Journal of Physics: Conference Series

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To cite this article: Maochang Yu *et al* 2022 *J. Phys.: Conf. Ser.* **2232** 012017

Motor fault diagnosis based on teaching and learning gray wolf algorithm optimized support vector machine

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Abstract. To quickly and accurately identify motor faults, this paper proposes the gray wolf algorithm based on teaching and learning improvement to adaptively optimize the parameters of the multi-class support vector machine. Finally, based on the improved algorithm, the seven types of fault data such as the air gap eccentricity of the motor, the broken bar of the rotor, the bearing seat damage, and the bearing wear were carried out fault diagnosis experiments, and a comprehensive comparison and analysis were carried out with the widely used algorithm. The results show that the motor fault diagnosis accuracy rate of this method is 97.88%, which is better than other methods in classification accuracy.

1. Introduction

Because the motor is always under different pressures in the industrial environment and affected by the power supply and load conditions, the motor will inevitably have various faults in the long-term operation process. These faults will have a serious impact on the reliability and safety of the motor. If they cannot be diagnosed and corrected in time, they may cause serious consequences. Therefore, the fault diagnosis technology for the motor is particularly important[1].

The motor vibration signal data is a linear indivisible data set, and the support vector machine can use a nonlinear mapping to transform the vector points in the original data set into a higher-dimensional space [2], in this high-dimensional space Find a linear hyperplane to perform classification processing. However, the parameters of support vector machines are difficult to optimize and most rely on empirical selection. It is difficult to meet the requirements of fault diagnosis only using specific support vector machines. Therefore, some scholars optimize the support vector machine model by combining classic evolutionary algorithms, such as genetic algorithm [3], particle swarm algorithm [4], quantum particle swarm algorithm [5], and fruit fly optimization algorithm [6], etc. [7].

Based on this, this paper proposes a motor fault diagnosis method based on the teaching and learning gray wolf algorithm to optimize the support vector machine. First, the teaching and learning algorithm is deeply integrated with the gray wolf optimization algorithm to adaptively optimize the kernel function and penalty function parameters of the support vector machine; then through training The latter support vector machine performs pattern recognition on the feature vector; finally, through experiments and comparative analysis, the superiority and applicability of the method are verified.

2. Support vector machine

Support vector machine is a machine learning model used for classification. Its basic model is defined as a linear classifier with the largest interval in the feature space. Its learning strategy is to maximize the interval, which can eventually be transformed into a convex quadratic programming problem.

Currently, the most widely used kernel functions include linear kernel function, polynomial kernel function, Sigmoid kernel function, and RBF kernel function. Based on the characteristics of the RBF kernel function that can approximate any nonlinear function, this paper adopts the RBF kernel function as the kernel function of the support vector machine. The RBF kernel function is

$$K\left(\mathbf{X}_i,\mathbf{X}_j\right)=\exp\left(-\frac{\left|\mathbf{X}_i-\mathbf{X}_j\right|^2}{2\sigma^2}\right),g=\frac{1}{2\sigma^2} \tag{1}$$

The smaller g in the kernel function, the more support vectors, the more likely it is to cause over-fitting, otherwise the data is difficult to distinguish; the smaller the penalty constant C is, the easier it is to under-fit, and if C is too large or too small, the generalization ability becomes worse. Therefore, the gray wolf optimization (GWO) algorithm is introduced to optimize the parameters of the support vector machine and build an adaptive model. The structure of the support vector machine is shown in Figure 1.

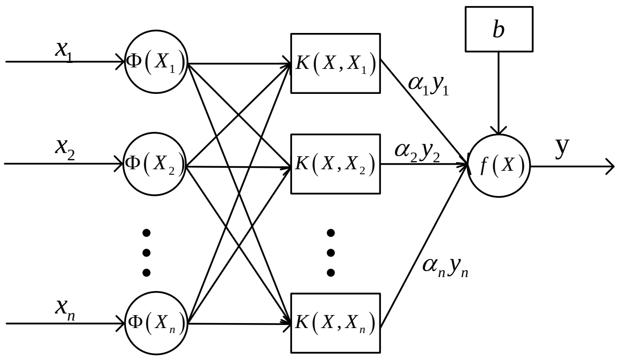

Figure 1. The structure of the support vector machine.

