Intelligent Electrical Fault Detection and Recognition Based on Gray Wolf Optimization and Support Vector Machine

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Abstract. With the increase of electrical equipment, the hidden danger of its failure also rises. Aiming at the problem that the classification accuracy of the basic traditional classification algorithm is not high when judging whether the electrical failure occurs, this paper proposes a Gray Wolf Optimization Support Vector Machine model to improve the recognition rate of electrical diagnosis, referred to as GWO-SVM. We first collected the most common linear (incandescent lamps) and non-linear (microwave ovens) household electrical appliances in normal working and arc fault waveform signals in real life, and then carried out frequency domain feature extraction. Finally, compared with no-optimized SVM and BP neural network, we employed the gray wolf optimization algorithm to optimize support vector machine, and the accuracy of GWO-SVM reaches 90%.

1. Introduction

Based on various electrical fault data from different sources, methods such as expert systems, Petri nets, multi-source fusion and analytical models [1-7] are derived. But there is the problem of poor recognition accuracy, so the optimization of the model has become the main research direction. Swarm intelligence optimization algorithm is a biological heuristic method, which is widely used in solving optimization problems. Traditional swarm intelligence algorithms provide new ideas for solving some practical problems, but they also expose shortcomings in some experiments. Swarm intelligence optimization algorithms are widely used in solving complex problems due to their simple structure and easy implementation. The more popular algorithms include genetic algorithm (GA), particle swarm optimization (PSO) [8], differential evolution (DE), ant colony optimization (ACO) and fruit fly optimization algorithm (FOA). The new swarm intelligence optimization algorithm provides new ideas and methods for solving a variety of practical problems. Taking Brain Storm Optimization (BSO) as an example, this is a new swarm intelligence optimization algorithm. The characteristic of this algorithm is that it combines the group optimization method and the data mining/data analysis method, and selects a relatively better solution based on the data analysis method.

Since the GWO algorithm was proposed in 2014, it has attracted wide attention from many scholars due to its superior performance [9-10]. The artificial fish swarm algorithm and particle swarm optimization AFSA-PSO is used to develop aircraft path planning [11]. L. Ge et al. [12] made a hybrid forecast of short-term photovoltaic power generation based on the PCA-GWO-GRNN algorithm.
Since the GWO algorithm has not been proposed for a long time, its theoretical research has not yet formed a system. Most scholars have improved and applied research on GWO from a specific perspective and for specific problems.

2. Gray Wolf Optimization Support Vector Machine Model

2.1. Support Vector Machine Model

Support vector machine (SVM) is a machine learning for supervised classification which maps the samples in the low-dimensional feature space to the high-dimensional through the kernel function and establishes a hyper-plane in the high-dimensional space to classify the samples. When the sample is linearly inseparable, SVM solves the problem by introducing relaxation variables. Therefore, SVM transforms the classification problem into a planning problem as in formula (1). The selection of the kernel function of SVM is particularly crucial. If the kernel is not selected properly, it means that the sample is mapped to an inappropriate feature space, which may lead to poor classification performance. Commonly used kernel functions include linear, polynomial, RBF, Laplacian and Sigmoid kernels. The specific analytical formula is shown in (2). Where \( g \) is the kernel parameter, which represents the width of the function.

\[
\min \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} \xi_i, \quad y_i (\omega^T x_i + b) \geq 1 - \xi_i, \quad i = 1, 2, \ldots, n
\]  

Among them, \((x_i, y_i)\) represents the \( i \)th group of samples; \( \omega \) represents the normal vector of the hyperplane; \( n \) represents the sample size; \( b \) is the coefficient in the hyper-plane equation; \( c \) is the penalty parameter; \( \xi_i \) is the relaxation factor.

