th group and the whole group, respectively. Similarly, the individual best value p_{ibest} and global best value g_{best} represent the optimal number of nodes in i.th group and the whole group, respectively. The algorithm is organized as follows:

Step 1: Randomly initialize the α group of double hidden layer nodes and put them into P whose size is $\alpha \times 2$, and initialize fine-tuning parameter V. Using P to train the DNN and calculate the initial fitness value of each particle $p_{fit}(i)$. Select g_{fit} and g_{best} from P.

Step 2: Adjust P by using the fine-tuning parameter V with the following equations

$$\begin{aligned} V_i &= wV_{i-1} + c_1 rand_1 (p_{ibest} - P_{i-1}) \\ &\quad + c_2 rand_2 (g_{best} - P_{i-1}) \end{aligned} \tag{24}$$

$$P_i = P_{i-1} + V_i \tag{25}$$

Step 3: Calculate new $p_{fit}(i)$ by training DNN with the updated P.

Step 4: Compare the value of new $p_{fit}(i)$ and the previous step's, and assign the new $p_{fit}(i)$ to p_{ibest} if the value is smaller. Meanwhile, if the value of new $p_{fit}(i)$ is smaller than g_{fit}, update g_{fit} and g_{best} with the new $p_{fit}(i)$ and p_{ibest}, respectively.

Step 5: Determine whether g_{fit} is less than an intended error, if it is, the iteration is stopped, otherwise return to the second step until the condition is satisfied or the iteration is terminated.

Step 6: Return the minimum error g_{fit} and the optimal neural nodes g_{best}.

The specific optimization process can be described by **Algorithm 1.**

Algorithm 1 PSO Process for Optimizing DNN

Required: Number of particle in a swarm α, Cognitive coefficients c, Inertia weight w
Required: Initial velocity V, Initial the nodes of double hidden layers P
Required: Initial individual best fitness value p_{fit}, Individual best value p_{ibest}
Required: Initial global best fitness value g_{fit} calculated by DNN, Global best value g_{best}

While $g_{fit} > 0$ **do**
 For each i = 1: α **do**
  Calculate update: $V_i \leftarrow wV_{i-1} + c_1 rand_1(p_{ibest} - P_{i-1})$ $+c_2 rand_2 (g_{best} - P_{i-1})$
  Calculate update: $P_i \leftarrow P_{i-1} + V_i$
  Calculate $p_{fit}(i)$ through DNN using P_i
  If $p_{fit}(i) < p_{fit}(i-1)$ **do**
   Update global best value: $p_{ibest} \leftarrow P_i$
   If$p_{fit}(i) < g_{fit}$ **do**
    Update global best fitness value: $g_{fit} \leftarrow p_{fit}(i)$
    Update global best value: $g_{best} \leftarrow p_{ibest}$
   End if
  End if
 End for
End while
Return g_{fit}, g_{best}

IV. SIMULATION AND RESULTS ANALYSIS

A. DATA DESCRIPTION

To verify the significance and effectiveness of the proposed PSO-DNN structure, the simulations with MATLAB are performed in this section. Specifically, for all experiments performed in this paper, the feature vectors are marked

TABLE 1. Parameters of proposed PSO-DNN recognition model.

Symbol	Quantity	Value
M	Number of input nodes	12
H_1	Number of nodes 1st hidden layer	[20,60]
H_2	Number of nodes 2nd hidden layer	$N_{output}<H_2<H_1$
N_{output}	Number of output nodes	6
α	Number of particle in a swarm	30
c	Cognitive coefficients	[0,3]
w	Inertia weight	[0,1]
I	Iterations number of optimization	5
r	Learning rate	0.1
k	Iteration number of training	300

by six labels that correspond to the following modulation modes: BPSK-1, QPSK-2, 8PSK-3, 16QAM-4, 64QAM-5, and 256QAM-6. In order to model the actual output in various channel conditions reasonably, the SNR is set to vary from 0dB to 12dB at 1dB steps. Combine the extracted 12 signal features into a column vector and make each modulation generate 4 thousand samples, noting that a total of 12000 feature vectors are used as the training set. After training, the performance of 3 methods is tested with other 6000 test feature vectors. The output of the Softmax function is regarded as a binary sequence with one-hot state, thereby the modulation format can be determined according to the non-zero position $\hat{y} \in \mathcal{R}^6$. Other parameters of our proposed method are shown in Table I.

