Evaluation method of degradation index based on AdaBoost regression

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Abstract. In the field of bearing monitoring, it has always been a difficult problem in the industry to judge the performance of the degradation index. A degradation index evaluation method is proposed based on AdaBoost regression. In this method, AdaBoost regression method is used for the bearing degradation index correlation evaluation criteria. The comprehensive weighted evaluation of degradation characteristics was obtained by the combination with robustness and monotonicity. Features were optimized according to the evaluation score. The analysis of accelerated life experimental data shows that the degradation feature evaluation method based on AdaBoost regression can effectively select the degradation features with good characterization.

1. Introduction

Bearing is one of the three core components of rotating equipment, and its performance is related to the safety of the whole equipment [1,2]. Excellent degradation characteristics can well reflect the degradation degree of bearing performance, that is, the state of bearing fault development in bearing monitoring. It is a long-term coveted evaluation index of bearing health. However, how to judge whether a degradation feature is good or not has always been a difficult problem in the monitoring industry [3,4].

The common bearing degradation characteristics include time domain statistical characteristics, frequency domain statistical characteristics and time-frequency domain statistical characteristics. These statistical characteristics can reflect the change of bearing running state with time to a certain extent. However, the ability of a single degradation feature is very limited affected by the quality of the collected original vibration acceleration signal and the degradation feature extraction method [5]. For example, kurtosis index is sensitive to pulse impact with good effect in early fault. However, kurtosis index does not increase but decreases, which is difficult to reflect the severity of fault with the development of fault and the deepening of damage degree [6-8]. Moreover, more and more degradation features have been constructed with the deepening of research. It has become impossible to use artificial experience to evaluate whether the degradation features are good or not. Therefore, a scientific standard is needed to evaluate whether the degradation characteristics are excellent or not.

This paper proposes a degradation feature evaluation method based on AdaBoost regression [9], which applies AdaBoost regression to the correlation analysis of degradation features, evaluates and optimizes high-dimensional degradation features from three different degradation stages, that is, normal operation stage, initial fault stage and fault development stage. We optimizes the degradation features with good characterization performance. An excellent degradation feature set is constructed to ensure...
that the fusion degradation features constructed later have good characterization performance for different degradation stages.

2. AdaBoost regression model

AdaBoost is an excellent supervised learning method, which can promote multiple base learners to strong learners [10]. The principle of AdaBoost method is as follows. Firstly, a basic learner is trained by using the initial training set. Then, the distribution of training samples is adjusted by using the performance of the base learner, so that the training samples with the wrong classification of the previous base learner can obtain a larger weight in the subsequent calculation. And then train again to obtain a new base learner, repeat the above process until the number of base learners reaches the set value $K$. Finally, all base learners are weighted and combined to obtain the final strong learner according to the AdaBoost regression strategy. The principle of AdaBoost method can be understood in this way. When solving a problem, it consults many experts at the same time, and finally obtains a comprehensive conclusion combined with the opinions of all experts. This conclusion is undoubtedly the most authoritative.

The advantages of AdaBoost regression method are mainly reflected as follows. under the framework of AdaBoost, various regression models can be used to construct the basic learner, which is very flexible, not easy to fit, and the prediction results of regression are understandable and interpretable [11].

The AdaBoost regression model construction process algorithm is as follows:

1) $T=\{(x_i,y_i)\}_{i=1}^m$ is set as the input sample set, with the base learner regression model $G$, and the number of iterations $K$;

2) $f(x)$ is the output of the strong learner function.

3) Initialize the weight distribution of training samples:
\[ D_i = (w_{i1}, w_{i2}, \cdots, w_{im}) , w_{ij} = \frac{1}{m}, i=1,2,\cdots,m \]

4) Iterate $K$ times as follows until all base learners are obtained.

The base learner $G_k(x)$ is obtained by the input sample set training with the weighted sample $D_k$.

Then we calculated the maximum error on the training set, $E_k = \max |y_i - G_k(x_i)|, i=1,2,\cdots,m$.

