The Degradation State Recognition of Rolling Bearing Based on GA and SVM

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Abstract—In order to accurately recognize the degradation state of rolling bearing, a hybrid method combining Genetic Algorithm (GA) and a Support Vector Machine (SVM) was proposed, and the model for degradation state recognition of rolling bearing was constructed. Firstly, the feature vectors of degradation state were extracted through the combination of GA and SVM from statistical characteristic. Then the degradation state probability distribution and historical remnant life of rolling bearing are calculated to determine the optimal number of degradation state, which is employed to construct the SVM model for degradation state recognition. Finally, the characteristic vectors which have been optimized and deleted by GA from the test data of different degradation states, and then using the characteristic vectors as the input of SVM which parameters have been optimized by GA to identify the degradation state of rolling bearing. The analytical results for full lifetime datasets of a certain bearing demonstrate the validity of the method.

Keywords—genetic algorithm (GA); support vector machine (SVM); rolling bearing; fault; degradation state

I. INTRODUCTION

The core idea of PHM is that acquire all kinds of data information with as little as possible sensors firstly, then with the aid of intelligent reasoning algorithm to assess the health status of system itself, and forecast the fault of machine. Failure prediction includes three important steps: feature extraction, degenerate state recognition and the forecast of residual life or failure probability. Among them, the degradation state recognition is the key technology of fault prediction, it directly relationship to the accuracy of fault prediction and the accuracy of the residual life prediction.[1-2].

Rolling bearing is an important component of rotating machinery, its condition directly affects the run of rotor and even the whole machine.[3-4]. The reliable identify of degradation state of rolling bearing mainly includes two key problems: one is establish a correct model of degradation state; the other is select a suitable degradation state indicators. To solve above two problems, scholars has carried out a preliminary study on the performance degradation recognition of rolling bearing. Hack-Eun[5] presented a method that using SVM to estimation the state probability of equipment and applied the experimental data verified it. Vachts evanos[6] has studied the fault diagnosis using the method of dynamic wavelet neural network.

The main problem of above method is the number of degradation condition of rolling bearing need artificial setting according to our experience. So, this article presents a method of discretization and identification of degradation state automatically based on GA and SVM. Using the method of health state probability evaluation for degradation state discretization of rolling bearing from the signal of fatigue experiments of whole life cycle firstly, determine the optimal number of degradation state automatically. Then the method of genetic algorithm (GA) is used to optimize parameters of SVM, the model of degradation state recognition of rolling bearing then will be set up to recognition the degradation state.

II. DEGRADATION STATE FEATURE SELECTION BASED ON GA

The statistical characteristics of vibration signal contains abundant information. When the degradation of bearing in a different state, the statistical characteristics of the signal will corresponding changes.

In the classification method of intelligence, sometimes because of the redundant or irrelevant features covered the main classification features, then will lead to "dimension disaster". To eliminate these redundant or irrelevant features, feature selection is required, it can reduce the dimensions of feature space and improve the accuracy of classification. The fitness function of GA as a evaluation standard for the performance of feature subset, will search the effective feature subset. This article introduced the algorithm of [7], construct the fitness function of Genetic algorithm to feature optimization according to the recognition rate of degradation state model of SVM in the following section.

The fitness function for feature extraction is as follows:

\[ f(x_i) = \frac{\exp(A_{x_i} - \eta \cdot A)}{\gamma \cdot (\sum_{j=1}^{n} x_j) / n} \]  \hspace{1cm} (1)

Where \( X_i(x_1, x_2 \cdots x_j \cdots x_n) \) reflects a possible
feature subsets, then $f(X_i)$ is the corresponding fitness function value of $X_i$, $n$ is the total number of features, $A_X$ is the corresponding training accuracy of $X_i$, $A$ is the accuracy of including all the training characteristics. The two parameters are used to adjust the tolerance of threshold value of classification accuracy and the contribution weight of characteristics reduce to the fitness function.

We can search the feature subset which have the highest fitness by the algorithm, it can improve the characteristic optimization effect of degradation condition greatly.

III. DEGRADATION STATE RECOGNITION MODEL

A. The Model of Regression Classification Based on SVM

SVM is a kind of machine learning algorithm which is usually used to solve the problem of classification and prediction of small sample. Given target sample set \{$(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i)$\}, $x_i \in R^N$, $N$ is the dimensions of each training sample. Suppose that there are $k$ classes, $y_i \in \{1, \ldots, k\}$, then the model have $k(k-1)/2$ binary classifiers. For training data from the $i$th and the $j$th classes, SVM solves the following classification problem:

$$\min \frac{1}{2} \sum_{i=1}^{m} (\phi(x_i))^T \Phi C \sum_{i=1}^{m} \xi_{ij} (\phi(x_i))^T \Phi$$

s.t. $$(\phi(x_i))^T \Phi C \sum_{i=1}^{m} \xi_{ij} (\phi(x_j))^T \Phi \geq 1 - \xi_{ij}, \text{if } y_i = i,$$

$$(\phi(x_i))^T \Phi C \sum_{i=1}^{m} \xi_{ij} (\phi(x_j))^T \Phi \geq 1 + \xi_{ij}, \text{if } y_i \neq j,$$

$$\xi_{ij} \geq 0$$

Where $\xi_{ij}$ is the relaxation factor, $C$ is the penalty factor, $\Phi$ is the coefficient vector, $\phi(x_i)$ is the kernel function.

