Dual-Optimized Support Vector Machine for Fault Diagnosis of Rotating Equipment Based on CM-GA

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***Abstract*—Since the rotary machinery equipment is the fundamental and crucial part of mechanical equipment, the fault diagnosis of rotary machinery has become a particularly important issue in mechanical engineering. This paper adopted a genetic algorithm (GA) based on the cloud model (CM) to optimize traditional SVM for fault diagnosis of rotating machinery with dual optimization levels. The first optimization level is to use the CM to optimize crossover operators in GA (CM-GA), so as to obtain a faster search process and achieve more effective optimization results. The second optimization level is using CM-GA to optimize SVM. In addition, we have proposed an optimized framework of SVM model based on CM-GA for fault diagnosis of rotating machinery. In the end we used two kinds of rolling bearing fault database for experiments and the diagnosis results have proved the validity and feasibility of the proposed method.**

Keywords—fault diagnosis; rotary machinery equipment; support vector machine; genetic algorithm, cloud model

I. Introduction

Mechanical equipment has become the fundamental of modern industry and has been widely used in our daily life. Rotary machinery equipment is one of the most important mechanical equipment in modern industrial production. Therefore, the fault diagnosis of rotary machinery equipment has become a hot topic and more and more important nowadays [1]. Support vector machine (SVM) is a machine learning method [4]. It has various advantages, including strong generalization ability, good robustness, adaptability, simple calculation and high training efficiency. Although SVMs have excellent generalization performance, there still lack theoretical guidance in the selection of kernel functions and parameter settings [7]. GA [8] is a widely used method for parameter optimization, but it has some problems such as delayed convergence and local optimum still needs to be further studied [10].

Aiming at the problem that the evolutionary direction of GA is random, which will lead to the slow convergence of the algorithm, we consider using cloud model to optimize it. The cloud model can transform qualitative and quantitative concepts. Meanwhile, the standard cloud model has the characteristics of randomness and stability tendency. The randomness can avoid the GA search falling into local extremum, and the stability can better protect the optimal individuals so as to carry out adaptive positioning for the global optimum. For the fault signal of rotating machinery with large sample size, we explore the use of cloud model optimized GA to optimize SVM, and verify the feasibility of the algorithm from the perspective of theory and experiment.

II. DUAL OPTIMIZED SVMS FOR FAULT DIAGNOSIS

Considering the disadvantage of slow overall evolution speed, cloud model is adopted to optimize the GA(CM-GA). The main idea is to use the cloud model to realize the crossover operation, so that the whole group can develop towards the direction of evolution as soon as possible, and achieve rapid optimization.

A. Operations of CM-GA

1) Selection operation

This paper adopts the tournament method, which can ensure that the individuals with larger fitness values are retained for the following genetic operation, thus accelerating the overall evolution of the population.

2) Crossover operator

The cloud model is an uncertainty model proposed by Li et al. [13], which can be used to convert between qualitative concepts and quantitative values based on traditional probability and statistics theory and fuzzy theory. Y-condition cloud generator is a cloud generator under the condition of given three numerical characteristics and given membership

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degree. The Y-condition cloud generator algorithm is shown in TABLE I.

TABLE I. THE Y-CONDITION CLOUD GENERATOR ALGORITHM

Input	$\{E_x, E_n, H_e\}, n, u$
Output	$\{(x_1,u),(x_2,u),...,(x_n,u)\}$
For i=1 to n $E_n^{'} = Randan(E_n, H_e)$ $x_i = E_x \pm E_n^{'} * \sqrt{-2\ln(u)}$ Drop (x_i, u)	

To reduce unnecessary searches and move evolution in a faster direction, Y-condition cloud model is adopted to replace crossover probability for crossover operation. The basic idea of the crossover operation is shown in TABLE II.

TABLE II. THE BASIC IDEA OF CROSSOVER OPERATION

Step1: Generate the degree of certainty by a linear function;
Step2: Calculate the digital characteristics of the cloud model; $E_x = \frac{F_f}{F_f + F_m} * X_f + \frac{F_m}{F_f + F_m} * X_m$; $E_n = \frac{x_{f\max} - x_{f\min}}{c_1}$; $H_e = \frac{E_n}{c_2}$
Step3: Perform the *Y*-conditional cloud generator.

