Performance Degradation Prediction of IF Conversion Circuit Based on DE-GWO-SVM Model

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Abstract. Due to the complex structure, nonlinearity and tolerance of IF conversion circuit, the failure probability of IF conversion circuit is greatly increased. To solve the above problems, a differential evolution adaptive grey wolf algorithm (DE-GWO) was proposed to optimize the parameters of support vector machine model, and the model was applied to the fault diagnosis of IF conversion circuit for the first time. Firstly, the energy feature of the output signal of IF conversion circuit was extracted by wavelet packet decomposition, which effectively reduced the dimension of feature vector. Secondly, the improved grey wolf algorithm was used to optimize the parameters of SVM model and establish DE-GWO-SVM fault diagnosis model; Finally, taking the IF conversion circuit as an example, the fault diagnosis experiment was carried out and compared with other methods. Comparison results show that the fault diagnosis accuracy rate of this method reaches 97.33%. Compared with the traditional methods, this method can better improve the fault diagnosis rate and shorten the diagnosis time.

1. Introduction
As the main component of accelerometer, the performance of IF conversion circuit directly affects the overall performance of inertial navigation system. At present, the domestic research on IF conversion circuit mainly focuses on the hardware design, so as to improve the conversion accuracy of IF conversion circuit. However, due to the complicated design of the circuit, the probability of failure of the IF conversion circuit is greatly increased, and power accidents and circuit board damage caused by parametric changes of components in the circuit are common occurrence [1]. In order to ensure the reliability and stability of inertial navigation system, it is particularly important to study the fault diagnosis means of the IF conversion circuit.

With the rapid development of artificial intelligence technology, intelligent algorithm is introduced into the field of analog circuit fault diagnosis, which promotes the further development of fault diagnosis technology. By imitating the behavior of natural creatures, many scholars have proposed optimization algorithms such as ant colony, bee colony, frog colony and particle swarm [2]. Mei Hengrong et al. proposed an improved particle swarm optimization algorithm to optimize SVM parameters, and introduced a new dynamic inertia weight, which has a fast convergence speed [3]. Enmin Tan et al. proposed a cloud model improved firefly algorithm to optimize LSSVM parameters, which enhanced the global convergence ability of the population [4]; Ailian Li et al. established a model based on ant colony algorithm to optimize parameters of support vector machine, which improved the classification accuracy of SVM [5]. However, these methods have some defects, such as
particle swarm optimization algorithm lacks dynamic adjustment of speed, which is easy to fall into local optimum [6]; the firefly algorithm search method is so much dependent on excellent individuals, which reduces the convergence speed [7]. In ant colony algorithm, the initial pheromone is scarce and the search time is long [8].

As a new intelligent optimization algorithm, grey wolf algorithm was first proposed by Griffith University scholar Mirjalili and others in Australia in 2014 [9]. In this paper, based on the traditional grey wolf algorithm, a differential evolution adaptive grey wolf algorithm (DE-GWO) was proposed to optimize the parameters of SVM model, and a DE-GWO-SVM fault diagnosis model was established, which was applied to IF conversion circuit for the first time. The results show that the fault diagnosis accuracy of this method reaches 97.33%, which is higher than the traditional SVM model. This research not only broadens the application field of grey wolf optimization algorithm, but also supplements the performance detection of IF conversion circuit, which is beneficial to the realization of automatic detection function of IF conversion circuit in the future.

2. Grey Wolf Optimization Algorithm Based on Differential Evolution

2.1. Traditional Grey Wolf Algorithm

Imitating the social dominance hierarchy strictly observed by the gray wolf in nature, after the grey wolf encircles its prey, it is guided by the head wolf and assisted by and to carry out the hunting behavior, the individual location of the level in the wolf pack are updated by the location of , , and [10].

Gray wolves surround their prey after they find it. The mathematical description of surrounding behavior is as follows:

\[ D = |X_p(t) - X(t)| \]  
\[ X(t+1) = X_p(t) - A \times D \]  

In the formula, \( D \) is the distance between the individual gray Wolf and the prey; \( T \) is the current iteration number; \( X_p(t) \) is the position vector of prey in \( t \) iteration; \( X(t) \) is the position vector of gray Wolf individual in \( t \) iteration.

