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Rolling bearing fault diagnosis method based on rvm optimized with quantum behaved particle swarm optimization

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Abstract. In view of the traditional rolling bearing fault diagnosis method, the influence of human factors is more serious and the cause of the fault is relatively complex and so on. On these issues, the traditional method is difficult to solve. Putting forward a based on quantum behaved particle swarm optimization (QPSO) algorithm to optimize the relevance vector machine (RVM) fault diagnosis method. The quantum behaved particle swarm optimization QPSO-RVM relevance vector machine (RVM) model is applied to the rolling bearing fault diagnosis. The experimental results, the method can quickly and accurately diagnose the rolling bearing fault, indicating that the method has stability and effectiveness in addition; in addition, through the contrast analysis with the support vector machine (SVM), it shows the superiority of the RVM method in the field of intelligent fault diagnosis.

Key words. Quantum behaved particle swarm algorithm, fault diagnosis, correlation vector machine, eemd.

1. Introduction

As one of the key components of large rotating machinery, rolling bearing is easy to produce safety fault in the daily operation of high load. In addition, the installation, disassembly, and other different working conditions are also very easy

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to cause the failure of rolling bearing. So does a good job of rolling bearing fault diagnosis and operation and maintenance work are particularly important.

To this end, this paper proposes a quantum particle swarm optimization algorithm (QPSO) to optimize the relevance vector machine method; the method can also be effective to select the best parameters of the kernel function. At the same time, particle swarm optimization (QPSO) is used to optimize RVM and SVM, and the advantages and disadvantages of different algorithms are compared and analyzed, which shows the advantage of QPSO in kernel parameter optimization. The fault model of the RVM which is optimized through the quantum behaved particle swarm optimization is used to classify the faults.

2. QPSO-RVM Algorithm

RVM is a model of Bayesian framework and machine learning algorithm [1], by maximizing the marginal likelihood of the relevant vector and weight. Assuming that$\{x\}_{u=1}^{N}$and $\{t\}_{u=1}^{N}$ are input vectors and output vectors, the target T can be obtained by the regression model shown in the formula

$$t = y\,(x) + \varepsilon_n$$

Formula: $\varepsilon_n$is zero mean and variance σ^2 noise, y (x) is defined as:

$$y\,(x) = \int_{u=1}^{N} W_u K\,(x,x_u) + w_0$$

Formula: $K\,(x,x_u)$ is the kernel function. w_0 is the deviation. W_u is the weight vector.

Assuming that t is independent, its probability is defined as:

$$p\left(t \mid w,\sigma^2\right) = \left(2\pi\sigma^2\right)^{-N/2} \exp\left\{-\frac{1}{2\sigma^2}\, t - \varphi w^{2}\right\}$$

Formula: $t = (t_1, t_2, \ldots, t_N)^T$ $w = (w_0, w_1, \ldots, w_N)^T$ φ is the matrix of N x (N+1).

The maximum likelihood estimation of w and σ^2 in the above formula can lead to over fitting, for the constraint parameters, to make a zero mean Gauss a priori probability distribution:

$$p\,(w \mid \alpha) = \int_{u=0}^{N} N\left(w_u \mid 0, \alpha_u^{-1}\right)$$

Form in: A is a super parameter vector of B dimension.

According to the Bayesian formula, the posterior probability of the unknown parameters is:

$$p\left(w,\alpha,\sigma^2 \mid t\right) = p\left(w \mid \alpha,\sigma^2, t\right) p\left(\alpha,\sigma^2 \mid t\right)$$

The posterior distribution of the weights is described as:

$$p\left(w \mid t,\alpha,\sigma^2\right) = (2\pi)^{-(N+1)/2}\left|\sum\right|^{-1/N} \cdot \exp\left\{-\frac{1}{2}(w-\mu)^T\sum^{-1}(w-\mu)\right\}$$

The posterior mean is $\mu=\sigma^{-2}\sum\varphi^T t$ and the covariance is B, $\int=\left(\sigma^{-2}\varphi^T\varphi+A\right)^{-1}$ $A = \mathrm{diag}\left(a_0, a_1, \ldots, a_N\right)$

Gauss radial basis function has a powerful function in dealing with nonlinear problems, and is used as a kernel function:

$$K\left(x,x_u\right) = \exp\left(-\frac{\left(x-x_u\right)^2}{2\gamma^2}\right)$$

γ is the width factor, which has a great influence on the accuracy of the model, and it needs to be set up in advance[2].

