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Fault Diagnosis of Motor Rolling Bearing Based on GWO-SVM

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Abstract

The classification performance of Support Vector Machine (SVM) is greatly influenced by the characteristics of the sample and the selection of parameters of the SVM itself. Aiming at this situation, based on Shannon energy entropy, SVM and grey wolf optimization algorithm (GWO), a fault diagnosis method for motor rolling bearing based on GWO-SVM is proposed. The method adopts the fault-tolerant shannon energy entropy as the characteristic parameter, and extracts the first three IMF components as the characteristic signals by EMD decomposition, and calculates the Shannon energy entropy as the feature vector to obtain the sample set as the input of the multi-class SVM. When training SVM with samples, a new kernel function is constructed, and GWO is used to globally optimize the kernel function parameters of SVM, so that SVM can obtain the best classification performance and improve the accuracy of classification identification. Finally, the classification and identification of rolling bearing fault samples of Case Western Reserve University were carried out, and compared with other methods. The results show that the method has better reliability and classification accuracy.

Keywords

SVM,GWO, SVM-GWO,Shannon energy entropy, Troubleshooting.

1. Introduction

As an important rotating part of mechanical equipment, rolling bearing is also one of the important failure sources of mechanical equipment. Its working performance directly affects whether the mechanical equipment can work normally[1,2]. Therefore, the working parameters of the rolling bearing are monitored in real time and as much as possible. It is an important means to ensure the normal operation of mechanical equipment by timely and accurately diagnosing the fault type and eliminating the fault in the case of monitoring the fault to minimize the fault risk.How to extract the characteristic parameters that can effectively characterize the fault state from the non-stationary fault signal of the rolling bearing is the key to realize the diagnosis. However, no matter which feature extraction method is adopted, there are inevitably some features that are not related to fault diagnosis in the original feature parameter set, which will increase the calculation amount of fault diagnosis and reduce the accuracy of fault diagnosis. Therefore, it is especially necessary to optimize the selection of the original feature parameter set[3].

Suppo~vector machine (SVM) is a pattern recognition method developed on the basis of statistical learning theory[4]. It can obtain good classification and promotion ability under the condition of less sample number. It has better than artificial neural network. Better generalization ability is more applicable to problems such as small sample, nonlinear and high-dimensional pattern recognition. Therefore, it has become a research hotspot in the field of machine learning and has been widely used in mechanical fault diagnosis. The selection of SVM kernel functions and the setting of parameters largely determine the performance of SVM. Therefore, the selection and optimization of kernel

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function types, kernel parameters and SVM parameters are one of the key issues to be solved in SVM applications.

The Grey Wolf Optimization Algorithm (GWO) is a new meta-heuristic optimization algorithm proposed by Seyedali Mirjalili et al. Because of its good convergence speed and optimization precision, it has been widely promoted in many fields and has good performance. Application reference value. In this paper, the grey wolf optimization algorithm is applied to the parameter optimization of the motor rolling bearing fault diagnosis pattern recognition network. Through the optimization of the SVM training network parameters, the accuracy and efficiency of fault classification identification can be improved.

Therefore, this paper proposes a fault diagnosis method based on GWO-SVM by using the multi-classification performance of SVM and the global optimization ability of GWO optimization parameters.

2. Shannon Energy Entropy

For the noisy signals collected in the field and the early fault signals of mechanical equipment, the effective extraction of weak fault features is the key link of fault diagnosis. Selecting and extracting high-quality fault features can improve the efficiency and accuracy of diagnosis. Therefore, this paper adopts a weak fault feature extraction method based on morphological singular value decomposition EMD (empirical mode decomosition)[5].

The magnitude of Shannon's energy entropy reflects the uniformity of the probability distribution. When the rolling bearing is now faulty, the energy of its signal will be more concentrated in some of the same frequency bands, and its Shannon entropy is also smaller. Therefore, the fault-tolerant Shannon energy entropy is selected as the feature vector and the SVM is trained as an input to the SVM.

The first three IMF components are extracted by the morphological singular value decomposition-EMD method, and their Shannon energy entropy values are calculated as feature vectors. The Shannon energy entropy of the morphological singular value decomposition-EMD is as follows:

$$H_{\mathrm{j}}(x) = -\sum_{j}^{3} p_j^2(x_i)\log p_j^2(x_i) \tag{1}$$

In the formula:

$$p_j(x_i) = \frac{|IMF_j(i)|}{\sum_{j=1}^{3}|IMF_j(i)|}$$

In the formula: $IMF_j(i)$ is the eigenmode component of the EMD decomposition.

