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Improved Deep Neural Network for OFDM Signal Recognition Using Hybrid Grey Wolf Optimization

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ABSTRACT Orthogonal Frequency Division Multiplexing (OFDM), as the core technology in mobile communications, is a multi-carrier modulation technology with high frequency spectrum utilization, which has strong anti-multipath interference and anti-fading ability. The significant advantage of OFDM signals lies in the anti-multipath effect, so its application environment is mostly multipath fading channels. Therefore, it is of great significance to study the identification of OFDM signals in multipath channels. Deep learning, with superior big data processing and classification capabilities, is a potential solution to these problems. Based on the problem of OFDM signal recognition in complex signals in multi-path channel, an OFDM signal recognition method based on hybrid grey wolf optimization algorithm to optimize deep neural network model is proposed. Because the basic grey wolf optimization algorithm (GWO) is easy to fall into a stasis state when attacking prey, differential evolution algorithm (differential evolution algorithm) is integrated into GWO to force GWO to jump out of the stasis state with its strong search ability. The convergence speed and recognition performance of the proposed algorithm are greatly improved. The experimental results show that under the condition of low SNR, the recognition accuracy of proposed algorithm is 9.95% higher than the traditional DNN method, and nearly 4.5% higher than the other two intelligent optimization methods, and the values of *Precision* and *Recall* increase obviously, which indicates that the hybrid algorithm not only improves the accuracy of recognition, but also makes the search more complete and accurate. Compared with classical particle swarm optimization (PSO) and whale algorithm optimization algorithm (WOA), the hybrid algorithm has strong competitiveness both in recognition performance and optimization stability, which provides a new, simpler and more effective method for modulation recognition of OFDM signals in wireless communications.

INDEX TERMS OFDM, multipath channel, deep neural network, grey wolf optimization, differential evolution, modulation recognition.

I. INTRODUCTION

OFDM (Orthogonal Frequency Division Multiplexing), a multi-carrier (MC) digital modulation technology of great spectrum efficiency and anti-multipath ability, is widely used. However, because the features of OFDM signal are not easy to be extracted, the recognition of its blind modulation is still a difficult problem.

There are mainly two methods of automatic modulation classification (AMC): the likelihood-based (LB) [1] and the feature-based (FB) [2]. The LB method is based on the likelihood function of the received signal. Theoretically, this method can obtain the optimal solution under gaussian condition, but its computational complexity is really high. In addition, it is sensitive to model mismatch in many cases. In contrast, the FB method is very feasible for real-time implementation, although not optimal in performance. In short, FB method is an automatic modulation recognition method with low computational complexity, high work efficiency and strong anti-model mismatch capability. In FB method, there are many feature parameter extraction methods of modulation mode recognition, such as application

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of digital signal time-frequency characteristics [3], application of higher-order cyclic cumulants [4], algorithm based on cyclic spectrum [5], algorithm based on autocorrelation [6] and so on.

The deep neural network (DNN) is a branch of deep learning (DL) that has multiple fully connected layers. In recent years, DNN has made remarkable achievements in computer vision, natural language processing, speech recognition and other fields. DNN can automatically extract features through training, which is in sharp contrast to some methods that require manual pre-specified features for classification. The authors in [7] combined feature extraction with deep neural network, which significantly improved the recognition performance under multi-path channels. In the study of [8], the feature learning and automatic modulation classification (AMC) under different DL models was studied, and it was concluded that the double-hidden layer DNN model has the best performance, which is 3.2% better than other algorithms. However, the problem of low recognition rate under low SNR is always troubling us, and high recognition rate under low SNR is our constant pursuit. The traditional DNN model needs to manually determine the network structure and parameters to obtain the optimal results and the intelligent optimization algorithm has a strong ability of automatic optimization, so combining feature extraction with deep neural network and using intelligent algorithm to optimize neural network structure can provide new ideas for modulation recognition [9].

With the rapid development of modern science and technology, many intelligent simulation optimization algorithms (ISOAs), also known as meta-heuristic algorithms, have been developed. ISOAs has become a competitive method to solve many problems due to its powerful universality and parallel processing capability, and has become a hot research topic. ISOAs are high-performance global optimization algorithms that simulates evolutionary processes, physical laws or swarm intelligence. Among them, the most famous evolutionary algorithms are genetic algorithm (GA) [10], differential evolutionary algorithm (DE) [11] and biogeographic optimization algorithm (BBO) [12]. Physics-based typical algorithms include charge system search (CSS) [13], gravitational search algorithm (GSA) [14], ray optimization (RO) [15], etc. Swarm intelligence algorithm is the most common algorithm in meta-heuristic branch. SI usually imitate the social behavior of birds, insects, or fish. The most classic SI algorithms include particle swarm optimization (PSO) [16], artificial bee swarm (ABC) [17] algorithm, cuckoo search (CS) [18], etc.