3. Grey wolf optimization algorithm based on teaching and learning

3.1. Grey wolf optimization algorithm

The gray wolf optimization algorithm is proposed by Seyedali et al. based on the hunting behavior of wolves [8]. The mathematical model of wolves encircling and hunting is as follows

$$\begin{cases} X_1(t+1)=X_\alpha(t)-A_1\cdot\left|R_1\cdot X_\alpha(t)-X(t)\right| \\ X_2(t+1)=X_\beta(t)-A_2\cdot\left|R_2\cdot X_\beta(t)-X(t)\right| \\ X_3(t+1)=X_\delta(t)-A_3\cdot\left|R_3\cdot X_\delta(t)-X(t)\right| \end{cases} \tag{2}$$

where, 'A' and 'R' are the coefficients of the vector, $X_\alpha(t)$, $X_\beta(t)$ and $X_\delta(t)$ respectively represent the positions of α, β and δ wolves, $X(t)$ and $X(t+1)$ respectively represent the positions before and after the gray wolf moves. The calculation formulas of convergence factor A and swing factor R are as follows

$$A=2a\cdot r_1-a \tag{3}$$

$$R=2\cdot r_2 \tag{4}$$

where, r_1 and r_2 are a random number in the range of [0,1]. As the iteration progresses, the value of the distance control parameter a decreases linearly from 2 to 0. The calculation formula is as follows

$$a = a_{\text{start}} - \left(a_{\text{start}} - a_{\text{end}}\right)\frac{\text{i}}{I_{\max}} \tag{5}$$

where, a_{start} and a_{end} are the initial and final values of a, i is the current iteration number, $I_{\max}$ is the total number of iterations.

In the hunting process, the gray wolf cannot determine the position of the prey (the optimal solution). The search process is mainly completed by the guidance of the three best wolves. The alpha wolf, the beta wolf, and the gamma wolf are the closest to the prey, and the other wolves follow it. Move, get the GWO algorithm position update formula:

$$X_{gwo}(t+1) = \frac{X_1(t+1) + X_2(t+1) + X_3(t+1)}{3} \tag{6}$$

3.2. *Location strategy update based on teaching and learning*

However, the GWO algorithm ignores the communication and learning between wolves when hunting. It only relies on the guidance of α, β and δ wolves to reduce the difference after a certain number of iterations. Therefore, the introduction of the teaching and learning algorithm (TLOB) to improve. TLOB algorithm is divided into the teacher stage and the learning stage. In the teacher stage, the teacher $X_p(t)$ is the solution with the best fitness value in a group, here are the positions of α, β and δ wolves. $\overline{X}(t)$ is the average grade of this class, here is the average position of 10 gray wolves. Learners try to improve their average grades through teachers' teaching. The calculation formula is as follows

$$\Delta X_{tli}(t+1) = X_p(t) - T_f\,\overline{X}(t) \tag{7}$$

$$T_f = \text{round}\,[1 + \text{rand}()] \tag{8}$$

where, T_f is the teaching factor, 1 or 2 is randomly selected. The teacher stage of the TLBO algorithm is introduced into the GWO algorithm, and the positions of α, β and δ wolves are used as teacher positions, and the expression is obtained as follows

$$\Delta X_{tl}(t+1) = \frac{\Delta X_{tl1}(t+1) + \Delta X_{tl2}(t+1) + \Delta X_{tl3}(t+1)}{3} \tag{9}$$

where, $X_{tl}(t+1)$ is the hunting direction obtained by the individual wolves based on the differences in the average positions of α, β, δ wolves and the wolf group. Therefore, the gray wolf position update formula based on teaching and learning is obtained

$$X(t+1) = e_1 X_{gwo}(t+1) + e_2 \Delta X_{tl}(t+1) \tag{10}$$

where, e_1, e_2 is the weight factor, which respectively represents the weight of the best fitness of the entire wolf pack and the weight of the average moving direction of the population. Elite wolves play an absolute leading role in the wolves, so e_1 has a larger proportion than e_2, and the two factors in this paper are 0.7 and 0.3 respectively.