3. SVM and Kernel Function Construction

3.1 SVM Classification Theory

SVM evolved from the optimal classification plane in the case of linear separability. Assuming that the classification face is $\omega \bullet x + b = 0$, normalize it so that the linearly separable sample set $\{(x_i, y_i)\}$, $x \in R^n$, $y \in \{+1, -1\}$, satisfies:

$$y_i\left[(\omega \bullet x_i) + b\right] - 1 \geq 0 \quad ; \quad i = 1, 2, \cdots n \tag{2}$$

The classification plane that satisfies formula (2) and $\|\omega\|$ is the smallest is the optimal classification plane.

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The Lagrange function is introduced to solve the problem, and the above optimal classification surface problem can be transformed into the following simple dual problem. That is in the constraint:

$$\sum_{i=1}^{n} \alpha_i \gamma_i = 0 \tag{3}$$

$$\alpha_i \geq 0 \quad ; \quad i = 1, 2, \cdots n \tag{4}$$

Find the maximum value of the following functions for α_i:

$$\max Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j \gamma_i \gamma_j (x_i \bullet x_j) \tag{5}$$

This is a secondary optimization problem with no equal constraint, and there is a unique solution. The optimal classification function obtained after solving the above problem :

$$f(x) = \operatorname{sgn}\left\{(\omega^* \bullet x) + b^*\right\} = \operatorname{sgn}\left\{\sum_{i=1}^{n} \alpha_i^* \gamma_i (x_i \bullet x) + b^*\right\} \tag{6}$$

For nonlinear problems, SVM maps the input space into a high-dimensional feature space by introducing a kernel function, and then finds the optimal hyperplane in the feature space. According to the functional theory, as long as an operation satisfies the Mercer condition, it can be used as an inner product. If the inner product is used instead of the dot product in the optimal classification plane, it is equivalent to transforming the original feature space into a new feature space, and the nonlinear optimal classification function can be obtained as follows:

$$f(x) = \operatorname{sgn}\left\{\sum_{i=1}^{n} \alpha_i^* \gamma_i K(x_i \bullet x) + b^*\right\} \tag{7}$$

3.2 SVM Classification Performance Evaluation Function

In the SVM classification problem, it is expected that the classification surface with the structural structure as simple as possible can be obtained under the condition that the classification accuracy is close, so the classification performance can be measured by the classification accuracy rate (RR) and the structural complexity (SC).

3.3 Kernel Function Construction

In SVM applications, kernel functions play a very important role, so how to choose, construct kernel functions and how to set parameters is the key. Commonly used kernel functions are linear kernel functions, polynomial kernel functions, and Gaussian radial basis kernel functions. The choice of kernel function requires a certain prior knowledge, and there is no general conclusion yet. Therefore, this paper constructs a new kernel function while using radial basis and polynomial kernel functions to give full play to the advantages of these two kernel functions for different samples. The new kernel function is constructed as follows:

$$K(x, x_i) = \alpha \exp\left\{-\frac{\|x - x_i\|^2}{2\sigma^2}\right\} + \beta\left[(x \bullet x_i) + 1\right]^d \tag{8}$$

In the formula: α , β is two weight parameters, used to adjust the proportion of the above two kernel functions. In particular, when α =0, it is a polynomial kernel function, and when β =0, it is a radial basis kernel function.

In the parameter optimization of the kernel function, the parameters of the polynomial kernel function (order d) are selected in reference , and the parameters of the radial basis kernel function (width and penalty parameters) are based on the cross reference [6]. Validated grid search method for optimization.

ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0035

4. Using GWO to Optimize SVM Parameters

The reasonable choice of these two weight parameters is critical to the performance of the SVM classifier. Therefore, the grey wolf optimization algorithm (GWO) is used to optimize the two parameters globally. The generalization performance of the SVM is evaluated by the SVM classification performance evaluation function. The reciprocal of the classification performance evaluation function is used as the fitness value. The Hamming distance between individuals acts as a shared function and introduces the shared function into the NGA algorithm implementation.

4.1 GWO

Grey Wolf Optimizer (GWO) is a new meta-heuristic optimization algorithm proposed by Seyedali Mirjalili et al[7]. It has been widely popularized in many fields due to its good convergence speed and optimization precision. Has a good application reference value[8].

4.2 GWO-SVM

The GWO algorithm implements the modeling of the entire iterative optimization process based on the hierarchical division of wolves and the hunting behavior of the population. The grey wolf optimization algorithm is applied to the parameter optimization of the motor rolling bearing fault diagnosis pattern recognition network. By optimizing the network parameters α and β optimization of the SVM, the accuracy and efficiency of the fault classification identification can be improved.