In recent years, a variety of new SI algorithms, such as grey wolf optimizer (GWO) [19], ant lion optimizer (ALO) [20], whale optimization algorithm (WOA) [21], moth flame optimization (MFO) [22], have emerged one after another and become the generative power to solve practical optimization problems. In the study of [23], chaos enhanced grey wolf optimization optimized ELM was used for diagnosis of paraquat-poisoned patients. In [24], a short-term wind power prediction model based on an improved ant lion optimizer algorithm to optimize BP neural network was proposed. In [25], an improved optimization algorithm combining chaos and multi-group strategy was proposed and applied to medical diagnosis. The authors of [26] used the MFO algorithm to obtain the optimal location and size of multiple PV-DGs units in three IEEE RDSs. The effectiveness of the ISOAs to solve various problems has been proved. The Grey Wolf Optimizer (GWO) algorithm is a new population algorithm with advantages of excellent optimization ability and easy to set and implement [27]. In recent years, the application of GWO algorithm is relatively mature and shows great potential in many fields. Hence, GWO algorithm is adopted to optimize the weights and thresholds of Deep neural network in this paper. However, in the middle and late stage of the algorithm, all the individuals in the wolf group are close to the prey, and the algorithm is prone to fall into the local optimal solution, resulting in the lack of diversity. Therefore, the differential evolution algorithm is introduced into this algorithm to enhance the robustness of wolves and avoid the algorithm from falling into the local optimal solution.

In this paper, the HGWO algorithm is used to optimize the input weights and thresholds of DNN model. This method can identify the OFDM signal from the complex signals including SC signal, WPM signal and OFDM signal. In our proposed scheme, various features of the modulation signal are firstly extracted, and the extracted features are learned through DNN training, so as to classify the modulation pattern more accurately. HGWO algorithm is utilized to correct the defects in DNN structure effectively. The recognition performance of the proposed algorithm is investigated for multipath channel into numerical computations. The main contributions of this paper are summarized in three parts as follows.

- The differential evolution (DE) algorithm is integrated into GWO, in order to force GWO to jump out of the stagnation with DE's strong searching ability and accelerate the convergence speed. Then the hybrid optimization algorithm is used to optimize the initial weight and threshold of DNN, so as to improve the performance of recognition algorithm. As far as we know, this is the first attempt to apply the hybrid grey wolf optimization (HGWO) method to the modulation recognition field of OFDM signal, which is an important application field.
- The performance of the algorithm is evaluated by method of cross validation in this paper. Simulation results show that compared with the traditional DNN recognition method and the DNN model optimized by GWO algorithm and DE algorithm, the recognition performance of this method is greatly improved under different SNR. In addition, we compare the algorithm with classical intelligent optimization algorithms, and the simulation results show that the algorithm is superior to classical algorithms in both performance and convergence speed, which verifies the robustness and effectiveness of the proposed algorithm.
- We analyze the influence of important parameters on the experimental performance, and use the parameters with

the best performance in the experimental design through the experimental comparison.

This paper is structured as follows. The modulation signal models are presented in Section II. The feature extraction is introduced in Section III. The Section IV presents the proposed model. Simulation results are discussed in Section V, and conclusions are drawn in Section VI.

II. CHANNEL AND COMMUNICATION SIGNAL MODEL

A. CHANNEL MODEL

We assume that the received signals are superimposed with gaussian white noise (AWGN) after transmission through a multipath channel [28], which can be written as:

$$r(n) = \sum_{k=0}^{L-1} h_k(n)s(n-\tau_k) + \mu(n) \tag{1}$$

where $h_k(n)$ is the multipath amplitude factor, τ_k is the path time delays, and L is the number of paths, $\mu(n)$ is the additional white gaussian noise.

In the real multipath channel model, the multipath amplitude is exponentially attenuated, that means $h_l = \alpha^l(\alpha \leq 1, l = 0, 1, \ldots, \infty)$, α is the amplitude attenuation parameter, and θ_l is the phase shift factor, which randomly and independently selected between $[0, 2\pi]$. The SNR is defined as:

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

where S and N are corresponding to the effective power of signal and noise.

B. SIGNAL MODEL

The modulation set is composed of WPM, OFDM, PSK, FSK, QAM, in which, WPM and OFDM are multi-carrier (MC) signals, others are single-carrier (SC) signals.

In the OFDM modulator, the data string is firstly converted into a low-speed sub-data stream of size n, then the modulation mapping is carried out by using the modulation mode of PSK or QAM, and the inverse discrete Fast Fourier Transform (IFFT) is carried out for each sub-data stream. Therefore, each symbol PSK or QAM will be visualized in the frequency domain and assigned to a single subcarrier. Finally, the cyclic prefix is inserted. At the end of the transmitting chain, a D/A converter is set [29]. Therefore, the transmitted continuous-time OFDM signal is written as follows:

$$S_{OFDM}(t) = A\sum_k \sum_{n=0}^{N-1} d_{n,k}e^{j2\pi(f_c+n\Delta f)t}g(t-kT_s) \tag{3}$$

MPSK, MFSK and MQAM signal models are as follows [30]:

$$S_{MFSK}(t) = A\sum_k e^{j2\pi(f_c+f_k)t}g(t-kT_s) \tag{4}$$

$$S_{MPSK}(t) = A\sum_k e^{(j2\pi f_c t + j\Delta\varphi_k)}g(t-kT_s) \tag{5}$$

$$S_{MQAM}(t) = A\sum_k (I_k + jQ_k)e^{j2\pi f_c t}g(t-kT_s) \tag{6}$$

in (3) - (6): A is the average power of receive signal; M is the mode of modulation; N is the number of OFDM sub-carrier; Δf is the frequency interval, T_s is symbol period, f_c is the carrier frequency, $g(t)$ is the rectangular pulse, I_k and Q_k are respectively the I and Q signals of the kth baseband signal.