We use the deterministic linear function method as shown in (1) to generate the determinacy of TABLE II.

$$\mu = \mu_{\max} - \frac{F_{\max} - F'}{F_{\max} + F_{\min}} \times (\mu_{\max} - \mu_{\min}) \tag{1}$$

where $F_{\max}$ and $F_{\min}$ represent the global maximum fitness value and the minimum fitness value of the contemporary population, respectively. F' is the one with the higher fitness between the two crossed individuals. $\mu_{\max}$ and $\mu_{\min}$ are artificially assigned maximum and minimum determinations. In this paper, we choose $\mu_{\max} = 0.9$ and $\mu_{\min} = 0.1$.

From TABLE II, we choose the linear function of parent to express the expectation, which is beneficial for the next generation to get closer to the side with higher fitness. Entropy E_n is proportional to the search area and the larger the entropy E_n is, the larger the cloud coverage will be. According to the principle of "3σ" and combining the accuracy and speed of the evolutionary algorithm, we usually select $6 \le c_1 \le 3p$ (p is the population size). At the same time, with the increase of hyper entropy H_e , the stable tendency will decrease to a certain extent, while the hyper entropy H_e decreases, the randomness may be lost. Generally, we select $5 \le c_2 \le 15$. In summary, we choose $c_1 = 40; c_2 = 10$ in this paper.

3) Mutation operation

In this paper, each element is mutated with a given probability and the resultant population is returned.

B. The novel dual-optimized SVM based on CM-GA

We propose a framework of SVM based on CM-GA for the fault diagnosis of rotating machinery. We set the termination criteria of CM-GA as follows: (1) Has it evolved to the maximum evolutionary algebra? (2) Is there no significant change in fitness? The kernel function g and the penalty parameter C of SVMs are real coded to overcome the disadvantage of the binary coding and optimized by CM-GA algorithm.

1) The dual optimization of SVM by CM-GA

The framework of the SVM optimized by CM-GA is shown as Fig. 1. The method of it consists of the following steps.

Step1: Obtain training set.

Collect the working signals under different fault types of the rotating machine and carry out the time-frequency analysis (Specific fault information analysis methods will be detailed introduced in Section B.2)and we can obtain K features $(x_{i1}, x_{i2},..., x_{ik})$ which constitute the training set.

Step2: construct the multi-classification support vector machine and pre-optimize the parameters based on the *CM-GA*.

Use the RBF kernel function and a one-to-one method to construct the multi-classification SVM. To improve the diagnosis accuracy of SVM and shorten the diagnosis time as much as possible, a part of the training set data is randomly selected and the CM-GA algorithm is used to pre-optimize the g and the C of SVM. In addition, the cross-validation algorithm [14] is carried out on the training set, and the classification accuracy obtained is taken as the fitness function value. Then the pre-optimal parameters of SVM are obtained.

Step3: optimize parameters.

All the training set data is used as the input and the pre-optimized parameters are taken as the initial values, then we use CM-GA algorithm to optimize the g and C.

Step4: Train the constructed network.

The feature parameters $(x_{i1}, x_{i2},..., x_{ik})$ in *step1* are taken as the input, and the corresponding tags Y_n are taken as the expected output. We can train the multi-classification SVM optimized by the CM-GA in *step2* and *strp3,* and then we obtain the multi-classification SVM model.

Step5: Fault diagnosis.

Collect a working signal in the working process of a rotating machine and convert it into features by the same method in *step1*, which is input into the SVM model trained by *step4* to obtain the diagnosis result.

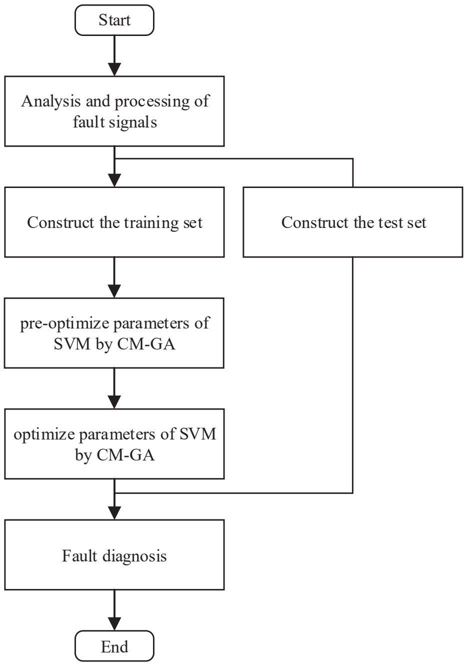

Figure. 1. The framework of the SVM optimized by CM-GA.