5. Diagnostic Case Analysis

5.1 Sample Collection

On the basis of theoretical analysis, the bearing vibration acceleration signals of the four working conditions of the motor rolling bearing, namely the normal working condition, the outer ring fault working condition, the inner ring fault working condition and the rolling element fault working condition, are collected. The test collected a loss length of 0.014 inches (0.3556 mm) with a sampling frequency of 12 kHz. At the load of 0 HP and a speed of 1797 r/min, 40 sets of motor bearing vibration acceleration signals were collected during normal and fault conditions (2048 samples per group) Point) as a training sample set; 20 sets of normal and fault motor bearing vibration acceleration signals are collected as test sample sets at load 1 HP, speed 1772 r/min; in order to consider the number of samples and the influence of motor load factors on prediction classification Then, when the load is 2 HP, the speed is 1750 r/min, the vibration acceleration signals of the motor bearing are collected in normal and faulty, 40 sets. EMD decomposition is performed on each data sample collected. Considering the feature extraction efficiency and network diagnostic efficiency, the energy characteristics of the first four IMFs are taken as the feature quantity set. The sample set is divided into two parts: training and testing. The mode label is applied to the four working condition states of the collected motor rolling bearing, and the four working conditions of normal, inner ring fault, outer ring fault and rolling element fault are numbered "1", "2", "3" and "4" respectively. The training set samples and the distribution of samples in each test set are shown in Table 1 to Table 5. In the table, only the training set and each test set have three sets of feature sample sizes for each case, and the feature values take the first 4 decimal places. The training vector machine is trained with the training sample set, and the support vector machine obtained by the test sample set test is used to test whether the diagnosis reaches the accuracy rate. Finally, the bearing can be intelligently diagnosed using the support vector machine network that reaches the requirements.

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Table 1 Normal bearing energy entropy

Operating status	E1/E	E2/E	E3/E	E4/E
0 HP,1797 r/min 1 HP,1772 r/min 2 HP,1750 r/min	0.8253 0.08345 0.8193 0.9782 0.9832 0.9779 0.9304 0.9289 0.1320	0.0732 0.0632 0.0638 0.0116 0.0104 0.0110 0.0032 0.0030 0.0027	0.0457 0.0489 0.0517 0.0020 0.0027 0.0019 0.0145 0.0162 0.0157	0.0482 0.0534 0.0529 0.0051 0.0039 0.0043 0.0389 0.0329 0.0368

Table 2 0 HP,1797 r/min Bearing energy entropy (train set)

Operating status	E1/E	E2/E	E3/E	E4/E
Inner ring failure Outer ring failure Rolling element failure	0.1319 0.0824 0.1921 0.1999 0.1960 0.1930 0.1922 0.1534 0.1627	0.0039 0.0040 0.0033 0.0082 0.0046 0.0081 0.0037 0.0030 0.0024	0.5213 0.5414 0.5341 0.4682 0.4212 0.4101 0.5234 0.5205 0.4236	0.0673 0.01456 0.0829 0.1542 0.1126 0.1183 0.0789 0.1732 0.0721

Table 3 1 HP,1772 r/min Bearing energy entropy (test set 1)

Operating status	E1/E	E2/E	E3/E	E4/E
Inner ring failure Outer ring failure Rolling element failure	0.8387 0.8428 0.8337 0.9689 0.9790 0.9804 0.9526 0.9478 0.9612	0.0672 0.0637 0.0726 0.0095 0.0132 0.0102 0.0018 0.0033 0.0045	0.0429 0.0430 0.0422 0.0039 0.0034 0.0052 0.0129 0.0120 0.0147	0.0439 0.0498 0.0210 0.0038 0.0049 0.0029 0.0169 0.0158 0.0132

ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0035

Table 4 2 HP,1750 r/min Bearing energy entropy (test set 2)

Operating status	E1/E	E_2/E	E_3/E	E_4/E
Inner ring failure Outer ring failure Rolling element failure	0.8320 0.8333 0.8417 0.9738 0.9767 0.9810 0.9523 0.9489 0.9478	0.0637 0.0723 0.0678 0.0118 0.0129 0.0089 0.0042 0.0037 0.0029	0.0517 0.0489 0.0420 0.0049 0.0052 0.0050 0.0149 0.0160 0.0168	0.0476 0.0464 0.0413 0.0039 0.0043 0.0037 0.0168 0.0157 0.0137