Wavelet modulation, also known as fractal modulation. Compared with other traditional modulation methods, like sine and cosine, wavelet modulation takes advantage of the good scale and orthogonal translation characteristics of wavelet function. In general, the wavelet modulated signal can be obtained by:

$$S_{WPM}(t) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} \beta^{-\frac{m}{2}}x(n)2^{\frac{m}{2}}\psi(2^m t - n) \tag{7}$$

where $x(n)$ is the signal modulated by the wavelet function. $\psi(2^m t - n)$ is the wavelet function. $\beta = 2^{2H+1}$, where H refers to the degree of the homogeneous signal.

III. FEATURE EXTRACTION

Feature extraction is based on mathematical analysis of signals. In the supervised pattern recognition method, feature extraction is carried out on the modulated signal and feature parameters are selected. On the one hand, it is necessary to show good separateness under different SNR to better suppress the influence of noise. On the other hand, we hope to get as high recognition accuracy as possible when training with this feature.

A. SEPARATION FEATURE EXTRACTION OF SC SIGNAL AND MC SIGNAL

This feature is based on the asymptotic gauss property of multi-carrier signal. WPM signal and OFDM signal are both multi-carrier signals, and each subcarrier is orthogonal to each other. According to the central limit theorem (CLT), the amplitude distribution of multi-carrier modulated signals can be regarded as an approximate gaussian distribution with asymptotic gauss property, and the degree of gauss property is related to the number of subcarriers. However, the single-carrier modulated signal does not possess this characteristic and presents non-gaussian distribution [31]. Therefore, we identify single-carrier and multi-carrier modulated signals by using the asymptotic gaussian characteristic of multi-carrier modulated signals.

Here, we adopt the mixed order moment v_{20}, the value in the multipath channel is shown in Fig.2(a), which can be expressed as:

$$v_{20} = \frac{M_{4,2}(y)}{M_{2,1}^2(y)} = \frac{E\left[|a(i)|^4\right]}{E\left[|a(i)|^2\right]} \tag{8}$$

B. RECOGNITION BETWEEN MULTI-CARRIER SIGNALS

This feature is based on the characteristics of the power spectrum, which directly reflects the power distribution of

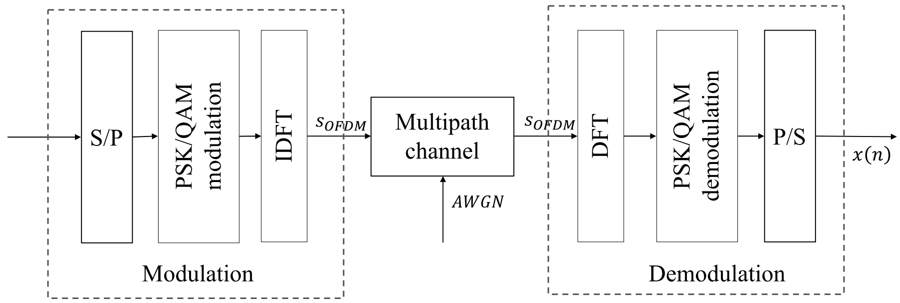

FIGURE 1. Modulation block diagram of OFDM signal.

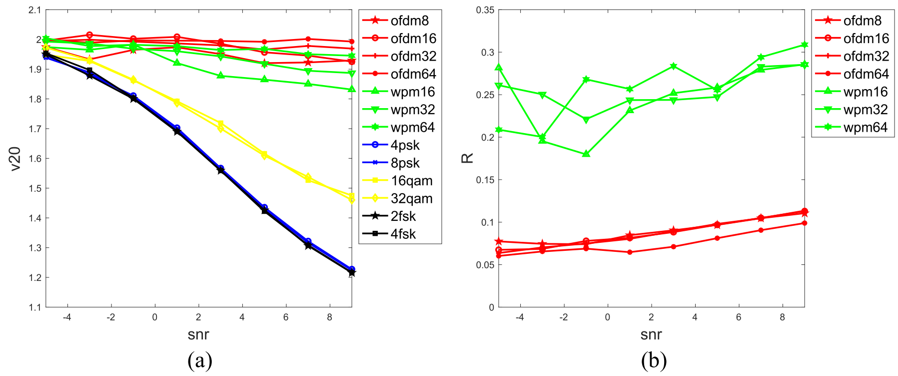

FIGURE 2. The value in the multipath channel (a) v_{20} (b)R.

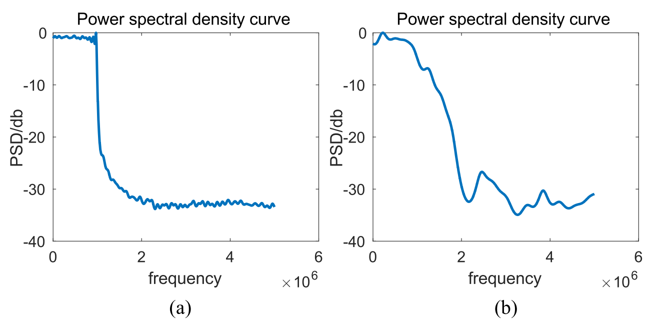

FIGURE 3. Power spectrum of 32OFDM(a) and 32WPM (b) signals in multipath channel.

each frequency component in the modulated signal. As shown in Fig.3, in the main frequency band, the OFDM signal energy distribution is relatively uniform and the power spectrum distribution is relatively flat. The energy distribution of WPM signal is in a peak shape, and the attenuation at both ends of the main peak is large. Therefore, the mean value and variance of the power spectrum envelope square can be used to define the characteristic parameter R, the value in the multipath channel is shown in Fig.2(b), and it can be described as follows [31]:

$$R = \frac{\sigma^2}{\mu^2} \tag{9}$$

C. RECOGNITION BETWEEN OFDM SIGNALS

This feature is based on peak-to-peak detection to obtain the number of subcarriers and achieve signal separation [32]. The actual transmitted OFDM signals overlap each other in the spectrum, but the center frequencies of the subcarriers are uniformly spaced on the frequency axis.