B. PERFORMANCE MATRIC

In order to better characterize the prediction accuracy of PSO-DNN model, it is significant to measure the matching degree of the true response values of the data the models observed. Thus, the probability of success recognition (PSR) is used to quantify the performance of the modulation recognition based on the output of the classifier. *PSR* can be calculated by the following formula:

$$PSR = \frac{success\ recognition\ samples}{all\ samples} \times 100\% \tag{26}$$

C. RECOGNITION PERFORMANCE

In this section, we performed a series of simulations to identify the practicability of the proposed method and the effectiveness of the optimization algorithm. In the first experiment, we compare the proposed PSO-DNN model with two existing methods, the conventional DNN approach [9] and the SVM approach [28], to evaluate its recognition performance of digital signals. These three modulation recognition techniques are applied to identify 6 modulations and the overall PSR can be seen in Fig. 5.

According to Fig. 5, the overall recognition accuracy of these recognition algorithms is significantly improved with the increase of SNR. This can be explained by the fact that the higher the signal-to-noise ratio is, the closer the signal is to its original appearance, and the extracted features make a contribution to separate different modulation methods.

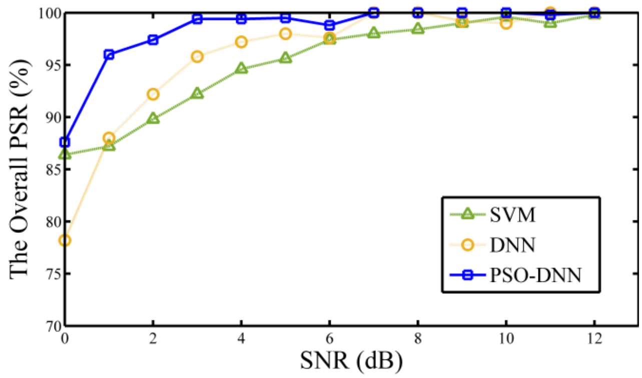

FIGURE 5. Performance result for 3 recognition schemes versus different SNR.

A dramatic phenomenon can be seen from the graph is that the PSR of SVM method is higher than the DNN method when SNR equals 0dB. For some applications, using a simpler SVM works well while using DNN only complicates things. Thus PSO is applied to optimize the performance of DNN and we can discover a significant improvement that the PSR is apparently higher than using other algorithms under the condition of low SNR. In addition, it is evident that the proposed method achieves the accuracy above 95%, which is 8% and 8.8% higher than the DNN algorithm and the SVM algorithm respectively (SNR $\geq$ 1dB). Therefore, the result implies that our scheme is able to identify these 6 modulation techniques effectively by searching for the optimal number of hidden layer nodes automatically, which also illustrates the effectiveness of our proposed PSO-DNN method in AWGN environment.

In order to understand the result better, Fig. 6 exhibits the detailed confusion matrices of six modulation classes calculated by the proposed method for the case of 1dB and 6dB SNR, respectively. It can be seen from Fig. 6(a) that the recognition accuracy in identifying 64QAM is relatively low compared with the rest which are above 90%, and it is easily recognized as 16QAM. The reason is that 16QAM is a subset of 64QAM making it hard to distinguish them. Besides, we can also observe from Fig. 6(a) that the accuracy of 16QAM and 64QAM is slightly lower than that of others. This can be attributed to the fact that the features extraction curves generated for 16QAM and 64QAM share high similarity after channel distortions, which makes the received samples indiscernible between two modulations. Specifically, the accuracy of BPSK and QPSK are both 100%. With a 5dB increase of SNR, the recognition rate of each modulation of the proposed technique in Fig. 6(b) has been greatly improved and all achieved above 95%.

We conducted comparative simulations with the other optimization algorithm GA in the second experiment to further prove the effectiveness of our proposed method. Both methods are used to optimize the DNN for digital modulation recognition and the PSR curves are shown in Fig. 7.