Table 5 Sample number distribution

Bearing status	train set	test set 1	test set 2	Status tag
Normal working Inner ring failure Outer ring failure Rolling element failurr	40 40 40 40	20 20 20 20	40 40 40 40	1 2 3 4

5.2 Experimental Results

Four kinds of working conditions of the motor rolling bearing extracted from the feature are preprocessed and imported into the Matlab simulation environment to obtain the test set. 1 Figure 1. Classification results. In the figure, 1 to 20 before the abscissa is the normal working condition number, 21 to 40 are the inner ring fault number, and 41 to 60 are the outer ring fault number.No. 61-80 is the rolling element fault number. In the figure, the blue band "○" indicates the predicted category, and the red band "*" represents the real category. The ordinate "1", "2", "3", and "4" numbers indicate the four working states of the bearing in Table 6, respectively. From the results of the classification, it can be seen that the actual inner ring faults of No. 21 to No. 40 have one sample being misdiagnosed as normal, three samples were misdiagnosed as outer ring faults, and two samples were misdiagnosed as rolling element faults; One of the actual outer ring faults of No. 60 was misdiagnosed as normal, one was misdiagnosed as an inner ring fault, and one was misdiagnosed as a rolling element fault; the actual rolling element faults from 61 to 80 were the most seriously misdiagnosed. The worst effect. Table6 and Table 7 summarize the test set 1, test set 2 identification, and to illustrate the effectiveness of the GWO algorithm parameter optimization identification network method used in this paper, compare CV-SVM, PSO-SVM, GWO-SVM Network training efficiency and accuracy.

Table 6 GWO-SVM recognition results

	Normal working	Inner ring failure	Outer ring failure	Rolling element failurr	Average recognition rate
Test 1	20/20	20/20	20/20	20/20	100%
Test 2	40/40	40/40	40/40	40/40	100%

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Table 7 Comparison of recognition results of different classification algorithms

	GWO-SVM		PSO-SVM		CV-SVM	
	Average time	Average recognition rate	Average time	Average recognition rate	Average time	Average recognition rate
Test 1	0.5011	100%	0.8764	85.43%	52.0276	84.17%
Test 2	0.5216	100%	1.0562	77.38%	53.6512	83.23%

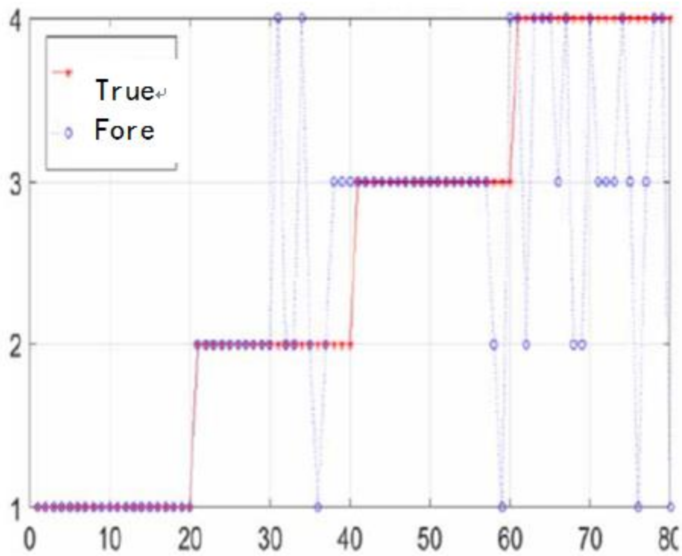

Fig. 1 SVM forecast result

At the same time, Table 7 gives the accuracy and recognition efficiency of GWO-SVM, PSO-SVM and CV-SVM classification network identification under the same EMD algorithm feature extraction conditions, and verifies the hybrid fault diagnosis based on GWO-SVM proposed in this paper. The feasibility and efficiency of the method model.

6. Conclusion

Aiming at the multi-fault classification problem in rolling bearing fault diagnosis, a new method based on GWO optimized SVM for fault diagnosis of rolling bearings is proposed by using EMD, Shannon energy entropy, niche genetic algorithm (NGA) and support vector machine (SVM).

The three types of fault samples (inner ring, outer ring, rolling element) of the actual rolling bearing are classified and identified by the method, which shows that it has good anti-noise and classification ability, and its validity and feasibility are verified.

Compared with the diagnostic results of PGWO-SVM, PSO-SVM and CV-SVM, the results show that the proposed method has better reliability and classification accuracy.

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