By correlation calculation, the magnitude of the signal implicit period can be obtained by calculating the distance between the peaks. Therefore, we do autocorrelation to the power spectrum of the signal, because of the equal spacing between the carriers, the spectrum will be impacted at the frequency position of the function. Although the single-frequency autocorrelation curve is of finite length, resulting in the leakage of its Fourier transform spectrum at the impact, the frequency position of the impact can still be detected to obtain the period of the autocorrelation curve, that is, the carrier frequency interval Δf.

In the OFDM modulation process, $T = N * T_s$, among them, f_b is the code rate of the signal, N is the number of points of IFFT, so the carrier interval is $\Delta f = 1/NT_S = f_b/N$. For OFDM signal, its bandwidth can be expressed as $BW = (Nc + 1) * \Delta f$. BW is the 3dB bandwidth of the signal, Δf is the frequency interval between carriers, and Nc is the number of subcarriers. Δf can be obtained by the spectral correlation method, and BW can be measured according to the power spectrum. Therefore, the number of subcarriers can be determined by the following equation:

$$Nc = \frac{BW}{\Delta f} - 1 \tag{10}$$

The identification process is shown in Fig.4.

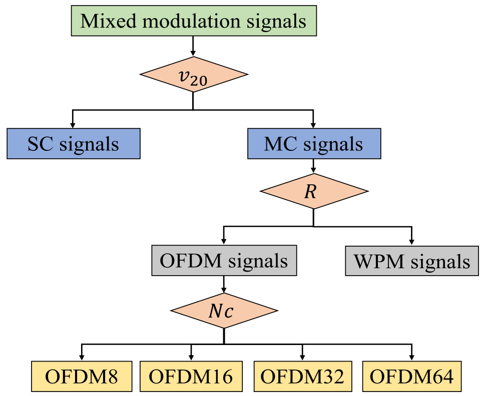

FIGURE 4. Flowchart for modulation recognition of OFDM signal.

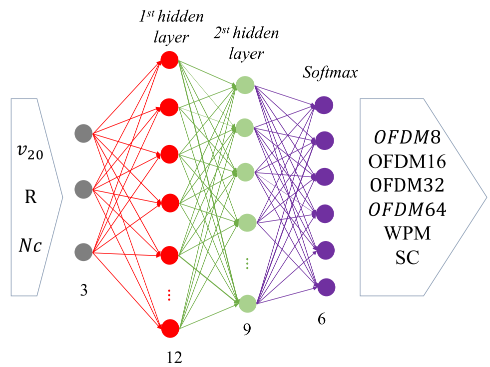

FIGURE 5. Structure of the proposed DNN model.

IV. PROPOSED RECOGNITION METHOD

A. BASICS OF DNN

DNN can be understood as a neural network with multiple hidden layers. Generally speaking, the first layer is the input layer, the last layer is the output layer, and the middle layer is the hidden layer. Its training stage consists of two steps: using the output of the upper layer to calculate the output of the next layer, known as the forward propagation, using the gradient descent algorithm to propagate the calculation error layer by layer, and modifying the weight of each layer, namely the back propagation. In this way, the network model is optimized by alternating forward propagation and back propagation [33]. Each hidden unit, j, typically uses a logical function (the sigmoid function is used in this paper) to map its total input from the previous layer, x_j, to the next layer, y_j [34].

$$y_j = \log istic(x_j) = \frac{1}{1+e^{-x_j}} \tag{11}$$

$$x_j = b_j + \sum_i y_i \omega_{ij} \tag{12}$$

where b_j is the bias of unit j, i is an index over units in the layer below, and ω_{ij} is the weight on a connection to unit j from unit i in the layer below.

For multiclass classification, output unit, j, the *soft* max function is used to convert its total input x_j to class probability p_j. k is an index over all classes.

$$p_j = \frac{\exp(x_j)}{\sum_k \exp(x_k)} \tag{13}$$

The schematic diagram of the network is shown in Fig.5. The input of the network is the extracted features, and the output is 6 signals.

B. BASICS OF HGWO

Because the randomness of input weight and threshold of DNN will affect the prediction results, the hybrid GWO algorithm is used to optimize the framework of DNN. The GWO algorithm is combined with DE algorithm in order to prevent falling into local optimum.

The GWO algorithm mimics the grey wolf's ranking system and hunting techniques.

Four types of grey wolves are [35]:

- Alpha (α), the leader of the pack
- Beta (β), obey and assist the α in making decisions
- Delta (δ), submissive towards α and β
- Omega (ω), obedience to wolves of other levels

In addition to the special feature of social class, group hunting is another special social behavior. The hunting stage of GWO is as follows [36]:

- Tracking, chasing, and approaching the prey.
- Pursuing and encircling the prey until it stops moving.
- Attack towards the prey.

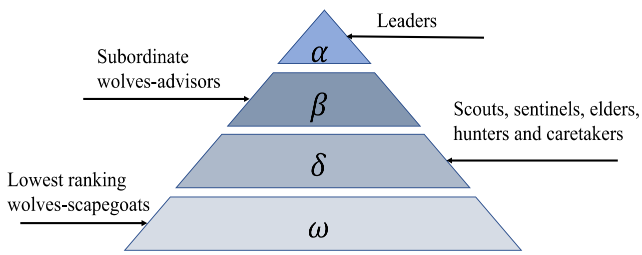

FIGURE 6. Hierarchy of grey wolves.