4. Motor fault diagnosis

In the experiment, the motor vibration acceleration data measured by Case Western Reserve University is used to verify the feature extraction and fault diagnosis method in this paper. The motor power is 1.5 k W, and the fan is used as the load to change the load of the bearing. This article chooses 2 turns short circuit [9] (F1), 4 turns short circuit (F2), 8 turns short circuit (F3), air gap eccentricity (F4), Rotor broken bar (F5), Bearing seat damage (F6), Bearing wear (F7) common faults as the research object, according to the selected fault type and deviation degree, change the data and calibrate the fault type (F1-F7) And normal type (F0) to form a motor vibration data failure set (size 8000×1024, 1000 data in each state).

4.1. Experiment procedure

The fault diagnosis model is divided into five stages: In the first stage, wavelet packet decomposition is performed on the motor vibration signal data set, and 8 frequency bands are obtained; in the second stage, 7 fault categories are defined (plus 8 categories in the normal state), and the data is divided into the training set and test set (800:200 for each category training set and test set); in the third stage, teaching and The teacher stage of the learning algorithm optimizes the position update formula of the gray wolf algorithm, builds a support vector machine model and trains to obtain the fault diagnosis classification model; the fourth stage, the test set is substituted into the classification model for comparison experiments; the fifth stage, the fault is determined Category, analysis, and evaluation of experimental results. The process of the fault diagnosis model in this paper is shown in Figure 2.

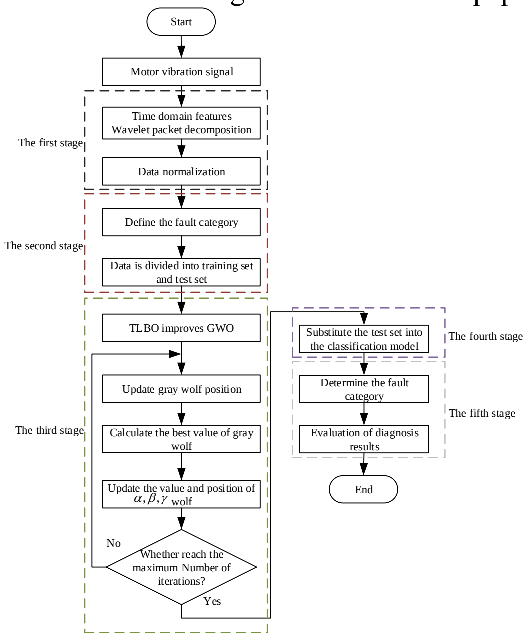

Figure 2. TLGWO-SVM fault diagnosis model process.

4.2. SVM grid optimization

Before the experiment, perform grid optimization on the SVM penalty parameter and the kernel parameter to obtain the relationship between the SVM classification accuracy rate for the fault data set and the two parameters. The color in Figure 3 represents the SVM classification accuracy rate, and the right side is the corresponding Color mark value. It can be obtained from the figure that when g takes a small value, the classification accuracy rate is relatively high, while the value of C is irregular, and it is necessary to rely on intelligent algorithms to iteratively optimize the model.