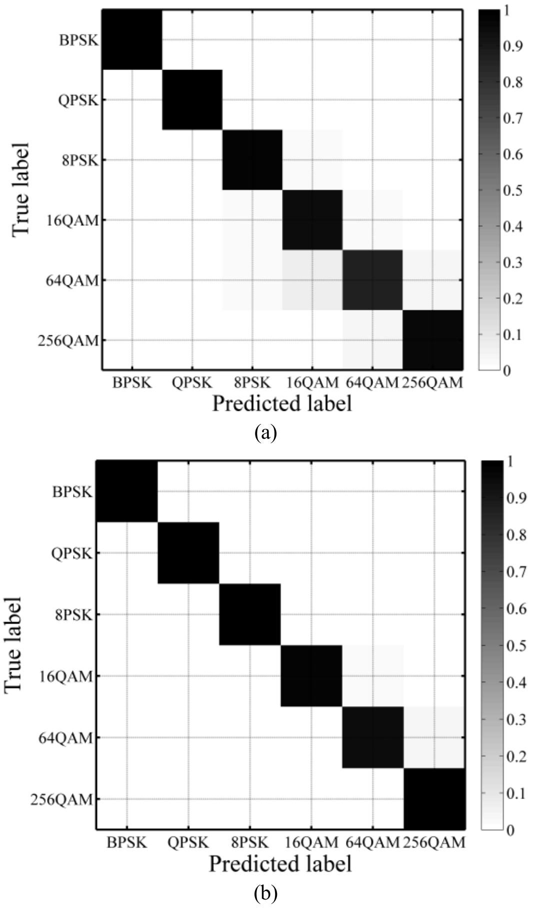

FIGURE 6. Confusion matrices for the modulation recognition data. (a) SNR = 1dB and (b) SNR = 6dB.

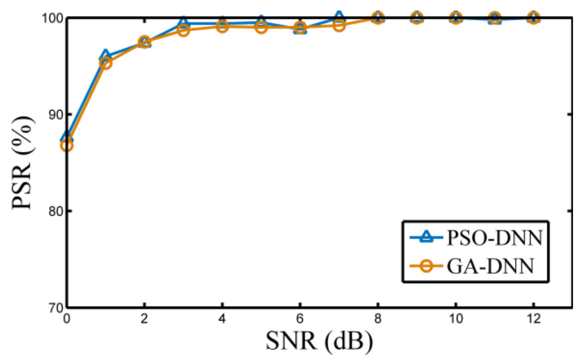

FIGURE 7. PSR result of 2 optimization schemes versus different SNR.

From Fig. 7 we can observe that the PSR curves of the two recognition schemes are similar. The accuracy of PSO-DNN algorithm is slightly higher than that of GA-DNN algorithm at low SNR, and both of them can achieve 100% accuracy at high SNR. The reason is that both algorithms select the optimal value based on the fitness of the individual population and both belong to the global optimization method, thereby reducing the possibility that the DNN is trapped in local minimum. Nevertheless, PSO algorithm does not require crossover and mutation operations like GA, and it has memory, which makes it simpler to use and can achieve

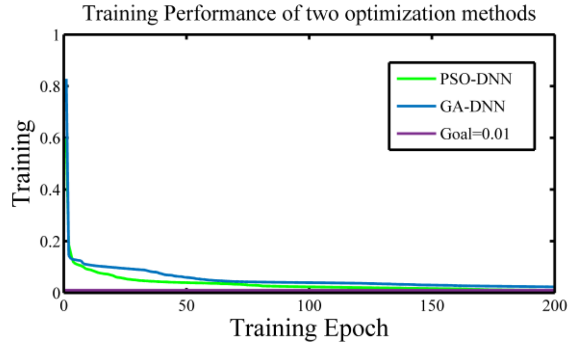

FIGURE 8. The training convergence performance of 2 optimization schemes.