Differential Evolution (DE) algorithm is a powerful searching algorithm, which mainly seeks the optimal population through mutation, crossover and selection strategies [37].

- Generation of initial population
- Mutation operation
- Crossover operation
- Selection operation

Then the details of the hybrid algorithm to optimize the weights and thresholds of DNN was described [38].

Firstly, the algorithm parameters are initialized, n is population size, *MaxGen* is iterative times, b max is upper bound of scaling factor, b min is lower bound of scaling factor, CP is crossover probability, *npop* is variable dimension.

Secondly, population *pop* is obtained by random initialization in the feasible region, and then substitute *pop* into DNN algorithm to calculate the parent target value *p_val*. Repeat this step to get the child target value c_val and the mutation target value m_val.

$$X_p^k = X_p^k(low) + (X_p^k(up) - X_p^k(low)) \times \text{rand}(0, 1) \quad (14)$$

where $X_p^k(up)$ and $X_p^k(low)$ are the upper bound and lower bound of p*th* component of the k*th* individual, $p = 1, 2, \ldots, d, k = 1, 2, \ldots, popnum$.

Determine the social rank of the individuals in the parental population. Calculate the fitness of each individual in the population, the three wolves with the best fitness are labeled with α, β, δ, respectively. The values of α, β, δ are expressed as $parent_\alpha, parent_\beta, parent_\delta$

Hunting process: D_α, D_β and D_δ are the distance between the current candidate grey wolf and the optimal three wolves, respectively, X_1, X_2 and X_3 represent the position vectors of α, β and δ in the current population. Equations of (18) and (19) are repeated to obtain the action radius D_β, D_δ and X_2, X_3. According to (20), the location X is obtained, r_1 and r_2 are random vectors in [0, 1].

$$A_1 = 2ar_1 - a \quad (15)$$

$$C_1 = 2r_2 \quad (16)$$

$$a = 2 - \frac{2t}{Maxiter} \quad (17)$$

$$D_\alpha = |C_1 X_\alpha - X| \quad (18)$$

$$X_1 = X_\alpha - A_1 D_\alpha \quad (19)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (20)$$

To prevent transgression, do the following:

$$parent_{pr}(t) = X, X \in [\min c, \max c] \quad (21)$$

After the iteration, position vectors of all the population are brought into DNN algorithm to obtain the parent target value p_val. Then determine whether we have the best parent target value.

DE algorithm obtains population Met_m by individual mutation, a, b, c are mutated individuals, F is scaling factor.

$$MC_m = parent_m(a) + F * (parent_m(b) - parent_m(c)) \quad (22)$$

To prevent transgression, do the following to obtain the intermediate population Met_m.

$$Met_m = MC_m, MC_m \in [\min c, \max c] \quad (23)$$

The crossover operation is carried out between the parental population and the intermediate population. In the case where the random probability is less than the crossover probability, the individuals are selected from the original population and the intermediate population to obtain the new generation population.

$$U_j^k(g) = \begin{cases} Met(g), & if\ (rand \le CP||j = j_{rand}) \\ parent(g), & otherwise \end{cases} \quad (24)$$

where CP represents the crossover probability, $j = 1, 2, 3, \ldots, D$.

New population is substituted into DNN algorithm to obtain child population target value c_val. The DE algorithm process is repeated to get all the child population.

The child population is compared with the parent population for selection, and the greedy algorithm is used to select individuals for the next generation.

$$X^k(g+1) = \begin{cases} U^k(g), & if\ (f(U^k(g)) \le f(parent(g)) \\ parent(g), & otherwise \end{cases} \quad (25)$$

Algorithm 1 HGWO-DNN

Input Objective function f, population size $npop$, the lower bound of feasible region $L = \{l_1, l_2, \ldots, l_n\}$ and the upper bound of feasible region $U = \{u_1, u_2, \ldots, u_n\}$.
Output The optimal solution and the best objective function value.
Initialize the parent population $parent_i$, mutant population $mutant_i$ and child population $child_i$ of grey wolf ($i = 1, 2, \ldots, npop$) with a random position in a feasible region using (14);
Initialize crossover probability CP and scaling factor F, a, A and C;
Evaluate f for all individuals in the parent population;
According to the value of the objective function, the parent population is sorted in non-descending order.
$parent_\alpha$ is the best individual in the parent population;
$parent_\beta$ is the second individual in the parent population;
$parent_\delta$ is the third individual in the parent population.
while($t < MaxGen$)
for each individual in the parent population of grey wolves
Update the position using (20);
end for
Obtain a mutant population using (22) and (23)
Obtain a child population using (24)
for each individual $parent_i$ in a parent population of grey wolves
if $f(child_i) < f(parent_i)$
Replace $parent_i$ with $child_i$
end if
end for
Update A, C and a using (15), (16) and (17);
Sort the parent population of grey wolves in a non-decreasing order; Update $parent_\alpha, parent_\beta, parent_\delta$
$t = t + 1$
end while
Return $parent_\alpha$ and $f(parent_\alpha)$.

After completing the iteration, the regression algorithm is used to predict results. The pseudo code of the HGWO algorithm is demonstrated in **Algorithm 1** [39].

