FAULT DIAGNOSIS OF TAMPER ROLLING BEARING BASED ON IPSO ALGORITHM FOR OPTIMIZING FSVM

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Rolling bearing is one of the most devices and easily damaged devices in mechanical system. Therefore it is of great practical significance to study the fault diagnosis method of rolling bearing. Because the fault signals of rolling bearings collected by sensors often contain noise points, this will affect the results of fault diagnosis. This problem can be solved well by the Fuzzy Support Vector Machines (FSVM) based on sampling points. In order to improve the diagnostic accuracy of FSVM, the Particle Swarm Optimization (PSO) algorithm was adopted to improve the diagnostic accuracy of FSVM. At the same time, in order to better coordinate the global and local optimization ability of particle swarm optimization algorithm, this paper will add the inertial factor in the process of algorithm optimization. The dynamic updating inertia weight of integration greatly improves the performance of the basic particle swarm optimization algorithm. Therefore, the fault diagnosis model with improved particle swarm algorithm (IPSO) and Fuzzy Support Vector Machine is chosen to process and classify the fault signals of the tamping machine bearing. The experimental results show that the proposed model has a good diagnosis effect in the field of rolling bearing fault diagnosis. The experimental results show that the proposed model achieves faster diagnosis speed and improved diagnostic accuracy in the field of rolling bearing fault diagnosis.

Keywords: rolling bearing; fuzzy support vector machine; particle swarm optimization; fault diagnosis

1. Introduction

The Tamping machine is a kind of large-scale maintenance machinery, which is mainly used for the construction of the new railway line and the fault clearing during the maintenance of the railway. Its purpose is to ensure that the

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train can operate stably and efficiently. Therefore, the rapid and accurate judgment of the various faults of the tamping machine has an engineering value that cannot be ignored [1-2].

Rolling bearing is an important component of mechanical equipment and it is also one of the components that frequently fail. It determines the normal operation of the entire mechanical equipment with a high probability [3-5]. The new classifier Support Vector Machines (SVM)[6] proposed by Vapnik et al. in 1995 has received widespread attention from scholars at home and abroad [7-9].

SVM is mainly used for linear classification problems, and the problem is classified by constructing an optimal hyperplane. The problems that are linearly inseparable are mainly the mapping of low-dimensional space into high-dimensional space through kernel functions, so as to achieve linear separability. Although SVM has good classification ability and global generalization ability, due to the influence of environmental factors, samples collected by SVM have fuzzy information such as noise points and isolated points, which ultimately results in a significant reduction in diagnostic accuracy. In order to solve this problem, Lin et al. proposed the concept of Fuzzy Support Vector Machines (FSVM) [10] in 2002. The fuzzy factor was introduced into the support vector machine to effectively improve the external factors on the classification accuracy. Impact.

Particle swarm optimization (PSO) has the advantages of simple structure, less parameter adjustment and easy integration with other methods. Therefore, it is deeply loved by many scholars and applied to the field of fault diagnosis [11-13]. However, the disadvantage of this algorithm is that it tends to produce premature convergence and poor local search ability. This paper creatively proposes a fault diagnosis method that combines improved particle swarm optimization algorithm and FSVM, and finally successfully applied to the field of rolling bearing fault diagnosis, and specifically to the fault diagnosis of rolling bearings of tamping machine. First, the wavelet decomposition method is used to extract the feature vectors of rolling bearing fault data and normalize it; then PSO is used to optimize the FSVM model; finally, in order to avoid the PSO algorithm falling into the local optimum, In this paper, the inertial factor is introduced in the PSO optimization process. The experimental results show that the IPSO-FSVM model incorporating the dynamic update inertia weight greatly improves the accuracy and efficiency of the fault diagnosis of rolling bearings.