2) Fault signal analysis and processing

(1) Feature extraction of fault signal

mixed-domain state features have low computational complexity and could be an appropriate option for fault diagnosis of rotating machinery [15]. Time-domain features such as Root-Mean-Square (RMS), mean square amplitude (MSA), the average amplitude(AA), maximum absolute value (MAX), Kurtosis Factor (KF), Waveform factor (WF), Kurtosis, Skewness, Pulse factor (PF), Peak value and Margin coefficient(MC) were evaluated in a study that classified fault signals. In addition, we choose frequency-domain features such as the mean square frequency (MSF), Center of gravity frequency (CGF) and Frequency variance (FV). Besides, we use the wavelet packet analysis method to analyze the time-frequency of the rotating machinery fault signal (E1-E8) to achieve the comprehensive diagnosis of the rolling bearing fault.

(2) Screen fault signal characteristic value by rough set theory

It is necessary to screen and reduce the features to obtain the features that have a significant influence on the diagnosis results, so as to simplify the diagnosis system model and improve the efficiency and accuracy of fault diagnosis. This paper selects the rough set theory [16], which has strong adaptability and information processing ability for incomplete and inaccurate information as the tool for fault feature screening

III. Experimental Results

In this section, firstly, based on theoretical research, the bearing data of Case Western Reserve University (CWRU) was used to verify the proposed algorithms. Next, carry on the experiment simulation design and build the rotating machinery fault diagnosis platform. Then the fault types are simulated and tested. Finally, the algorithm is verified with the data collected by the sensors.

A. Method validation based on public database

1) Database introduction

The data of rolling bearing from CWRU is chosen to validate the efficiency of the proposed method. The experimental platform details and the geometric dimensions of the bearing can be checked in [17].

2) Fault signals analysis and processing

According to time-frequency analysis method, features of the rolling bearing fault signal are extracted, and we use ROSETTA software to reduce the features and the result is listed in TABLE III.

TABLE III. FEATURE PARAMETERS OF CWRU

Sensor	DE	FE	BA
Features	MAX, RMS, MSA, WF, PF, PEAK, CGF, FV, E2, E3, E4, E5, E6	RMS, PEAK, PF, MC, skewness, E1, E3, E6	RMS, MSA, PEAK, skewness, CGF, E1, E2, E3, E4, E7, E8

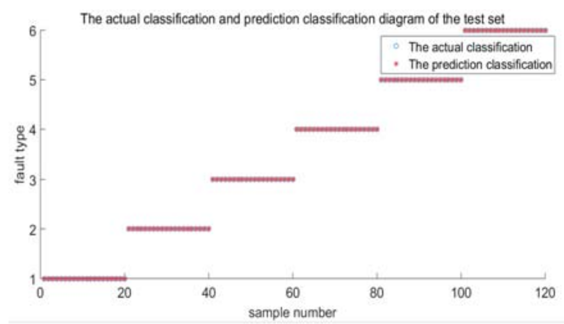

Figure. 2. Test result of CWRU database

3) Fault signals analysis and processing

The number of input layer nodes in SVM is set as 32, and the number of output layer nodes is set as 6. The diagnosis result is shown in Fig. 2. It can be seen that the proposed framework of SVM with CM-GA can effectively identify the test data. Several experiments are carried out to compare the classification results by SVM which are optimized by CM-GA method with traditional GA method, and the results are listed in TABLE IV. The computing accuracy of different methods are shown in Fig. 3 and the time consuming are also recorded and shown in Fig. 4.