Gray wolves surround their prey and hunt. The mathematical description of the hunting behavior is as follows:

\[ X(t+1) = \frac{X_\alpha(t+1) + X_\beta(t+1) + X_\delta(t+1)}{3} \]  

In the formula, \( X_\alpha(t+1), X_\beta(t+1) \) and \( X_\delta(t+1) \) respectively represent the location vectors of \( \alpha, \beta \) and \( \delta \) in \((t+1)\) iterations.

The grey wolf constantly adjusts the hunting direction and the distance from the prey, and captures the prey after many iterations. At this time, the location and fitness of the head wolf \( \alpha \) is the optimal solution[11].

2.2. Improved Grey Wolf Algorithm

When the traditional grey wolf algorithm is used to optimize SVM parameters, it is limited by its own optimization algorithm, and there are some factors such as early maturity and slow convergence speed[12]. Therefore, by introducing differential evolution theory, a differential evolution adaptive grey wolf algorithm was proposed in this paper, which improved the optimization performance of GWO.

DE algorithm realizes individual mutation through difference strategy, the variation population \( v_i(t+1) \) is obtained after \((t+1)\) iterations, where \( F \) is the scaling factor. The expression is as follows:

\[ v_i(t+1) = X_i(t) + F \times (X_{r1}(t) - X_{r2}(t)) \]  

The parent population and its variant population are cross-operated, and the offspring population \( u_{i,j}(t+1) \) is obtained after \((t+1)\) iterations, where \( CR \) is the cross probability. The expression is as
follows:
\[
u_{i,j}(t+1) = \begin{cases} 
    v_{i,j}(t+1), & \text{rand}(i) \leq CR \text{ or } j = j_{\text{rand}} \\
    X_{i,j}(t), & \text{otherwise}
\end{cases}
\]
\tag{5}

Using the greedy algorithm, according to the evaluation function \( f \), the better individual is selected as the next generation of the parent population, and the parent population \( X_i(t+1) \) is obtained after \((t+1)\) iterations. The expression is as follows:
\[
X_i(t+1) = \begin{cases} 
    u(t+1), & f(u(t+1)) \leq f(X_i(t)) \\
    X_i(t), & \text{otherwise}
\end{cases}
\]
\tag{6}

The specific steps of the improved GWO optimization algorithm are as follows:
(1) The initial population \( X_i (i = 1, 2, \cdots, N) \) is randomly generated, and parameters such as iteration times \( t \) and dimension \( D \) are initialized;
(2) Start the iteration, calculate the fitness value of each gray wolf, and realize the location update of the individual of the parent population;
(3) Perform cross-mutation operations on the parent and mutant populations to obtain the offspring population;
(4) Select the gray wolf individual from the original parent population and the offspring population to obtain a new generation of the parent population;
(5) Save that location of the individual with the best fitness, continuously carry out iterative operation, and judge whether \( t \) reaches the maximum iteration number. If yes, exiting the loop, otherwise, returning to step 2.

### 3. IF Circuit Diagnosis Model of SVM Optimized by DE-GWO Algorithm

In this paper, the improved grey wolf algorithm was used to optimize the penalty parameter and kernel parameter of SVM, and the specific process of fault diagnosis for IF conversion circuit is as follows:
(1) Signal excitation and data acquisition. Select the appropriate input signal to stimulate the circuit, and collect the output response signals in each state;
(2) Wavelet packet decomposition and reconstruction. Wavelet packet decomposition is used to reduce the dimension of the data, and the preprocessed sample data is obtained;
(3) Establish the diagnosis model of the SVM. The sample data constructed according to the optimal feature subset is input into the SVM model for training and testing, which is optimized by the improved grey wolf algorithm;
(4) The parameters of the SVM model are optimized by DE-GWO grey wolf algorithm, and the fault diagnosis experiment of the IF conversion circuit is carried out.