The relative error per sample is calculated as Eq. (1), with the regression error rate, Eq. (2)
\[
e_{ik} = 1 - \exp \left[ -\frac{y_i - G_k(x_i)}{E_k} \right] \quad (1)
\]
\[
e_k = \sum_{i=1}^m w_{ik} e_{ik} \quad (2)
\]

The coefficients of the base learner is calculated as Eq. (3).
\[
\alpha_k = \frac{e_k}{1-e_k} \quad (3)
\]

Eq. (4)–(5) updated the weight distribution of the sample.
\[
w_{ik+1} = \frac{w_{ik}}{Z_k} \alpha_k^{1+e_{ik}} \quad (4)
\]
\[
Z_k = \sum_{i=1}^m w_{ik} \alpha_k^{1+e_{ik}} \quad (5)
\]

The strong learner is finally constructed as Eq.(6).
\[
f(x) = \sum_{k=1}^K \left( \ln \frac{1}{\alpha_k} \right) G_k(x) \quad (6)
\]
3. Degradation feature evaluation method

The evaluation of degradation features is generally carried out from three aspects, such as correlation, monotonicity and robustness. Correlation, $M(x)$, refers to the correlation between degradation characteristics and time, as shown in Eq.(7). The larger the value means the better the correlation. Monotonicity, $R(x)$, refers to the degree of monotonic increase or decrease of degradation characteristics, as shown in Eq.(8). The bearing damage is the better reflected with the larger monotonicity. Robustness, $C(x)$, refers to the stability of degraded features, as shown in Eq.(9). The better stable is the goal the description of bearing performance degradation. Finally, the comprehensive evaluation, $J$, is obtained by fusing the information of correlation, monotonicity and robustness, as shown in Eq.(10). Represents the comprehensive evaluation results of degradation characteristics. The higher the value, the more favorable the degradation characteristics are to characterize the degradation trend of bearings [12].

$$
M(x_i) = \frac{\sum_{i=1}^{N-1} \delta(x_{i+1}' - x_i') - \sum_{i=1}^{N-1} (x_i' - x_{i+1}')}{N-1}
$$

(7)

$$
R(x_i) = \frac{1}{N} \sum_{i=1}^{N} \exp\left(-\frac{|x_{i}'|}{x_i'}\right)
$$

(8)

$$
C(x_i) = \sqrt{\frac{\sum_{i=1}^{N} (x_{i}' - \bar{x}_{i}')^2}{\sum_{i=1}^{N} (x_{i}' - \bar{x}_{i}')^2}}
$$

(9)

$$
J = \omega_1 M(x_i) + \omega_2 R(x_i) + \omega_3 C(x_i)
$$

(10)

There, $x_i$ represents a degraded feature. $x(i)$ is the sample in the degradation feature, $x_i$. $N$ represents the length of the degraded feature. $x(i)'$, $x(i)'$ represent the samples in the residual vector and trend vector of the degradation feature, $x_i$, respectively. $x(i) = x(i)' + x(i)'$. $\delta[x(i)]$ is the unit step function. $\omega_1$, $\omega_2$, $\omega_3$ are three weighting coefficients for evaluating degradation characteristics.

The degradation characteristic evaluation method based on AdaBoost regression is shown in Fig.1. The process is as follows:

1) The time-domain, frequency-domain and time-frequency-domain features of vibration signals are extracted and normalized to obtain high-dimensional feature set.

2) Combined with the experimental conditions and root mean square characteristics, the bearing is divided into four stages: normal operation stage $s_1$, early fault stage $s_2$, fault development stage $s_3$ and failure stage $s_4$.

3) In the normal operation stage $s_1$, early fault stage $s_2$ and fault development stage $s_3$, comprehensive evaluation $J$ is used for primary screening, and the initial good characteristics of the three stages are obtained respectively.

4) Build their own AdaBoost regression models in the normal operation stage $s_1$, early fault stage $s_2$ and fault development stage $s_3$, and then test all the features in the high-dimensional feature set to obtain the best degradation features in each stage.
4. Application to degradation characteristic evaluation of CRH bearing

As significant components of CRH, the unexpected failure of the high speed Une train-set roller bearings may cause huge economical loss, even personal casualties. It is important to whether the degradation index can correctly evaluate the health state of EMU bearings. The accelerated life test was carried out on 106GYL fatigue testing machine, as shown in Fig.2.

The test bearing (NU214) is loaded on the outer race. The basic dimension parameters of NU214 are listed in Table 1. A group of 32768 data points are collected every 10s with the sampling frequency, 25600Hz.

