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Diagnostic Study Based on Wavelet Packet Entropy and Wear Loss of SVM

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Abstract

Against the problems, the ratio of signal to noise of bearing wear is low, the feature extraction is difficult, there are few fault samples and it is difficult to establish the reliable fault recognition model, the diagnostic method is put forward based on wavelet packet features and bearing wear loss of Support Vector Machine *(SVM). Firstly, choose comentropy with strong fault tolerance as characteristic parameter, then through wavelet packet decomposition, extract feature entropy of wavelet packet in fault sensitivity band as input vector and finally, apply the Wrapper method of least square SVM to choose optimal character subset. The application in actual bearing fault diagnosis indicates the effectiveness of the proposed method in the article.*

Keywords: *bearing wear loss, wavelet packet feature entropy, SVM, optimization*

1. Introduction

The bearing wear fault diagnosis is to make use of signal processing and analysis technics to analyze the signal that contains information on wearing, to find out the characteristic parameters related to wearing and use these parameters to distinguish the wear state and real-time technology state of bearing. Here it involves two aspects: first, to conduct feature extraction in use of signal processing technology; second, to conduct fault diagnosis in use of mode recognition technology [1].

Because of its strong nonlinearity separating capacity, the algorithm of SVM has been widely used in fault diagnosis field. However, the SVM classifier needs to estimate normalized parameter, the kernel function should meet the condition of Mercer. Meanwhile, as the solved sparsity is not required in the model of the SVM classifier, it results in many support vectors, making the computation complexity of classifier got increased. There matters are especially important for the on-line wearing detection that highly requires instantaneity [2]-[4].

SVM based on statistical learning theory is used in many applications of machine learning because of its good generalization capabilities. SVM classifies better than Artificial Neural Network (ANN) because of the principle of risk minimization. In ANN, traditional Empirical Risk Minimization (ERM) is used on training data set to minimize the error. But in SVM, Structural Risk Minimization (SRM) is used to minimize an upper bound on the expected risk [2]-[4]. These parameters of SVM mainly include the penalty constant C, and the parameters in kernel function, and they affect the performance of SVM. Therefore, in this study, The high frequency demodulation analysis was used to abstract the characteristic of signals, The signals were decomposed into eight frequency bands and the information in the high band was used as a characteristic vector, an intelligent diagnostic method based on Genetic-Support Vector Machine (GSVM) approach is presented for fault diagnosis of roller bearings in the wood-wool production device [7].

Therefore, the article puts forward the online inspection method based on the wavelet packet entropy and bearing wear of SVM [5]. The article chooses the comentropy with strong fault tolerance to describe overall features of signal as the feature parameters, conducts wavelet packet decomposition in use of multiresolution feature of wavelet transform, extract the feature entropy of wavelet packet in the fault band as input vector, establish discrimination function by using the available fault samples and make wear loss and fault classifier of SVM [6]. After the test on the classifier in use of new samples, it indicates that the method has well solved the feature extraction of wear vibration signal and the nonlinearity of fault in the state of small

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sample as well as the identification of high-dimensional mode, can well distinguish the severity of fault and greatly decrease the time to detect fault while keep of high detection rate.

2. Feature entropy of wavelet packet of vibration signal

The inner and outer wearing as well as spalling of rolling bearing are the reasons to cause the impact of 207 rolling bearing, which has been proved after dissection. The vibration of bearing is mainly from wearing, so the vibration signal is to be extracted as the characteristic quantity of the analysis of wear loss. For the vibration signal u(t), the following recursion(1) to conduct wavelet packet decomposition [7].

$$\begin{cases} u_{2n}(t)=\sqrt{2}\sum_{k} h(k)u_n(2t-k) \\ u_{2n-1}(t)=\sqrt{2}\sum_{k} g(k)u_n(2t-k) \end{cases} \quad (1)$$

h is the high-pass filter group, g is the low-pass filter group.

In the analysis of multiresolution, the essence of wavelet packet decomposition is to let signal u get through high and low-pass junction filter group, always make the original signal decomposed into 2 channels of high and low frequency, then decompose the part of high and low frequency respectively in the same way till the demand is met.

The wavelet packet decomposition sequence s(j , k) (k get 0～2j - 1) is obtained after the J level wavelet packet of signal has been decomposed. Here the wavelet packet decomposition of signal can be regarded as the partition of signal. Define the measure of the partition.

$$\varepsilon(j,k)(i)=S_{F(j,k)}(i)/\sum_{i=1}^{N}S_{F(j,k)}(i) \quad (2)$$

S F(j , k) (i) is the ith value of Fourier transform sequence of S (j , k) (k get 0～2j - 1); N is the original signal length[8].