The parameter $g$ control the flexibility of RBF kernel function, the coefficient $c$ plays a role of balancing the complexity of the decision function and the number of sample error. These two parameters of support vector machine (SVM) are usually rely on experience or artificial test in practical application.

For the selection of the optimization parameters $c$ and $g$ of the SVM, the common method is using $K$-fold cross validation (K-CV) at present. The principle of it is divide the original data into $K$ groups (usually is divide equally) firstly, each subset will be a test set respectively, at the same time the rest of the $K-1$ set of subsets of the data will as a training set. Then we will get $K$ models, and acquire the best parameters $c$ and $g$ which make the test sets have the highest classification accuracy. But if we want to acquire the best parameters $c$ and $g$ in a larger range, it will be very time consuming. Nevertheless, using heuristic algorithm—genetic algorithm (GA) on the basis of the K-CV don't need to traverse all the parameters points can also find the global optimal solution.

Because the classification accuracy using K-CV reflected the pros and cons of the performance of classifier, so using K-fold cross validation (K-CV) accuracy as the fitness function value of genetic algorithm (GA) to find the best parameter $c$ and $g$ which make the classification effect of SVM better in this paper. The Group number $K$ usually will take $5$ or $10$. According to the existing research, $K=5$ will obtain good classification effect.

B. The Discretization of Degradation State

Traditional state monitoring and fault diagnosis usually divided the health status of bearing into two kinds—normal and fault simply. In fact, most of the bearing will experience a series of degradation state before the final function failure. The appropriate select of degradation state number has important influence on the accuracy of degradation state recognition. Through the residual lifetime error of health state, the method of health state probability evaluation can determine the optimal number of degradation state, this method can effective discretization the degradation state of bearing. The degradation state is divided into $9$ kinds state which are $2$ to $10$ firstly, using the model in 2.1 respectively to training and forecasting the samples, and then calculate the training and predicting accuracy of each case, finally select the optimal result to determine the final number of degradation state.

Specific steps are shown as follows:

(1) The initial sample data is $\bar{x}_t = (x_{t1}, x_{t2}, \ldots, x_{tm})$, $m$ is the data length, $t$ is the time index, $y_t \in \{1, \ldots, k\}$, $k=2,3,\ldots, 10$, the initial value of $k$ is $2$.

(2) Calculating the probability distribution of each state according to the smooth window and instruction function.

$$\text{Prob}(S_i = i | \bar{x}_t) = \sum_{i=1}^{m} f(y_j) / u$$

Where $S_i$ is the smooth health status, $u$ is the width of the smooth window function.

The sum of probability of each health state is shown as follows:

$$\sum_{i=1}^{k} \text{Prob}(S_i = i | \bar{x}_t) = 1$$

After the probability of each health state is obtained, then we will get the residual life of current state according to the history information of residual life of each state.
is the residual life of history at state \( i \), \( m \) is the number of degradation state.

(4) Calculating the average training and predicting accuracy according to the following formula.

\[
A = \left( \frac{1}{N} \sum_{i=1}^{N} | \mu'_i - \mu_i | \right) \times 100\%
\]  

(5) Where \( N \) is the number of data. \( \mu'_i \) is the actual residual life, \( \mu_i \) is the assessment residual life of training, then A is the average training accuracy, when \( \mu_i \) is the assessment residual life of test, then A is the average test accuracy.

(6) If \( k = 10 \), steering (5), or \( k = k + 1 \), jump to (2).

Contrast the status which have researched by drawing, finding the optimal number of degradation state.

IV. THE DEGRADATION STATE RECOGNITION OF ROLLING BEARING

To verify the effectiveness of the method which have been proposed, we select the vibration data of rolling bearing from the NSF 1/UCR Center for Intelligent Maintenance Systems (IMS). Each data consists of 20,480 points with the sampling rate set at 20 kHz. The model of rolling bearing is Rexnord ZA-2115, and rotation speed was kept constant at 2000 RPM by an AC motor coupled to the shaft via rub belts, all bearings are force lubricated.