\[
\begin{align*}
\text{Linear} : \kappa(x_i, x_j) &= x_i^T x_j \\
\text{Polynomial} : \kappa(x_i, x_j) &= (x_i^T x_j)^d \\
\text{RBF} : \kappa(x_i, x_j) &= \exp \left( -\frac{\| x_i - x_j \|^2}{2 \delta^2} \right) = e^{-g(x_i-x_j)^2} \\
\text{Laplacian} : \kappa(x_i, x_j) &= \exp \left( -\frac{x_i - x_j}{\delta} \right) \\
\text{Sigmoid} : \kappa(x_i, x_j) &= \tanh \left( \beta x_i^T x_j + \theta \right)
\end{align*}
\]  

2.2. Grey Wolf Optimization

Grey Wolf Optimizer (GWO) simulates the leadership level and hunting mechanism of gray wolves in nature. Four types of gray wolves, including alpha (alpha, \( \alpha \)), beta (beta, \( \beta \)), delta (delta, \( \delta \)), and omega (omega, \( \omega \)), are used to simulate leadership.

When designing GWO, it is necessary to abstract the social hierarchy of wolves as a suitable mathematical model. The default optimal solution is \( \alpha \), and the second and third optimal solutions are named \( \beta \) and \( \delta \), respectively. The remaining candidate solutions are assumed to be \( \omega \). In the GWO algorithm, the search (optimization) is guided by \((\alpha, \beta, \delta)\), and \( \omega \) follows these three wolves.

The wolves follow (alpha, \( \alpha \)), (beta, \( \beta \)) and (delta, \( \delta \)) to search for prey, and \( \Lambda > 1 \) means to force gray wolves to separate from their prey to determine the optimal attack target. After determining the attack target, the encircling line of the wolf pack can be expressed as formula (3). Among them: \( D \) is the Euclidean distance between the gray wolf and its prey; \( X(t) \) is the position vector after the gray wolf moves \( t \) times; \( X_p(t) \) is the position vector after the prey moves \( t \) times; \( A \) and \( C \) represent Coefficient vector. In the encircling process, the coefficient a linearly decreases from 2 to 0. The value of \( r_1 \) and \( r_1 \) modulus varies randomly between \([0, 1]\).
\begin{align*}
D &= \left| \mathbf{C} \cdot \overrightarrow{X_p}(t) - \overline{X}(t) \right| \\
\dot{X}(t+1) &= \overrightarrow{X_p}(t) - \mathbf{A} \cdot \dot{D} \\
\mathbf{A} &= 2\mathbf{a} \cdot \mathbf{r}_1 - \mathbf{a} \\
\mathbf{C} &= 2 \cdot \mathbf{r}_2 
\end{align*} \tag{3}

The specific optimization process is shown in Figure 1. The goal of this article is to treat the “penalty parameters \( c \)” and “kernel parameters \( g \)” in the SVM as prey, leverage GWO to perform global optimization, and find the parameters that can make the classification effect the best.

Figure 1 Schematic diagram and overall flow chart of gray wolf position update in GWO algorithm.

3. Experimental Results and Analysis

3.1. Data Collection and Processing

In order to verify the performance of the hybrid algorithm GWO-SVM, we selected the two most common household electrical appliances to conduct signal acquisition under normal operation and failure conditions.

Fourier transform is a mathematical formula that associates a signal sampled in time or space with the same signal sampled in frequency. In signal processing, Fourier transform can reveal important characteristics of the signal (that is, its frequency components). The continuous Fourier transform of the function \( f(t) \in L_1(\mathbb{R}) \) is defined as equation (4). The inverse Fourier transform of \( F \) is defined as equation (5). If \( f(t) \) is a function with \( 2p \) as the period on the real axis, that is, it satisfies \( f(t) \in L_2(0,2p) \), then \( f(t) \) can be expressed as the formation of Fourier series, as shown in equation (6), where \( C_n \) is the Fourier expansion coefficient.

\[
F(\omega) = \int_{-\infty}^{+\infty} e^{-i\omega t} f(t) dt \tag{4}
\]
\[ f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-i\omega t} F(\omega) d\omega \] (5)

\[ f(t) = \sum_{n=0}^{\infty} C_n e^{i\pi nt/p} \] (6)

Linear components choose "-220V, 100W" incandescent lamp as the resistance load. The time domain and Fourier transform of the current waveform are shown in Figure 2. When an arc fault occurs, the current amplitude has obvious high-order harmonics, and in the fringe frequency domain (0–2HZ and 18–20HZ), the amplitude distribution value is wider than normal.