TABLE IV. THE FAULT CLASSIFICATION RESULTS OF CWRU DATABASE

Optimization Method	Accuracy			Time(s)	
	Min	*Mean*	*Var*	*Mean*	*Var*
GA	54.2%	94.21%	0.111	162.40	32.0
CM-GA	99.2%	99.75%	0.005	148.65	12.3

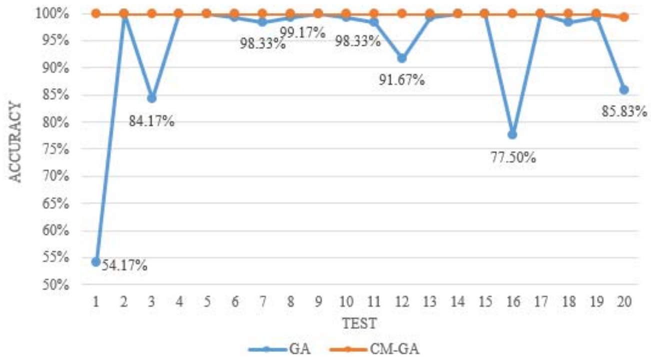

Figure. 3. The accuracy of different methods of CWRU database

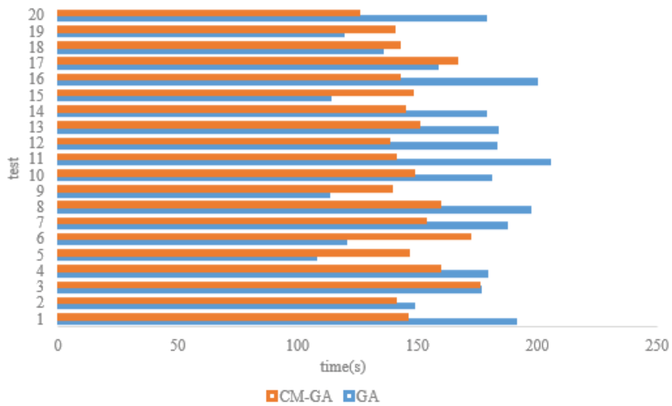

Figure. 4. The time of different methods of CWRU database

From TABLE IV, Fig. 3 and Fig. 4, the accuracy of the proposed framework of SVM is improved obviously and much more stable than the traditional GA optimized method.

B. *Fault diagnosis of rolling bearing based on dual-optimized SVMs*

1) Platform introduction

The experimental platform is shown in Fig. 5. five types of fault modes with fault depth of 0. 3mm for rolling bearings are selected: (1) the slight wear of the inner ring (I1: fault circumferential dimension is12.9°); (2) the moderate wear of the inner ring (I2: fault circumferential dimension is 38.6°); (3) the severe wear of the inner ring (I3: fault circumferential dimension is 64.3°); (4) the moderate wear of the outer ring(O2: fault circumferential dimension is 38.6° and fault circumferential angle position is 270°); (5)the slight wear of the outer ring(O1: fault circumferential dimension is 1° and fault circumferential angle position is 270°). Two acceleration sensors (HD-YD-221) are respectively located in the vertical(a0) and horizontal(a1) directions of the bearing housing for collecting acceleration vibration signals. Three displacement sensors(v0-v2) with 8V/mm sensitivity (WT0180) are used to measure voltage information in the vertical and horizontal directions of the shaft. The sampling frequency is set as 10 kHz.

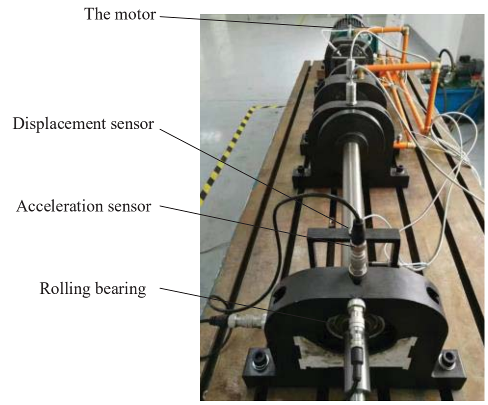

Figure. 5. The experimental platform diagram.

2) Analysis and Processing of Fault Signals

Time-frequency characteristic parameters are obtained for the signal collected by each sensor. We reduced the time-frequency feature parameters by ROSETTA software, which are listed in TABLE V.