The block diagram of the IF conversion circuit fault diagnosis process based on the DE-GWO-SVM is shown in Figure 1.
Data acquisition of the output signal
Wavelet packet decomposition and reconstruction
Establish SVM diagnosis model
Parameters of DE-GWO optimization model
Fault diagnosis of the IF circuit

**Figure 1.** Flow chart of the IF circuit fault diagnosis.

**4. Experiment of the IF Circuit Fault Diagnosis**

In order to verify the effectiveness of the proposed method, the IF circuit is simulated on the test bench. During the experiment, five health conditions of IF circuit were simulated, including threshold nonlinear fault at small current input, saturation nonlinear fault at large current input, fault with circuit component parameters too large or too small, and circuit characteristics under normal state. During the experiment, the IF conversion circuit was operated as follows: 0.005 mA current input, 2.95 mA current input (circuit allows the input current range of 0 ~ 3 mA), change integral resistors R1 value, by 1 kΩ increased to 3 kΩ, change the sampling resistor R2 value, by 5 kΩ reduced to 2.5 kΩ. It is assumed that the parameter range of the circuit element exceeds 50% of its tolerance range, which is considered as a soft fault. The experimental site is shown in the Figure 2.

30 groups of output voltage response signals were collected for each fault type, and the samples were decomposed at the scale of 3 layers by using wavelet packet analysis, and the energy on the corresponding frequency segment could be calculated to obtain the 150×8 fault characteristic matrix. Signal decomposition diagram was obtained by visual analysis of the characteristic vectors, as shown in the Figure 3.

**Figure 2.** Diagram of the experimental site.

**Figure 3.** Diagram of Signal decomposition.

In each fault mode, 80 groups of fault features are cross-selected as training samples to train support vector machines. As test samples, 70 groups were sent to support vector machine for diagnosis.
Using libSVM, its main use of two functions: training function svmtrain() and prediction function svmpredict(). After the model training is successful, the fault sample set is used to verify the training results of SVM, and the result is shown in Figure 4.

At the same time, in order to further illustrate the effectiveness of the grey wolf optimization support vector machine method proposed in this paper, the standard GWO-SVM algorithm, PSO-SVM algorithm and CS-SVM algorithm were used to diagnose the fault of the circuit. The data of training samples and test samples of each model are the same as those of DE-GWO-SVM model, and the population size, iteration times and optimization range of each parameter in each optimization model are the same, too. Taking the mean-square error (MSE) as the optimization objective function, the MSE curves of the SVM model optimized by different algorithms is shown in Figure 5. It can be seen from the figure that the MSE of DE-GWO-SVM algorithm reaches the minimum in the third iteration, and the mean square error and optimization time are lower than other optimization algorithms.

The optimization parameters of each model, the iteration time and the accuracy of test classification are shown in Table 1.

| Optimization algorithm | Parameter optimization | Iteration time(s) | Fault accuracy |
|------------------------|------------------------|------------------|---------------|
| DE-GWO-SVM             | Penalty factor $C$ 9.19 | 3.726            | 97.33%        |
|                        | Kernel parameter $G$ 33.59 |                  |               |
| GWO-SVM                | Penalty factor $C$ 6.09 | 9.907            | 95.33%        |
|                        | Kernel parameter $G$ 30.71 |                  |               |

Table 1. Comparison of the diagnostic results.
The analysis shows that the diagnosis rate of the CS-SVM model is the lowest among the four methods. Compared with the SVM model diagnosed by traditional GWO-SVM algorithm, the accuracy of the DE-GWO-SVM model is improved from 95.33% to 97.33%, which has obvious optimization effect. Compared with other optimization algorithms, it shows that the optimization algorithm proposed in this paper has faster convergence speed, better optimization ability and algorithm stability while ensuring higher accuracy.

5. Conclusion
In this paper, the differential evolution adaptive gray wolf algorithm (DE-GWO) was proposed to optimize the SVM model for fault detection, and the model was applied to the fault diagnosis of the IF conversion circuit for the first time. Compared with the traditional SVM modeling method, the proposed method showed better classification performance, shortened the diagnosis time, and had better fault classification effect and better convergence.

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