PSO algorithm is a heuristic evolutionary algorithm proposed by Dr.Kennedy [3-4], through the simulation of bird foraging behavior to find the optimal solution space.The convergence mechanism of QPSO algorithm is introduced into the PSO algorithm. According to the definition of QPSO, the particles are optimized by iteration:

$$\mathrm{mbest} = \frac{1}{M}\int_{j=1}^{M} P_j$$

$$P = \mu P_j + (1-\mu) P_g$$

$$X_j(t+1) = P \mp a|\mathrm{mbest} - X_j(t)|\mathrm{In}\left(\frac{1}{u}\right)$$

Form in:M is the size of the population, u and μ are the presentation of the interval [0, 1] uniform distribution random number. mbest is the point of the average value of each particle's best position, while$P_j$and P_g are the best position of the individual j of the particle and the best position of the overall situation. X is the position of the particle j and t is the current iteration number and is a compression expansion factor.

The fitness function is selected in the optimization process:

$$\mathrm{MSE} = \frac{\int_{=1}^{L}\left(z^*(\theta)\right)^2}{L}$$

Form in: MSE is the mean square error, which is used to characterize the degree of deviation between the predicted data and the real data. $\theta = 12,, L, L$ is used for the number of training data; $z(\theta)$and $z^*(\theta)$ represent the real data and forecast data[5-8].

3. Bearing Faultdiagnosis Based on RVM – QPSO

The principle of bearing fault diagnosis based on QPSO-RVM is shown in Figure 1.

The calculation steps are as follows:

Get the vibration signals of various rolling bearing fault conditions,set up the training sample set$\{x_i, y_i\}$ $(i = 1, \ldots, M)$.The training sample data is mapped to the high dimensional feature space by kernel function, and the appropriate control error. Using PSO, SPSO and QPSO three kinds of optimization algorithms to obtain the optimal kernel parameter ,d and the penalty parameter c. At the same time, the is two times to obtain and the corresponding support vector .Obtained by the and the corresponding support vector , the bearing fault pattern recognition modelsgn $\left(\omega^T \emptyset\left(x\right) + b\right) = \operatorname{sgn}\left(\int_{i=1}^{l} y_i a_i K\left(x_i, x\right) + b\right)$is obtained[9-11].In recognition of the bearing fault pattern, the bearing vibration signal collected by the sensor is processed to get the characteristic quantity of the corresponding vibration signal. The feature is put into the fault diagnosis model to identify, and finally achieve the identification of the type of rolling bearing fault.

4. Experiment And Resultanlysis

The data used in this study come from the experimental data of rolling bearing fault in the west of the United States. The experiment is the use of bearings is 6205-2RS JEM SKF type of rolling bearings and the sampling frequency of the rolling bearing is f_s=12 000 Hz, its speed is 1748 r/min. In the experiment, the vibration test data of three kinds of bearing fault and the normal bearing data were obtained, respectively, with different loads (0 ph ,1 ph,3 ph). Three kinds of faults are outer rings pitting failure, inner rings pitting failure and rolling element pitting failure.

In order to verify the QPSO in the RVM parameters optimization of effectiveness, the Gaussian radial basis function as the kernel function of this experimental section. Select standard UCI database of wine, iris and Cancer: three standard data as the experimental data, respectively, using QPSO, SPSO and PSO selected RVM to classify the experimental data when the optimal kernel parameters. Table 1 is Description of 4 kinds of test data in UCI database, the number of samples, the dimension of the sample and the number of classes.

Table 2 shows the average classification accuracy and the average running time of the 50 kinds of data after the UCI standard database is optimized by the different methods to optimize the RVM. By comparison, the average classification accuracy of -RVM QPSO is the highest, and the test results of PSO-RVM and SPSO-RVM on different data is high and low. The results show that QPSO algorithm in the testing process every time adaptive selection to the best kernel function parameter, SPSO and PSO algorithm in the testing process appeared kernel function parameter value into a local optimum and premature convergence problem did not converge to the optimal kernel parameter values. The average running time of QPSO-RVM is the lowest from the test time, which reflects the advantage of QPSO algorithm in optimizing the RVM process.

The experimental data of 3 pH and fault degree of 1.63 cm was chosen as the experimental data. Each sample is composed of 2048 successive samples. Each of the 1200 samples is selected as the training sample of the RVM diagnostic model (a total of 2048), and the rest of the sample is a test sample of the model.

Table 1. description of test data set

test data	Sample number	dimension	Category number
Wine	178	13	3
Iris	150	4	3
Glass	214	13	6

Table 2: classification results of different algorithms on test data

Method	data set	Classification accuracy /%	Test time /s
QPSO -RVM	Wine	99.438	113.5
	Iris	97.333	101.3
	Glass	73. 832	121.6
SPSO-RVM	Wine	97.753	281.6
	Iris	96. 667	260.3
	Glass	71.945	294.1
PSO-RVM	Wine	98. 876	340.3
	Iris	96. 667	322.5
	Glass	71.963	368.1

4 kinds of vibration signals of the rolling bearing are decomposed by EEMD, and the IMF energy of the 4 state is extracted as the fault features of the rolling bearing . Take the outer ring fault signal as an example, set M=100, the amplitude of the white noise is 0.2. Figure 2 shows the EEMD decomposition process. See Figure 2, a sample of the outer ring fault signal is decomposed into 9 IMF: c_1 (t), c_2 (t),..., c_9 (t) and a residual error: r(t).