TABLE V. THE FEATURES OF EXPERIMENTAL DATABASE

Sensor	Features
a0	MAX, RMS, PEAK, AA, Kurtosis, PF, MC, skewness, KF, MSF, CGF, E1, E2, E3, E4, E5, E7, E8
a1	Kurtosis, WF, PEAK, PF, MC, KF, CGF, E1, E4, E5, E7, E8
v0	RMS, MSA, AA, Kurtosis, WF, PEAK, PF, skewness, KF, CGF, FV
v1	MSA, AA, Kurtosis, WF, PEAK, PF, MC, skewness, KF, CGF, FV
v2	RMS, MSA, AA, WF, PEAK, PF,MC, skewness, MSF, CGF, E2, E3, E4, E5, E6, E7, E8

3) Fault diagnosis results

The experimental results are shown in Fig. 6 and Figure. 7 and the statistics of fault classification results are listed in TABLE VI.

TABLE VI. THE FAULT CLASSIFICATION RESULTS OF EXPERIMENTAL DATABASE

Optimization Method	Accuracy			Time(s)	
	Min	***Mean***	***Var***	***Mean***	***Var***
GA	20%	67.2%	0.34	850.3	245.4
CM-GA	92%	98.9%	0.02	481.0	41.2

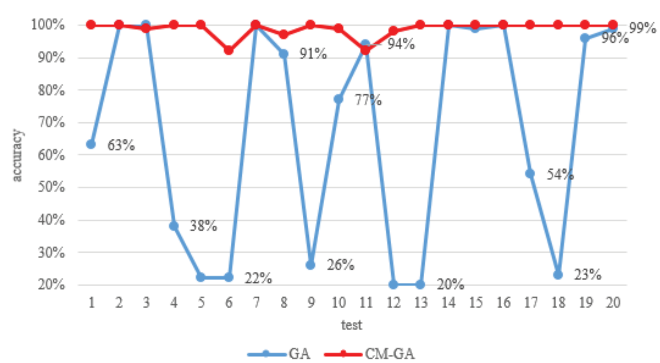

Figure. 6. The accuracy of different methods of experimental database

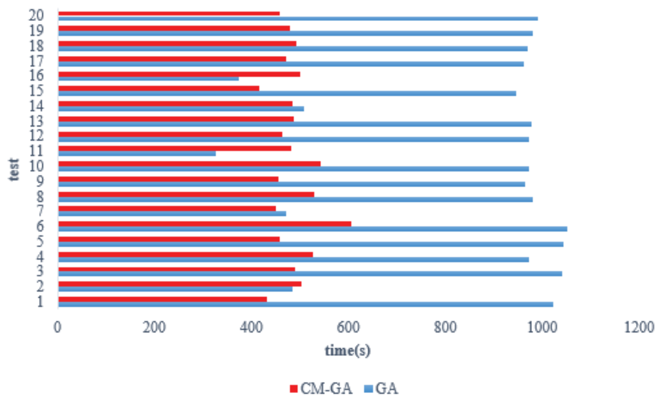

Figure. 7. The time of different methods of experimental database

It can be seen from the result in Fig. 6 and Fig. 7, for data processing and fault diagnosis with larger sample size, the traditional GA optimized SVM method is more unstable and CM-GA optimized SVM models showed better stability and accuracy than GA. Therefore, in the case of big data and large samples, CM-GA optimized SVM method will show obvious advantage for fault classification and diagnosis with higher accuracy and shorter computing time.

Through the experiments of the above two sets of data, we can conclude that CM-GA optimized SVM methods show more advantages and can achieve better results in a relatively short time with a certain high efficiency. It also shows that the CM-GA can apply in the fault diagnosis of rotary machinery equipment and it performs much better than GA.

IV. CONCLUSIONS

This paper aims to investigate a novel fault classification and diagnosis method with high accuracy and fast speed for rotating machinery. A framework of dual optimized SVM model is proposed, which adopted a cloud mode optimized GA to optimize SVM, and used for fault diagnosis of typical rolling bears. From the perspective of theoretical analysis and practical experiment respectively, the proposed model is verified with different data. Through the comparison of the experimental results, the advantages with better stability, higher accuracy and shorter time consumption are clearly shown for the presented CM-GA optimized SVM.

The above experiments have shown an excellent performance of the application of CM-GA optimized SVMs for fault diagnosis of rotating machinery. But all the fault modes are considered to be independent, and the fault classification and diagnosis for multiple fault location with multiple fault model are still to be a problematic research issue. In the future, we will consider to make some improvement on those methods and apply those methods to investigate the fault diagnosis of multiple fault model for typical rotating machinery.

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