C. ANALYSIS OF TIME COMPLEXITY

The time complexity reflects the running efficiency of the algorithm and is an important factor to judge the performance of the algorithm. The computational costs of the standard GWO involve the initialization (T_{ini}), position update (T_{upd}), and fitness evaluations (T_{eva}) for the population. We assume that the population size is N, the solution dimension is D and the maximum iteration number of the algorithm is $MaxIter$, the computational complexity of the standard GWO can be calculated as:

$$\begin{aligned} T &= T_{ini} + (T_{upd} + T_{eva}) \cdot MaxIter \\ &= N + (N \cdot D + N) \cdot MaxIter \\ &= N \cdot (1 + (D + 1) \cdot MaxIter) \end{aligned}$$

Therefore, the time complexity of the standard GWO is $O(N \cdot D \cdot MaxIter)$.

In HGWO algorithm, the computational costs involve the initialization (T_{ini}), position update (T_{upd}), the computational costs of the hybrid GWO and DE operation (T_{hgd}), and fitness evaluations (T_{eva}) for the population. In the worst cases, the time complexity $T_{hgd} = N \cdot D$, Hence, the worst-case time complexity of HGWO can be estimated as:

$$\begin{aligned} T &= T_{ini} + (T_{upd} + T_{hgd} + T_{eva}) \cdot MaxIter \\ &= N + (N \cdot D + N \cdot D + N) \cdot MaxIter \\ &= N \cdot (1 + (2 \cdot D + 1) \cdot MaxIter) \end{aligned}$$

The HGWO has an $O(N \cdot D \cdot MaxIter)$ time complexity, also linear to $MaxIter$.

Based on the above analysis, it can be seen that the hybrid grey wolf optimization algorithm proposed in this paper has the same time complexity as the standard grey wolf optimization algorithm and does not reduce the execution efficiency of the algorithm.

V. SIMULATION AND RESULTS ANYLYSIS

A. GENERAL DESCRIPTION

To verify the effectiveness of the proposed HGWO-DNN model, the MATLAB simulations are carried out in this part. The path number of channel is set to 6, the multipath amplitude factor is $h_n = [1.0, 0.631, 0.398, 0.251, 0.159, 0.1]$, and the phase shift factor is randomly selected independently between $[0, 2\pi]$. The subcarrier modulation modes of OFDM signals and WPM signals are both 4PSK. Two hidden layers are set in the model. Through exhaustive test, when the number of hidden layer nodes is set as {12,9}, the network performance is the best, that is, the network structure is 3-12-9-6, and the mean square error function is selected as the fitness function.

In all the experiments in this paper, the feature vector is marked with six labels, these labels correspond to the following modulation modes: OFDM8-1, OFDM16-2, OFDM32-3, OFDM64-4, WPM signal contains {WPM16 WPM32, WPM64}, marked as WPM-5, single-carrier (SC) signal including {PSK4 PSK8, QAM16, QAM32, FSK2, FSK4}, tag to SC-6, so as to various actual output model. The signal is transmitted through multipath channel for an SNR range between -5dB and 10dB. The three extracted signal features are combined into a column vector, each modulation method generates 300 samples, with a total of 3900 eigenvectors as the data set. 1000 samples is used as the training set and 500 samples is used as the test set.

For the main controlling parameters of the proposed algorithm, we adopt the control variable method to keep the other parameters unchanged, change the current parameter, and determine the optimal parameters based on the comprehensive identification accuracy and time complexity, the final parameters adopted are shown in the Table. 1.

TABLE 1. Parameters of proposed model.

Symbol	Quantity	Value
M	Number of input nodes	3
H	Number of hidden layer nodes	[12,9]
N	Number of output nodes	6
$npop$	Population size	10
F	Scaling factor	[0.25,1.25]
CP	Crossover probability	0.5
lb	Lower bound of parameter	-5
ub	Uper bound of parameter	5
I	Iterations number of optimization	50
r	Learning rate	0.1
$goal$	Training goal	0.00001
k	Iteration number of training	1000

B. PERFORMANCE MEASUREMENT

After training the model, we measure some performance measurement parameters like *Accuracy*, *Precision*, *Recall* and *F1 score*. In the confusion matrix, there are four classification performance indices are present. The indices are (1) True Positive (TP), (2) True Negative (TN), (3) False Positive (FP), and (4) False Negative (FN).

Accuracy: the proportion of all samples predicted to be correct. In general, the higher the accuracy is, the better the performance of the classifier will be.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{26}$$

Precision: the proportion of the correct prediction of positive sample number (TP) in the total prediction of positive (TP and FP), and it can be writed as:

$$Precision = \frac{TP}{TP + FP} \tag{27}$$

Recall is the proportion of the number of samples (TP) correctly predicted to be positive to all the actual positive (TP and FN). It can be calculated by the formula as follows:

$$Recall = \frac{TP}{TP + FN} \tag{28}$$

F1 score is the ratio of the arithmetic average to the geometric average, and the bigger the better. The formula is as

TABLE 2. Evaluation metrics of different algorithms.

Evaluation Metrics	DNN		GWO-DNN		DE-DNN		HGWO-DNN	
	SNR=-5dB	SNR=0dB	SNR=-5dB	SNR=0dB	SNR=-5dB	SNR=0dB	SNR=-5dB	SNR=0dB
Accuracy(%)	77.70	99.24	82.34	99.24	82.20	99.40	87.65	99.19
Precision (%)	78.86	99.24	82.34	99.24	83.28	99.40	87.60	99.21
Recall (%)	79.95	99.26	82.42	99.26	83.24	99.42	87.56	99.22
F1 score	0.79	0.99	0.82	0.99	0.83	0.99	0.88	0.99

follows:

$$F1Score = \frac{2TP}{2TP + FP + FN} \tag{29}$$

C. PERFORMANCE EVALUATION

In this section, a series of simulation experiments are carried out to verify the practicability of the proposed method and the effectiveness of the optimization algorithm. In all models, main controlling parameters and the training parameters of DNN model are the same as those in Table. 1, that is, the settings are the same as the HGWO-DNN model to ensure the fairness of comparison.