By analyzing,the extracted IMF energy is divided into training samples and test samples. Figure 3 shows the IMF energy distribution in the 4 different states of the rolling bearing. In order to illustrate the effectiveness and stability of the diagnostic model, the average fault diagnosis rate after the 10 faults diagnosis experiments are used as the evaluation index. At the same time, the IMF energy input of the rolling bearing to RVM, SVM and QPSO optimized SVM (QPSO-SVM) are compared and analyzed. All the models are applied to the Gauss radial basis function as the kernel

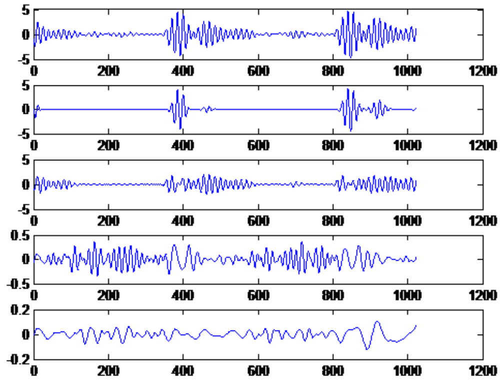

Fig. 1. Model of bearing fault diagnosis based on qpso-rvm

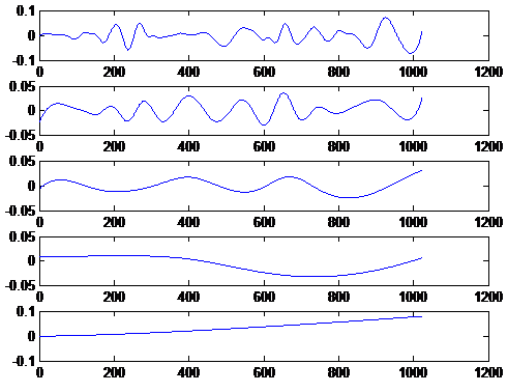

Fig. 2. Eemd decomposition of the outer ring fault signal

function. Because the RVM and SVM did not use the optimization algorithm, the nuclear parameters were set up, and the final diagnosis results were shown in table 3.

Table 3. experimental results of fault diagnosis of different kinds of diagnostic model

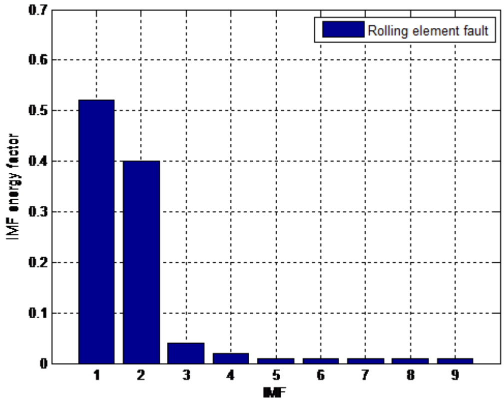

Fig. 3. Eemd energy distributions in different states

Recognition device	Diagnostic rate /%	training time /s	Test time /s
QPSO-RVM	96.56	60.63	0.16
QPSO-SVM	96.56	38.12	0.65
RVM	93.36	4.72	0.65
SVM	93.36	1.61	1.85

Results from table 3 showed that the average diagnosis rate of -RVM QPSO-model and SVM QPSO model was the highest, reaching 96.56%. It shows that the kernel parameter selection method based on QGA can reach the optimal value in the optimization of RVM and SVM parameters. Table 3 also shows the training time and testing time of each model,the longest is QPSO-RVM. For the diagnostic model of the test time, QPSO-RVM test time at least, RVM times, QPSO-SVM and SVM test time are the longest. Therefore, based on the above analysis, RVM is more suitable for dealing with small sample problems, and it is more suitable for on-line fault diagnosis.

5. Conclusions

A bearing fault diagnosis model based on quantum behaved particle swarm optimization is proposed in this paper. Firstly, the fault vibration signal is decomposed into several IMF components by using the EEMD method. Then, the energy of the IMF component is chosen to construct the fault feature vector of the reaction fault feature, and the RVM model is used as the fault diagnosis model. In addition, the basic particle swarm optimization algorithm and the quantum particle swarm optimization algorithm is used to obtain the relevant parameters of the optimal diagnostic model, and the optimal fault diagnosis model is established. Test data show that the bearing fault diagnosis model based on quantum particle swarm optimization can accurately and effectively classify and identify the fault types of rolling bearing. At the same time, it has strong robustness and generalization ability, which provide an effective diagnostic method for the research of the fault diagnosis of rolling bearing.

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