Non-linear components selected eddy current load (induction cooker). The time domain and Fourier transform of the current waveform are shown in Figure 3. When an arc fault occurs, the current waveform is irregular and the amplitude increases with time. When an arc fault occurs, the maximum amplitude reaches 800.

3.2. Classification Effect Analysis
To further verify the performance of the proposed algorithm, this paper collects the signals of 2 kinds of electrical loads, a total of 400 sets of data, 200 sets of each load. We randomly select 80% of the data for training and the remaining 20% for testing.

The optimization process of GWO can be seen in Figure 4. It can be seen that the optimal penalty parameter \( C \) of SVM is equal to 1.2097, and the classification effect is optimal when the kernel parameter \( g \) is equal to 0.0001. Figure 5 shows the specific classification effects on the two types of load test sets, where 0 represents normal and 1 represents failure. The linear load incandescent lamp

(a) The current waveforms (b) Frequency domain distribution [normal] or [fault]

Figure 2 Incandescent lamp (linear) time domain and frequency domain characteristics.

(a) The current waveforms (b) Frequency domain distribution [normal] or [fault]

Figure 3 Microwave oven (non-linear) time domain and frequency domain characteristics.
achieves 100% accuracy in the first 20 groups of normal signals. In the remaining 20 groups of fault signals, the accuracy of the 31st and 40th groups is incorrect, and the accuracy is 90%. The non-linear load microwave oven has a 10% error rate in the 20 groups of normal signals, and the classification error rate in the remaining fault signals is 20%.

![Image of GWO optimized parameter space and GWO iteration process.](image1)

**Figure 4** GWO optimized parameter space and GWO iteration process.

![Image of Detection results of incandescent lamp and microwave oven.](image2)

**Figure 5** Detection results of incandescent lamp and microwave oven.

| Model          | Incandescent lamp | Microwave Oven | Correct Rate |
|----------------|-------------------|----------------|--------------|
|                | Normal | Fault | Normal | Fault |        |
| BPNN           | 18     | 15    | 15     | 14    | 77.5% |
| SVM [linear]   | 18     | 16    | 15     | 17    | 82.5% |
| SVM [polynomial] | 17     | 14    | 16     | 16    | 78.8% |
| SVM [RBF]      | 19     | 17    | 17     | 15    | 85.0% |
| SVM [Laplacian] | 18     | 15    | 14     | 16    | 78.8% |
| SVM [Sigmoid]  | 19     | 18    | 16     | 16    | 86.3% |
| GWO-SVM        | 20     | 18    | 18     | 16    | 90.0% |

**Table 1. Classification accuracy statistics of the paper algorithm and comparison model.**
Non-linear load classification effect is inferior to linear load. In summary, the overall accuracy of GWO-SVM classification is 90%, which is better than the comparison model, as shown in Table 1. It is worth noting that this article comprehensively compares the selection of different SVM kernel functions, and finally chooses the RBF kernel for the experiment.

4. Conclusion
Based on the poor generalization performance of traditional classifiers in electrical fault detection, this paper proposes a support vector machine model for wolf pack optimization. Through experiments, it can be seen that the proposed model has a significant improvement in linear and non-linear loads. Compared with the optimal SVM [Sigmoid], the performance improvement is about 5%. In addition, the gray wolf algorithm has strong competitiveness in the optimization process. At present, the distribution of samples of different categories is uniform. Our next research direction is to start with the problem of class imbalance and solve the classification problem of electrical faults.

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