According to the basic theory of comentropy, define the feature entropy of wavelet packet as H j. k the kth feature entropy of wavelet packet in the jth level of signal.

$$H_{j,k}=-\sum_{i=1}^{N}\varepsilon(j,k)(i)\lg\varepsilon(j,k)(i)$$
$$(k=0\sim 2^{j}-1) \quad (3)$$

3. Feature Extraction Using Shannon Entropy

Entropy is a measure of uncertainty that is used in various fault conditions after the signal processing of the original signal by using WPT. To reduce data set in size, wavelet entropy is applied to wavelet coefficients. The wavelet entropy is the sum of square of detailed wavelet transform coefficients. The entropy of wavelet coefficients is varying over different scales dependent on the Input signals. This wavelet entropy of coefficients can be defined as.

$$E_n=\sum_{n=0}^{7}\log\left|W^{n}{}_{j,k}\right|^{2} \quad (4)$$

Where $W^n j,k$ is the coefficients of the subspace after wavelet packet decomposition and $n=0,1,2,\cdots 7$.

Let $E_{3j}(j=0,1...,7)$ is sequence of the energy of wavelet packet decomposition of The third layer, there are:

$$E_{3j}=\sum_{k=1}^{n}\left|W_{j,k}\right|^{2} \tag{5}$$

Order by scale, feature vector is composed of each layers high-frequency Sequence wavelet of energy as a sub-vector, that,

$$T=[E_{30},E_{31},E_{32},E_{33},E_{34},E_{35},E_{36},E_{37}]$$

Normalized, Let $E=\left(\sum_{j=0}^{7}\left|E_{3j}\right|^{2}\right)^{1/2}$ then

$$T'=[E_{30}/E,E_{31}/E,E_{32}/E,E_{33}/E,E_{34}/E,E_{35}/E,E_{36}/E,E_{37}/E] \tag{6}$$

T' is the normalized eigenvector.

4. Support vector machine

The main aim of an SVM classifier is obtaining a function f(x) which is use to determine the decision hyper plane. Margin is the distance from the hyper plane to the closest point for both classes of data points [9].

Given a training data set $\{(x_i,y_i)\}_i^n$, where $x_i \in R^n$ denotes the input vector, $y_i \in R$ denotes the corresponding output value and n denotes the number of training data set. The regression function is defined as:

$$f(x)=w\cdot\varphi(x)+b \tag{7}$$

where w denotes the weight vector and b denotes the bias term.

The coefficients w and b can thus be gained by minimizing the regularized risk function.

$$R(C)=C\frac{1}{n}\sum_{i=1}^{n}L_{\varepsilon}(y)+\frac{1}{2}\|w\|^{2} \tag{8}$$

$$L_{\varepsilon}(y)=\begin{cases}\left|f(x)-y\right|-\varepsilon & \left|f(x)-y\right|\geq\varepsilon\\ 0 & \left|f(x)-y\right|<\varepsilon\end{cases}$$

where C denotes a cost function measuring the empirical risk. $\|w\|^2/2$ denotes the Euclidean norm. The ε-insensitive loss function is employed to stabilize estimation.

The Lagrange multipliers a_i and a_i^* are introduced, which satisfy the equalities $a_i\cdot a_i^*=0$, $a_i\geq 0$, $a_i^*\geq 0$. This constrained optimization problem is solved using the following Lagrange form:

Maximize

$$-\sum_{i=1}^{n}y_i(a_i-a_i^*)+\varepsilon\sum_{i=1}^{n}(a_i+a_i^*)+\frac{1}{2}\sum_{i,j}^{n}(a_j-a_j^*)(a_i-a_i^*)k(x_i,x_j) \tag{9}$$

Subject to

$$\sum_{i=1}^{n}(a_i - a_i^*) = 0 \quad a_i, a_i^* \in [0, C]$$

where $K(x_i, x_j) = \varphi(x_i)\varphi(x_j)$ is positive definite kernel function. The kernel function can have different forms, and at present, Gaussian function is the most widely used.

Hence, the regression function is:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)k(x_i, x) + b \tag{10}$$

5. SVM wear loss diagnosis based on wavelet packet feature entropy

5.1. Diagnostic model building of SVM of bearing wear

Bearing wear extend can be divided into non-wear, slight-wear and severe-wear. The article constructs the multiple classifier by using one-to-one method. Its basic idea is: establish N (N- 1)/2 SVM for the classification problems of N yuan, train a SVM between 2 categories to separate each other. The article is about the identifying the problem of 3 categories, so it need to construct 3 SVM classifiers.