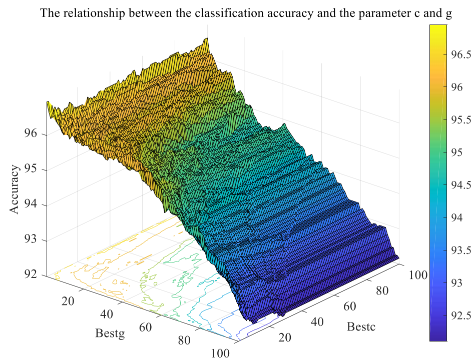

Figure 3. SVM grid optimization results.

4.3. Analysis of results

To verify the effectiveness of the algorithm in this paper, compare the classification results of TLGWO-SVM and other intelligent algorithm optimization (cuckoo algorithm, firefly algorithm, artificial bee colony algorithm, gray wolf algorithm) support vector machine in the motor fault data set. Algorithm parameter setting: All kernel functions based on support vector machines use RBF kernel function, the range of penalty parameter C and kernel parameter g are set to (0.01-100), and the number of iterations is set to 10. The average precision and mean square error of the test samples are obtained by the five-fold cross-validation method, and the classification results are shown in Table 1.

Table 1. Motor fault diagnosis result.

Algorithm	Accuracy	Time/s
SVM	0.9425±0.02	**1.2**
CS-SVM	0.9707±0.002	160
FA-SVM	0.9693±0.01	42
ABC-SVM	0.9701±0.002	179
GWO-SVM	0.9738±0.01	31
TLGWO-SVM	**0.9788±0.001**	24

From the experimental results, compared with the other five algorithms, the standard SVM has the shortest diagnosis time due to the absence of parameter optimization process, while TLGWO-SVM is the shortest time-consuming except for the standard SVM, and its classification accuracy rate is the highest, and the standard deviation is the lowest, which shows that the algorithm has high accuracy and stability in motor fault diagnosis. The fault diagnosis result of TLGWO-SVM is shown in Figure 4. The fault 4 turn short circuit (F2) and 8 turn short circuit (F3) as well as bearing seat damage (F6) and bearing wear (F7) is due to the way the fault occurs. Similarly, there is little difference in vibration signals, and it is prone to situations that are more difficult to diagnose.

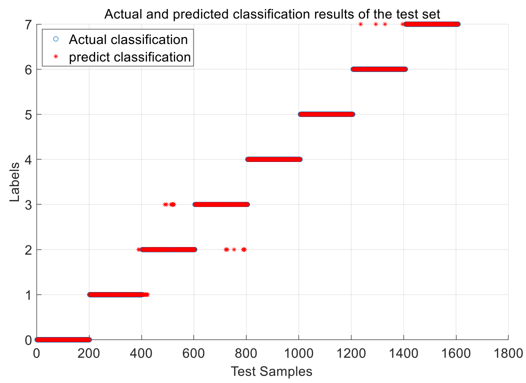

Figure 4. Actual classification and predicted classification results of the test set.

The algorithm in this paper adopts a one-by-one comparison and substitution method to improve the population initialization strategy in the initialization position stage, which improves the convergence of the algorithm. The introduction of teaching and learning strategies in the iterative process strengthens the communication between wolves and the learning of the individual's own experience, and the algorithm's global search ability is improved. The classification accuracy of the support vector machine after parameter optimization is greatly improved, and the learning process does not require intervention, which greatly improves the automation and accuracy of motor fault diagnosis.

5. Conclusion

In the motor fault diagnosis, the fault diagnosis model structure is difficult to choose, and the fault data is high-dimensional and nonlinear. This paper adopts the fault diagnosis model based on wavelet packet, teaching and learning improved gray wolf algorithm and support vector machine, and uses wavelet packet decomposition to have multiple frequency bands. The characteristics of the analysis have carried out feature extraction on the collected vibration data, explored the effectiveness of using the improved gray wolf algorithm based on teaching and learning to optimize the parameters of the SVM model, and compared the TLGWO parameter optimization method with the other five intelligences through experiments. The advantage of the algorithm is that it not only has the characteristics of short optimization time but also makes the fault classification accuracy of the support vector machine fault diagnosis model higher.

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