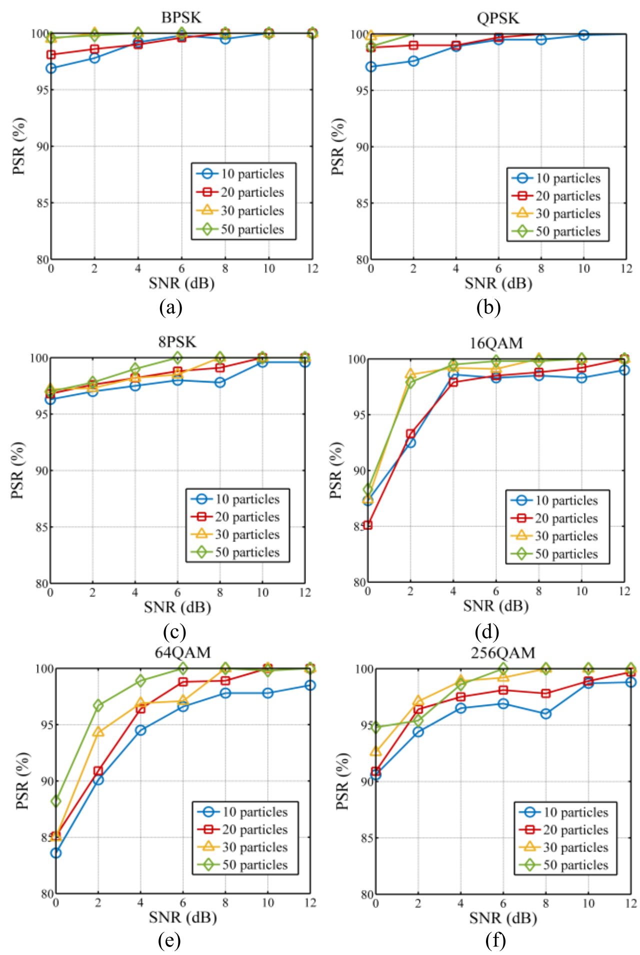

FIGURE 9. The PSR versus different α. (a) BPSK, (b) QPSK, (c) 8PSK, (d) 16QAM, (e) 64QAM, and (f) 256QAM.

better results most of the time. Another advantage of PSO is that it has a faster convergence speed compared to GA, the simulation result is shown in Fig. 8.

In Fig. 8, the DNN is trained by using PSO algorithm and GA respectively. The training performance intuitively demonstrates the superior capability of PSO, which meet the requirements of the objective function only by iterating 200 steps while the training performance of GA-DNN stops at epoch 300. In the GA, the chromosomes share information with each other, so the movement of the entire population moves more evenly toward the optimal region. The particles in the PSO share information only through the current search to the best position, which belongs to a single information sharing mechanism. Therefore, particles may converge to the optimal position faster than the evolutionary individuals in GA in most cases. Here comes to the conclusion that our approach performs better than the existing methods or optimization algorithm and demonstrates the suitability for other DL applications.

D. ANALYZING THE IMPACT OF THE PARTICLE NUMBER IN A PARTICLE SWARM

The above simulation results demonstrate that the DNN model with PSO optimization has the best performance compared with conventional methods. Furthermore, we executed another experiment to measure the effect of the number of particle α in a particle swarm on recognition accuracy in the PSO-DNN algorithm. Let α be 10, 20, 30, and 50, the step size of the SNR is changed from 1dB to 2dB and the other parameters remain the same. The PSR curve corresponding to the six modulations under different α is presented in Fig. 9.

Intuitively, these six figures jointly illustrate that the more the number of particles is, the higher the accuracy of recognition under different SNR will be. This can be attributed to the fact that as the number of particles increases, fine-tuning the particles can traverse more possible options, thereby increasing the accuracy accordingly. Another observation drawn from the figure is that the PSR curve with 30 particles almost coincides as it is with 50 particles (such as Fig. 9 (d)). Although making use of 50 particles achieves relatively high precision, the calculation is very time-consuming. Therefore, the number of particles in one particle swarm can neither be too little nor too much. For the algorithm proposed in this paper, we think it is reasonable to set the number of particle to 30 which is the same as the number utilized in the above experiments.

V. CONCLUSION

In this paper, we first propose particle swarm optimized deep neural network model to recognize digital modulation modes. The approach can identify 6 kinds of digital signals including BPSK, QPSK, 8PSK, 16QAM, 64QAM, and 256QAM from the disturbed environment. In our method, modulated signals are first preprocessed as the input to the neural network. Subsequently, PSO algorithm is applied to optimize the structure of DNN. Finally, we utilize the proposed method and traditional method to perform modulation recognition. Although time complexity is high in the case of large training datasets or particle quantity, the method presented in this paper achieves higher recognition accuracy with 8.8% and 9.4% promotion comparing with traditional DNN method and SVM method respectively under the condition of low SNR. In addition, it also solves the problem of setting the number of hidden layer nodes artificially and demonstrates the best performance of the proposed model. Experimental results further verify the reliability of the proposed algorithm, which provides a simpler and more effective novel method for signal modulation recognition in the field of wireless communication. Nevertheless, our method is implemented based on the existing modes, and future work will concentrate on applying this technique to the unknown modulated signals.

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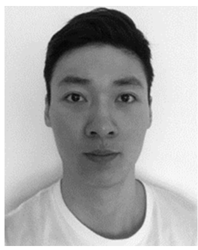

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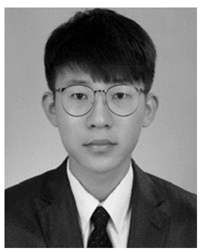

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