The accurate diagnosis of rolling beating was studied. The high frequency demodulation analysis was used to abstract the characteristic of signals [10]. The signals were decomposed into eight frequency bands and the information in the high band was used as a characteristic vector. GSVM were used to realize the map between the feature and diagnosis. Based on the characteristics of different fault types of roller bearings, three SVM's are developed to identify the four states, including normal, ball fault, outer ring fault, inner ring fault, which is shown in Fig.2. With all training samples of the four states, GSVM1 is trained to separate normal state from fault states. With samples of fault states, GSVM2 and GSVM3 is trained to separate discharge from thermal heating [11]-[13].

5.2 Extraction of feature entropy of wavelet packet

The obvious impulse signal can be seen from original sampled signal of Figure 2. But the amount of information obtained is limited, so it cannot make further diagnosis. Therefore, use the daubechies5 wavelet packet to conduct three-level decomposition of the original sampled signal, to make the original signal divided onto 8 bands. As shown in figure 3, choose reconsitution of (3,0) decomposition band (As shown in figure 4)and (3,1) band (As shown in figure 5)that contain defect signal frequency of 207 rolling bearing. By using wavelet packet decomposition, power spectrum analysis of reconsitution technology, the defect signal of the rolling bearing inner race, which is submersed by noise signal, has been detected. After analysis, the inner and outer ring wearing and spalling of bearing are the reason to cause the impact of 207 rolling bearing, which has been proved after dissection.

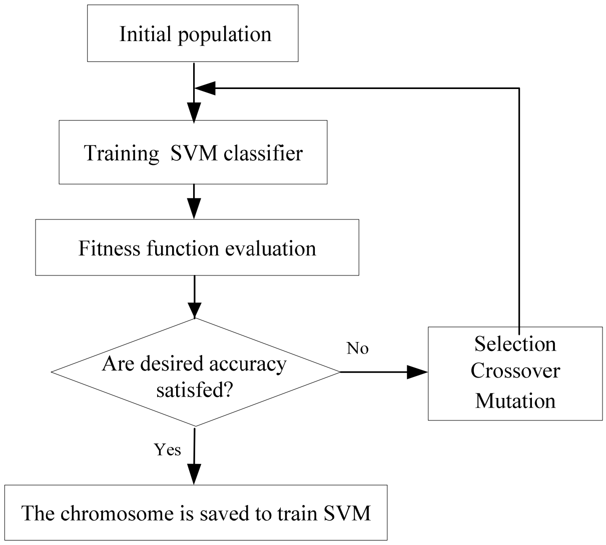

Figure 1. The framework of optimizing the SVM's parameters with genetic algorithm

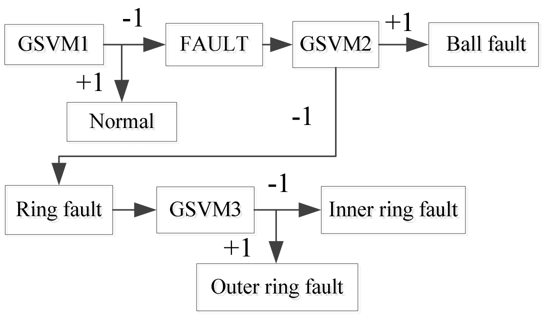

Figure 2. Fault diagnosis for gearbox based on genetic- SVM classifier

5.3 Optimization diagnosis

SVM algorithm, which is against the prediction on small samples, has big advantage itself. Because the obtained samples are few according to the actual test, In table 1, the first 10 group of data of the 20 groups of data obtained in the experiment are used as training sample and the last 10 groups are used as the test sample to examine and predict the results.