2. Particle Swarm Optimization Algorithm and Its Improvement

2.1 Basic Particle Swarm Optimization Algorithm

In 1995, Dr. Kennedy and Dr. Eberhart proposed a heuristically optimized global optimization algorithm, Particle Swarm Optimization (PSO) [14]. In particle swarm optimization, the two vectors of position and velocity are particularly important. Assume that the particle's search space is N-dimensional space and the total number of population particles is M. The position of the i-th particle at the t-th optimization is represented as $X_i(t) = [X_{i,1}(t), X_{i,2}(t), \cdots, X_{i,N}(t)]$, this positional fitness function is expressed as $f[X_i(t)]$.Velocity is expressed as $V_i(t) = [V_{i,1}(t), V_{i,2}(t), \cdots, V_{i,N}(t)]$, individual extrema of particles Expressed as $P_i(t) = [P_{i,1}(t), P_{i,2}(t), \cdots, P_{i,N}(t)]$, fitness function of individual extremum Expressed as $f[P_i(t)]$. The global extremum is expressed as $G(t) = P_g(t) = [P_{g,1}(t), P_{g,2}(t), \cdots, P_{g,N}(t)]$, $1 \le g \le M$. Using formula (1) for individual extrema updates of particles:

$$P_i(t) = \begin{cases} X_i(t) & ,if \quad f[X_i(t)] < f[P_i(t)] \\ P_i(t-1) & ,if \quad f[X_i(t)] \ge f[P_i(t)] \end{cases} \tag{1}$$

Formula (2) and (3) were used to update particle velocity and position of particle swarm optimization algorithm at time (t+1) :

$$V_{i,j}(t+1) = V_{i,j}(t) + c_1 \cdot r_{1,i,j}(t) \cdot \left(P_{i,j}(t) - X_{i,j}(t)\right) + c_2 \cdot r_{2,i,j}(t) \cdot \left(G_j(t) - X_{i,j}(t)\right) \tag{2}$$

$$X_{i,j}(t+1) = V_{i,j}(t+1) + X_{i,j}(t) \tag{3}$$

Among them, $1 \le i \le M$, $1 \le j \le N\ t$, t represents the particle t-th optimization; both c_1 and c_2 are constants, which are represented as learning factors, c_1 is used to ensure the distance of the particles move to the local optimal position, and c_2 is used to ensure the distance that the particles move to the global optimal position; $r_{1,i,j}(t)$ and $r_{2,i,j}(t) \sim U(0,1)$.

2.2 Improved Particle Swarm Optimization Algorithm

In order to balance PSO's global search ability and local search ability, this paper introduces the inertia factor ω to achieve the above purpose. After the inertia factor ω is added to formula (2), the speed update formula is changed to (4):

$$V_{i,j}(t+1) = \omega V_{i,j}(t) + c_1 \cdot r_{1,i,j}(t) \cdot \left(P_{i,j}(t) - X_{i,j}(t)\right) + c_2 \cdot r_{2,i,j}(t) \cdot \left(G_j(t) - X_{i,j}(t)\right) \quad (4)$$

In general, the size of learning factors seriously affects the convergence rate of the population, so that $c1 = c2 = 2$.

In order to avoid information loss and achieve global optimization as far as possible in PSO, the idea of cross mutation can be introduced to improve the ability of PSO to search the global extremum in the update and adjustment of speed. In order to make the adjustment of the particle inertia weight ω more reasonable, the author in ensuring ω has obvious adaptive characteristics at the same time, will be the result of the fitness function into the adjustment process of the particle inertia weight ω. The inertial weight ω of particles can be obtained by the equation (5) :

$$\omega(t) = \begin{cases} \frac{(\omega_{max}-\omega_{min})(f-f_{max})}{f_{avg}-f_{max}} + \omega_{min}, & f \le f_{avg} \\ \omega_{max}, & f > f_{avg} \end{cases} \quad (5)$$

In the above formula, ω_{min} and ω_{max} represent the minimum and maximum value of the inertial factor respectively. According to previous experimental experience, set $\omega_{min} = 0.3$ and $\omega_{max} = 1.0$.

f represents the fitness function value of the current particle's position, f_{max} represents the fitness function value of the global extreme particle, and f_{avg} represents the average fitness function value of all particles in the population. In the iterative process, the inertial factors ω are dynamically changed according to the fitness function corresponding to the particles.