Firstly, we compare the proposed HGWO-DNN model with the traditional DNN model, GWO-DNN model and the DE-DNN model to evaluate its recognition performance. When the SNR is -5dB and 0dB, the evaluation metrics of these four methods are shown in Table. 2. It can be seen from Table 2 that the recognition accuracy of DNN optimized by intelligent algorithm is obviously better than that of traditional DNN algorithm, and we can see that the hybrid algorithm proposed in this paper is superior to the other two algorithms, when the SNR is -5dB, the recognition accuracy of proposed algorithm is 9.95% higher than the traditional DNN method, and nearly 4.5% higher than the other two intelligent optimization methods, which significantly improves the recognition accuracy under the condition of low SNR. In addition, the two metrics of *Precision* and *Recall* are significantly improved. The single DNN has less than 80% precision and recall, however, the *Precision* value of HGWO-DNN reaches 87.6% and the *Recall* value reaches 87.56%, which is significantly improved. *F1 Score* reflects the comprehensive performance of *Precision* and *Recall.* It can be seen that compared with the single DNN algorithm and GWO-DNN algorithm, it is improved by 0.09 and 0.06,respectively. According to the analysis, it is shown that the algorithm in this paper not only improves the accuracy of recognition, but also makes the search more complete and accurate. The overall recognition performance is shown in the Fig.7, we can see that the proposed method is superior to other methods as a whole. Synthesizing the above analysis, it shows that the hybrid algorithm successfully overcomes the shortcomings of the traditional DNN method and GWO algorithm, and also confirms the effectiveness of the intelligent optimization algorithm.

In any evolutionary algorithm, the speed of convergence is more important than the quality of the solution to the optimization problem. The convergence curve of the three methods of HGWO-DNN, GWO-DNN and DE-DNN is shown in Fig. 8. As can be seen, in this paper, the convergence speed of algorithm is faster compared with the single GWO algorithm and DE algorithm, it mainly for that we successfully enriched the diversity of population with DE's variation and selection in the hybrid algorithm, and then expand the search scope of the algorithm, and thus can get a better solution to avoid the late fall into local optimal, which shows that the algorithm effectively improves the convergence speed and optimization accuracy of the grey. wolf optimization algorithm, improves the ability of the algorithm to jump out of

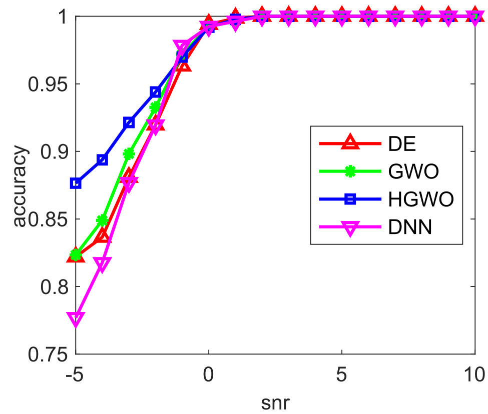

FIGURE 7. Performance comparison of different methods.

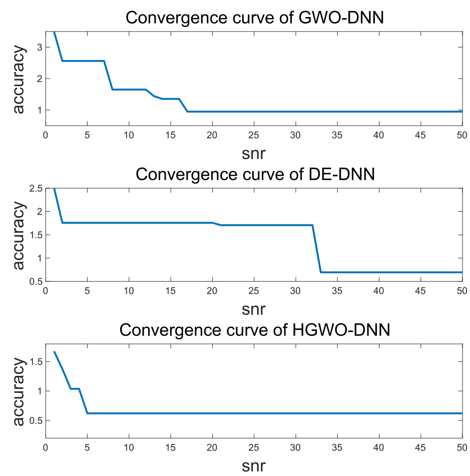

FIGURE 8. Convergence comparison of different methods.

TABLE 3. Comparison of different methods in multiple experiments when SNR =−5dB.

Number of training	1	2	3	4	5	Optimum accuracy
HGWO(%)	86.42	86.77	86.98	87.65	87.55	87.65
PSO(%)	81.53	82.15	82.54	81.76	82.46	82.54
WOA(%)	80.90	79.10	84.10	82.25	74.15	84.10
GWO(%)	82.83	83.25	82.34	83.46	83.14	83.46

TABLE 4. Evaluation metrics of different crossover probability (CP).

Evaluation Metrics	CP=0.2		CP=0.5		CP=0.8	
	SNR=-5dB	SNR=0dB	SNR=-5dB	SNR=0dB	SNR=-5dB	SNR=0dB
Accuracy(%)	84.59	99.24	87.65	99.19	84.63	99.24
Precision (%)	84.59	99.24	87.60	99.21	84.63	99.24
Recall (%)	84.77	99.26	87.56	99.22	84.54	99.26
F1 score	0.85	0.99	0.88	0.99	0.85	0.99

local optimization, and avoids the defects of the basic GWO algorithm.