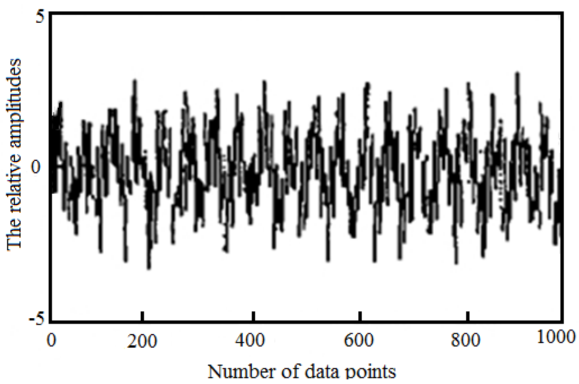

Figure 3. Raw vibration signal of 207 bearings

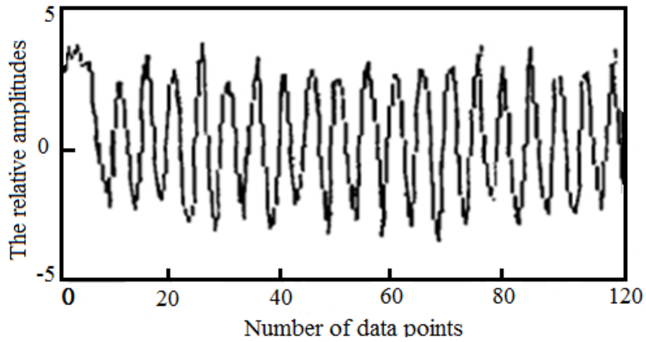

Figure 4. The first three-band wavelet packet decomposition

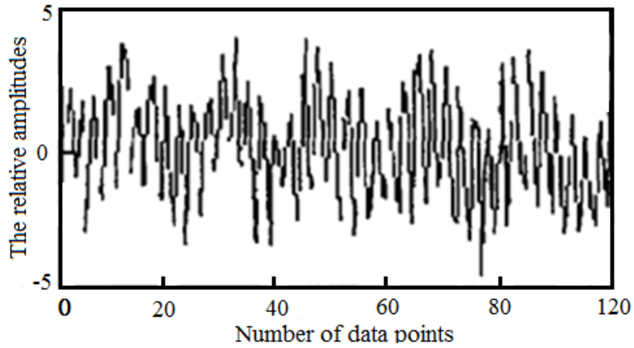

Figure 5. The second three-band wavelet packet decomposition

Table 1. The data of experiment

Number	Characteristic vibration signal			Load /N	Speed/ (r.min^{-1})	Running time (10min)	Temperature Of Oil/ ℃	Wear Loss Q
	Meanμ	Peak P	Kurtosis K					
1	-17.613	1001	4.100	35.1	500.1	5	25.1	21.2
2	-18.215	998	3.988	79.8	500.1	10	24.5	35.2
3	-19.064	1285	3.984	135.9	500.1	20	26.9	52.6
4	-18.920	1396	4.102	165.1	500.1	35	30.4	83.9
5	-20.862	1402	4.126	173.2	500.1	45	31.1	90.1
6	-21.042	1408	4.065	30.5	1000.4	10	30.5	95.6
7	-21.348	1211	4.108	60.1	1000.4	80	33.1	98.9
8	-20.912	861	4.213	121.4	1000.4	90	35.1	108.5
9	-21.004	970	4.234	156.9	1000.4	105	34.8	116.9
10	-20.897	1065	3.996	179.8	1000.4	115	34.9	129.8

Table 2 takes the last 10 data as the data to predict and testify and verify the predicted results of the proposed the SVM algorithm of optimal scheduling model. Apply the SVM algorithm of radial basis kernel parameter optimized by optimal scheduling model method in the article to predict wear loss. It is clear that the article provide a very favourable new method to solve the wear prediction issues.

Table 2. The later 10 sample's results of 4 optimized algorithm

Number	Characteristic vibration signal			Load /N	Speed/ ($r.min^{-1}$)	Running time (10min)	Tempe-rature Of Oil/□	Real Wear Loss Q	Predictive Wear Loss ((BP-NN)	Predictiv Wear Loss Q (GA)	Predictive Wear Loss Q (AC)
	Mean μ	Peak P	Kurtosis K								
11	-21.644	1201	4.100	30.5	1500.5	120	25.1	131.1	119.1	113.5	117.2
12	-21.015	1008	4.018	50.8	1500.5	145	24.5	140.2	180.01	140.2	172.8
13	-21.100	985	3.974	100.9	1500.5	150	26.9	149.5	165.9	125.4	159.6
14	-22.120	896	4.152	140.1	1500.5	165	30.4	156.1	171.4	142.6	155.0
15	-23.162	1301	4.106	178.2	1500.5	175	31.1	158.7	189.9	168.7	187.4
16	-22.642	1318	4.085	31.0	2000.0	184	30.5	163.8	160.4	151	188.7
17	-22.438	1281	4.177	80.1	2000.0	189	33.1	164.1	191.1	144	158.9
18	-22.912	1261	4.003	111.4	2000.0	200	35.1	171.2	207.9	205.7	220.7
19	-23.004	1170	3.934	153.9	2000.0	225	34.8	190.1	223.8	201.2	205.7
20	-23.789	1160	4.096	180.9	2000.0	232	34.9	195.7	219.0	199.8	218.5

6. Conclusion

Through the proposed the application of extraction method of energy feature of wavelet packet band and pattern recognition method of SVM in the diagnosis of antifriction bearing wear loss, extraction of vibration signal by using wavelet packet entropy as the characteristic quantity of the analysis on the wear loss, the optimization model being obtained with radial basis kernel parameter of SVM algorithm optimization to be used in prediction of wear loss, and the wearing verification to be conducted in the example of the bearing wear data. It indicates that the computational efficiency of the diagnostic method of SVM wear is high, based on wavelet packet, and the SVM has very good recognition capability in the state of small sample. From the above, the SVM has very good practical value and application prospect in solving problems of bearing fault diagnosis.

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