3. Fuzzy Support Vector Machine and Its Improved Algorithm

3.1 Fuzzy Support Vector Machine

Fuzzy support vector machine (FSVM) uses fuzzy membership functions and mapping optimization techniques to preprocess training samples and give them different weights according to the important level of training samples, and further study them according to the feature information of training samples to achieve high precision classification. Suppose the training set of FSVM is: $S = \{(x_1, y_1, \mu_1), (x_2, y_2, \mu_2), \cdots, (x_l, y_l, \mu_l)$, where $x_i \in R^n$;$0 < \mu_i \le 1$; $y_i \in \{-1,1\}$, $i = 1,2,\cdots,l$. The fuzzy membership degree μ_i indicates the degree to which the sample x_i belongs to a certain class. The relaxation variable ζ_i is used to detect the classification error of the sample. In this way, the $\mu_i\zeta_i$ was expressed as a relaxation variable with fuzzy information in the sample, which was used to reduce the possibility of misclassification of variables of different importance. The optimal classification hyperplane of FSVM is formula (6) :

$$min\phi(\omega) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\mu_i\zeta_i \quad (6)$$

$$\text{s.t.} \quad y_i(\omega \cdot \phi(x_i) + b) - 1 + \zeta_i \geq 0 \quad (7)$$

In the formula, ζ_i≥0; the penalty coefficient C is a constant, and the FSVM method fuzzifies the penalty coefficient C to ensure that samples with different membership degree have different effects in the learning model. In general, if μ_i is larger, then the importance of the sample is higher and it is not easy to misclassify it. A smaller membership value can then be given to the sample to reduce the effect of the sample on the learning model, thereby greatly reducing the impact of unascertained information such as noise on the fuzzy support vector machine.

3.2 Improved Particle Swarm Optimization Algorithm to Optimize Fuzzy Support Vector Machine

The purpose of this paper is to solve the problem of the design of multi-value classifier for the fault diagnosis of the rolling bearing of tamping machine.

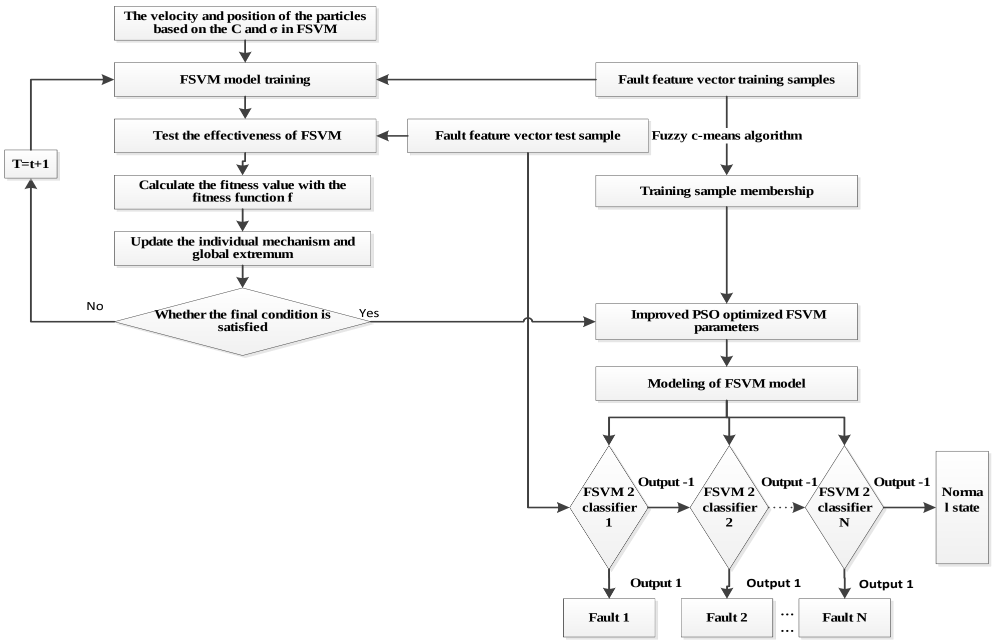

Fig. 1. Multiple classification FSVM fault detection model based on improved PSO

Multi-class classification methods can be decomposed into groups of two classes of classification methods, usually using a number of two types of FSVM classifier, according to the binary tree structure in series to classify the samples, and finally through an improved adaptive inertia weight adjustment particle swarm optimization algorithm to optimize the model parameters so that the constructed N-type fault classifier has the best performance. Its model is shown in Fig. 1.