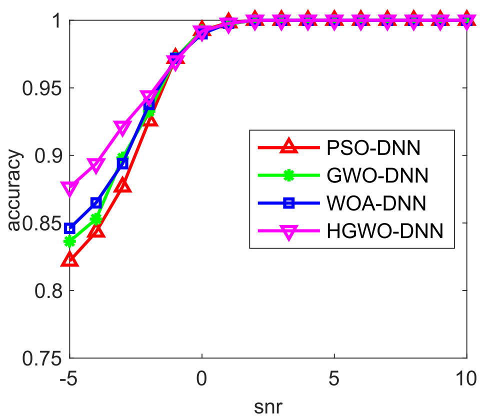

FIGURE 9. Comparison with classical algorithms.

Select the same data set to optimized by cross-validation train and compare the performance of the proposed algorithm with the classical particle swarm optimization (PSO) algorithm and whale optimization algorithm (WOA) similar to GWO algorithm. In PSO-DNN, acceleration factor c_1c$_1$ and c_2 are initialized to 1.495. The recognition accuracy under different SNR is shown in Fig.9. The simulation results show that the recognition rate of the proposed method is obviously higher than that of the other three methods under the condition of low SNR, and the recognition rate of all the methods reaches 100% under the condition of high SNR. The GWO and WOA methods perform better than the PSO methods because both of them have the advantages of simple structure and easy to implement, and the recognition accuracy of WOA algorithm is slightly better than that of GWO algorithm. We conduct five repetitive experiments, the recognition accuracy of various methods are shown in Table. 3. The results show that the recognition accuracy of WOA algorithm fluctuates greatly. Most of WOA algorithms are inferior to GWO algorithm, only few are superior to GWO algorithm and the optimal recognition accuracy is higher than GWO. In addition, a considerable part of WOA algorithm's recognition accuracy is less than 80%, with obvious fluctuation in the recognition accuracy, therefore, its optimization stability is inferior to GWO algorithm and PSO algorithm. Hence, GWO algorithm has the advantages of high recognition accuracy and stable performance, and its comprehensive performance is better than WOA and PSO algorithm. As a result, experimental results show that the HGWO-DNN method is effective and practical, and the GWO algorithm is superior.

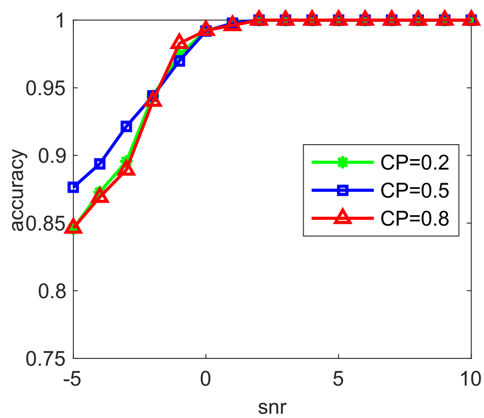

FIGURE 10. Comparison of different crossover probability.

Then, we explore the influence of crossover probability (CP) parameter setting on experimental performance by changing the size of crossover probability. When the crossover probability is set to 0.2, 0.5 and 0.8, the experimental performance is shown in Fig.10. It can be seen that the experimental performance is the best when the crossover probability CP=0.5, which can be verified by the values of the three metrics in Table. 4. This can be explained as that when the crossover probability is too small, the population diversity is low, it is not easy to accept the mutation of individual genes, so the local search ability and convergence rate are reduced, when the crossover probability is too large, the individual gene structure is damaged too much, which is not conducive to the evolution of individuals and the maintenance of population diversity. This indicates that the size of the crossover probability factor affects the diversity of population evolution and the rate of population convergence, and the parameter selection should be moderate.

VI. CONCLUSION

In this paper, an OFDM signal recognition method based on hybrid grey wolf optimization algorithm to optimize deep neural network model is proposed, because the basic grey wolf optimization (GWO) is easy to fall into stagnation when it carries out the operation of attacking prey, and differential evolution (DE) is integrated into GWO in order to force GWO to jump out of the stagnation with DE's strong searching ability. This method can identify the OFDM modulation signal from the complex signals including single-carrier signal, OFDM signal and wavelet packet signal (WPM) in the multipath channel. Firstly, we extract the features of the modulation signal as the input of the classifier, and then use the HGWO algorithm to optimize the weights and thresholds of the DNN. Finally, we conduct a series of comparative experiments. Experimental results show that the proposed algorithm effectively accelerates the convergence speed of GWO and improves its performance. Compared with classical algorithms such as particle swarm optimization (PSO) and whale optimization algorithm (WOA), this algorithm is obviously superior to the two algorithms. Finally, we analyze the influence of the crossover probability on the experimental performance by changing the value of the crossover probability and verify the rationality of the parameter selection. Experimental results show the effectiveness and reliability of the proposed model, which provides a new, simpler and more effective method for modulation recognition of OFDM signals in wireless communications. The limitation of the algorithm in this paper is that the HGWO algorithm is only used to optimize the weight and threshold of the DNN model, and the structure of the network needs to be determined manually. Applying the intelligent optimization algorithm to the structure of the deep learning network may improve the accuracy of recognition. In future studies, we will try our best to make the intelligent optimization algorithm intelligently determine the structure and parameters of the neural network. In this paper, a hybrid optimization algorithm is adopted to overcome the shortcomings of the intelligent optimization algorithm, other variants can be tried in future studies.

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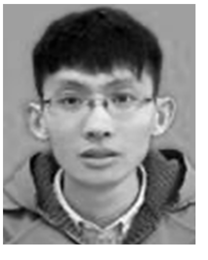

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