Because of the statistical characteristics of vibration signal contains abundant information, so statistical characteristics are used to recognize degraded state of rolling bearing in this paper. Using the reconstruction signal through the combination of GA and SVM to optimize the characteristics of degradation state. The input feature vectors of SVM contains 16 statistical characteristics, including seven time-domain dimensional characteristics, four time-domain dimensionless characteristics, and five frequency domain characteristics.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>STATISTICAL CHARACTERISTICS</th>
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</thead>
<tbody>
<tr>
<td>Time domain features</td>
<td>Frequency domain features</td>
</tr>
<tr>
<td>Dimensional</td>
<td>Dimensional</td>
</tr>
<tr>
<td>1. Mean</td>
<td>8.S factor</td>
</tr>
<tr>
<td>2. Var</td>
<td>9.C factor</td>
</tr>
<tr>
<td>3. Root</td>
<td>10.1 factor</td>
</tr>
<tr>
<td>4. RMS</td>
<td>11.L factor</td>
</tr>
<tr>
<td>5. Peak</td>
<td>12. MSF</td>
</tr>
<tr>
<td>6. Ske</td>
<td>13. FC</td>
</tr>
<tr>
<td>7. Kvar</td>
<td>14. VF</td>
</tr>
<tr>
<td>15. RMSF</td>
<td>16. RVF</td>
</tr>
</tbody>
</table>

Using the 16 features which has been extracted to reduce the dimension. The parameter setting of GA is as follows: the number of population and maximum evolution generation are 60 and 300 respectively. The value of \( P_c \) is 0.65, \( P_m \) is 0.005 respectively. The parameters of fitness function \( \eta \) and \( \gamma \) are 0.91 and 0.6 respectively. The result of feature selection is showed by Fig. 6, the final results of SVM parameters optimization are \( C = 1.3785 \), \( g = 11.0259 \).

According to the features of the support vector machine (SVM) which has already been acquired, and the theory which has been given in III, we can determine the specific number of the degradation state based on the different status of training and prediction accuracy which has been analyzed. As shown in Fig.1, different degradation state represents the process of bearing fault effectively, according to physical change of degradation process, despite the state of high number have higher training accuracy, but with a lower prediction accuracy. On the contrary, the state of low number has higher prediction accuracy, but with a higher training accuracy. Beyond five health states the prediction accuracy decreased rapidly and without significant increased in the training accuracy value. So the number of degradation state is 5.

**Figure 1.** The training and prediction accuracy of different state

Using the feature vector T which has been dimension reduction to recognition the degradation state of rolling bearing. The data are divided into 5 groups, and each group has 60 samples, including 30 samples for training the model and other 30 samples for the recognition test of degradation state.

Selection the test data which has been acquired to identification the degradation state after the SVM
model of degradation state has been trained. The division of state categories and recognition accuracy of degradation state are shown in Table 2.

**TABLE II THE RECOGNITION ACCURACY OF SVM**

<table>
<thead>
<tr>
<th>Class</th>
<th>Training/test samples</th>
<th>Sample points</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30</td>
<td>20480</td>
<td>96.6667</td>
</tr>
<tr>
<td>2</td>
<td>30</td>
<td>20480</td>
<td>93.3333</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>20480</td>
<td>96.6667</td>
</tr>
<tr>
<td>4</td>
<td>30</td>
<td>20480</td>
<td>96.6667</td>
</tr>
<tr>
<td>5</td>
<td>30</td>
<td>20480</td>
<td>100</td>
</tr>
</tbody>
</table>

The recognition result of the test sample is shown in Fig. 2. From the figure we can see that the 1st, 3rd and 4th class status have only one sample data was wrong points, the 2nd class status has two sample data were in the wrong points, and the fifth class status of the sample data in identifying when no fault point. The graph shows that the SVM has a high classify accuracy to the test sample, and the SVM technology which has been optimized by genetic algorithm is effective for the degradation state recognition of rolling bearing.

To validate the advantages of GA in feature extraction, comparing GA with other traditional commonly method—principal component analysis (PCA) method and particle swarm Optimization (PSO). The contrast analysis of classification results of feature extraction are shown in Table 3.

**TABLE III THE RECOGNITION ACCURACY OF THREE FEATURE SELECTION METHODS**

<table>
<thead>
<tr>
<th>Manner</th>
<th>Accuracy (%)</th>
<th>Correct samples/Total samples</th>
<th>Feature number</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>96.6667</td>
<td>145/15</td>
<td>6</td>
</tr>
<tr>
<td>PCA</td>
<td>86.6667</td>
<td>130/15</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 3 shows the result that GA has significant advantage in terms of feature extraction relative to other two methods, and it has lower dimension and high accuracy. This is because the technology of GA eliminate the initial characteristics which has nothing to do with the recognition of degradation state comparing with other two kinds of methods, making the classification accuracy become better.

**V. CONCLUSION**

The accurate assessment of degradation state of current equipment is the basic of implementation status maintenance and predictive maintenance. This paper mainly studies the following conclusions:

1) GA could extract the sensitive feature which reflect the degradation state of rolling bearing realize the optimal selection of the characteristics, and it can also realize the parameters optimization of SVM.

2) The optimal number of degradation state can be determined through the combination of health state probability evaluation method and SVM.

3) The method of degradation state recognition based on the GA and SVM can identify the degradation state of mechanical system accurately.

Through the actual data validation shows that the effect of proposed technology is remarkable to the degradation state recognition of rolling bearing.

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