4. Experiment and result analysis

4.1 Experiment Preparation and Feature Extraction

In order to verify the good performance of the improved PSO optimized FSVM fault diagnosis model, relevant data of the roller bearing of the tamping machine provided by Kunming China railway corporation were used for the experiment. According to the wavelet three-layer decomposition principle, the energy features of the bearing are extracted in the experiment, and part of the experimental data are shown in table 1. Four types of bearings (Normal bearing, Inner race fault, Outer race fault, and Ball fault) were selected for the experiment [16]. For each fault, 30 samples were selected as training samples. In total, 120 feature vectors were selected and the selected 120 feature vectors were entered into the data sample to prepare for training. Then select 20 feature vectors for each fault, a total of 80 feature vectors are stored in the data sample as the test sample set.

The experiment set the penalty coefficient C=[0.01,100], the radial basis kernel function parameter σ=[0.05,100], and the number of iterations were 200.

Table 1

Partial sample of fault energy characteristics of the wavelet extraction bearing

Fault	E1	E2	E3	E4	E5	E6	E7	E8	Label
Normal bearing	0.5613	0.3569	0.0112	0.1378	0.0000	0.0007	0.0012	0.0018	1
Inner race fault	0.0424	0.0983	0.3186	0.0910	0.0014	0.0052	0.3951	0.0521	2
Outer race fault	0.0280	0.0176	0.2145	0.0077	0.0005	0.0043	0.6452	0.0346	3
Ball fault	0.0369	0.0243	0.2684	0.0162	0.0026	0.0028	0.6187	0.0209	4

4.2 Analysis of experimental results

In order to reflect the advantages of the proposed method, the experiment will use the IPSO optimization FSVM and the basic PSO optimization FSVM two models to train the rolling bearing sample data of the tamper m and compare the optimization speed and diagnostic accuracy of the two models. Fig. 2 shows the relationship between the number of iterations and fitness function values for the above two fault diagnosis models.

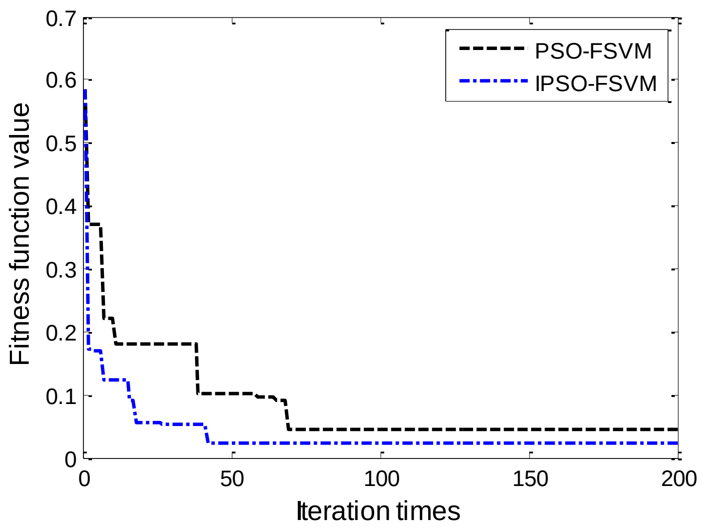

Fig. 2. The relationship between the number of iterations of PSO-FSVM and IPSO-FSVM and the degree of adaptability

In this paper, relative error is selected as the fitness function value of the two models. When the fitness function value converges, it means that the FSVM model takes the optimal parameters, which means that its prediction relative error is the minimum. It can be seen from the figure that when the parameters of the improved particle swarm optimization algorithm reach the optimal value, the algorithm iterates to the 42th time. When the parameters of the basic particle swarm optimization algorithm are optimized, the algorithm is iterated to the 69th time, and the effect is obviously not as good as IPSO. Therefore, it can be concluded that IPSO has a faster optimization speed for FSVM parameters than basic PSO, and the error rate is lower.

In order to prove the superiority of the IPSO-FSVM model, the comparison experiment was set up to identify fault types when the training data and test data of the two models were the same, and the robustness of the IPSO-FSVM diagnostic model was confirmed by the experimental results. Figure 3 shows the test set classification results for these two fault diagnosis models:

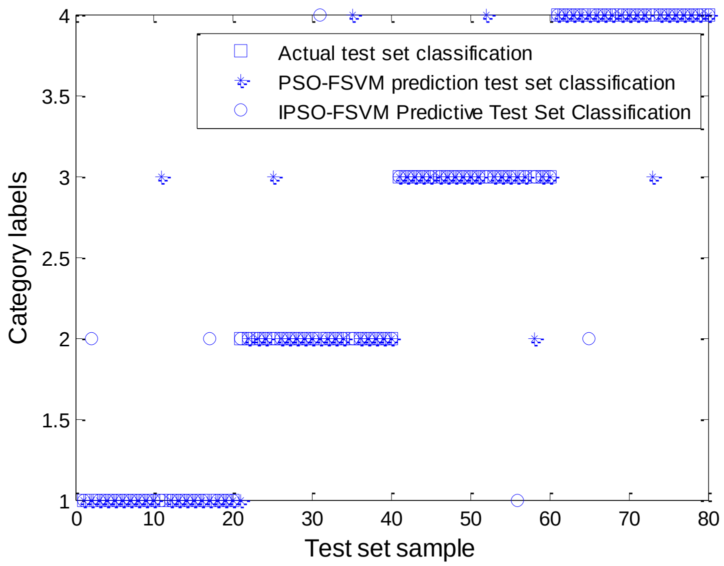

Fig. 3. Prediction and actual classification results of PSO-FSVM and IPSO-FSVM

Table 2

Diagnostic accuracy of IPSO-FSVM and PSO-FSVM fault diagnosis models

methods	Number of correct diagnosis				Number of misdiagnosis	The total number of diagnosis	Diagnostic accuracy
	1	2	3	4			
PSO-FSVM	18	17	18	19	8	80	90.00%
IPSO-FSVM	18	19	19	19	5	80	93.75%

According to Fig. 3 and table 2, we can see that when using the PSO-FSVM model for fault diagnosis, the diagnostic accuracy rate is 90.00%; when using the IPSO-FSVM model for fault diagnosis, the diagnostic accuracy rate is as high as 93.75%, and it has been fully able to identify and classify all kinds of faults of the rolling bearing of the tamping machine. The experimental results show that the accuracy rate of classification using IPSO-FSVM model is much higher than that of PSO-FSVM model for small sample sets. It is proved that the IPSO-FSVM fault classification model presented in this paper has high classification accuracy and can be efficiently completed for small sample fault diagnosis.

The FSVM multi-classification model based on the binary tree structure is constructed according to the optimal parameters obtained by the improved particle swarm optimization algorithm. and then the test set is classified and identified by using the model, and the classification effect is shown in Fig. 4.

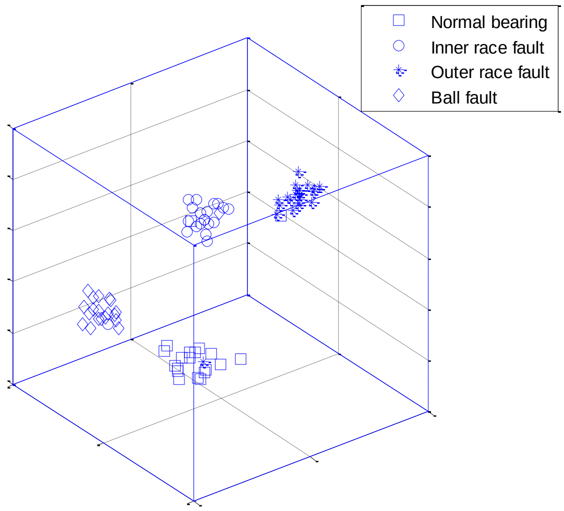

Fig. 4. Multi-valued FSVM classification diagram constructed with optimized parameters optimized by IPSO algorithm

From Fig. 4, it can be seen that the multi value FSVM classification model constructed with the optimized parameters optimized by the improved PSO algorithm can be well divided into the fault types, and the classification effect is excellent and has high practical value.

5. Conclusion

In this paper, the wavelet three-layer decomposition principle is used to extract the fault signals of the rolling bearing, then the fault classification of the rolling bearing based on the fuzzy sample point FSVM method is used to solve the problem of the influence of noise and fuzzy points on the classification result effectively. At the same time, in order to improve the efficiency and accuracy of classification, this paper proposes to optimize the relevant parameters of FSVM by using particle swarm optimization algorithm with inertial factors.

The experimental results show that the improved particle swarm optimization algorithm has the advantages of fast searching speed and strong searching ability; The IPSO-FSVM model has excellent effect on the fault classification of the rolling bearing of the tamping machine and has good application value.

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