![Fig.2. Test bench of CRH roller bearing](image1)

![Fig.1. Evaluation process of degradation characteristics based on AdaBoost regression](image2)
### Table1. Parameter in the experiment

| Parameter          | Value       |
|--------------------|-------------|
| Bearing specs      | NU214       |
| load               | 95 KN       |
| Inner race diameter| 70mm        |
| Outer race diameter| 125mm       |
| Roller diameter    | 13mm        |
| Roller number      | 16          |
| Contact angle      | 0°          |
| Sample frequency   | 25.6kHz     |
| Rotating speed     | 4000r/min   |

In order to test the effectiveness of the degradation characteristic evaluation method based on AdaBoost regression, the whole life data of NU214 bearing are analyzed. The process is as follows. 52 degradation features in time domain, frequency domain and time-frequency domain of NU214 bearing monitoring data are extracted, and 156 features in X, Y and Z directions are marked as $T_i^{xy}$, $T_i^{yz}$, $T_i^{zx}$, respectively. For the setting of weighting coefficient, set it to the same weight, $\omega_1=\omega_2=\omega_3=1/3$.

The degradation feature evaluation method based on AdaBoost regression is used to optimize the above 156 degradation features. The process is as follows. AdaBoost regression models are build in each stage, such as, AdaBoost regression model 1 in normal stage, AdaBoost regression model 2 in early fault stage and AdaBoost regression model 3 in fault development stage. These three regression models are used to evaluate the correlation of high-dimensional degraded feature sets, Then, combined with the two evaluation criteria of robustness and monotonicity, three kinds of optimal degradation feature sets are weighted and optimized, which are good degradation feature sets in normal stage, good degradation feature sets in early fault stage and good degradation feature sets in fault development stage.

The evaluation results of the three preferred degradation features with good characterization are shown in Table 2 ~ 4. Fig. 3 shows (a) and (b) are the two features with good characterization in the normal operation stage with the highest evaluation; Fig.4 shows (a) and (b) the two features with good characterization in the early operation stage with the highest evaluation, and Fig.5 shows (a) and (b) the two features with good characterization in the fault development stage with the highest evaluation.

From the above evaluation results, it is not difficult to see that. The degradation features with good characterization of degradation features are optimized, and the effectiveness of this method is verified, through the degradation feature evaluation method of AdaBoost regression. As shown in Fig.3, the amplitude of two degradation features increases gently and shows good stability with good characterization in the normal operation stage. As shown in Fig.4, the amplitude of two degradation features increases gently in the normal operation stage with good characterization in the early fault stage. When the fault occurs at 110h, the amplitude increases significantly and maintains continuous change. These reflect the sensitivity of this kind of degradation features to weak faults, which is conducive to the fusion of degradation features to detect early weak faults as soon as possible. As shown in Fig.5, the amplitude of two degradation characteristics with good characterization in the fault development stage increases very gently in the normal operation stage. When a fault occurs and the fault continues to develop, the amplitude increases rapidly and has a relatively good trend. From the analysis of the fault development degree, the amplitude of degradation characteristics does not increase in the last failure stage. The reason is inferred that the fault has developed to the failure stage, with the more serious damage and the larger vibration amplitude. The collected data shows violent vibration fluctuation with the short operation time at this stage. The fault damage degree has not developed further.
A single degradation feature is difficult to take into account the three evaluation criteria of correlation, robustness and monotonicity at the same time from Table 2-4. Some degradation features are evaluated higher under a single evaluation criterion, but their comprehensive evaluation value decreases after weighted evaluation, which needs to be considered comprehensively. It can also be found that the evaluation of all degraded features under the monotonicity criterion is far lower than the

![Graphs showing degradation features in different stages](image)

Fig.3 Two optimal degradation features in normal operation stage

Fig.4 Two optimal degradation features in early failure stage

Fig.5 Two optimal degradation features in fault development stage
Table 2. Five optimal degradation features in normal operation stage

| Feature | Relevance (C) | Monotonicity (M) | Robustness (R) | Comprehensive |
|---------|---------------|------------------|----------------|---------------|
| Feature $T_{19}$ | 0.968 | 0.099 | 0.938 | 0.668 |
| Feature $T_{20}$ | 0.988 | 0.063 | 0.949 | 0.667 |
| Feature $T_{19}$ | 0.914 | 0.087 | 0.956 | 0.652 |
| Feature $T_{5}$ | 0.863 | 0.133 | 0.960 | 0.652 |
| Feature $T_{11}$ | **0.803** | **0.135** | **0.960** | **0.633** |

Table 3. Five optimal degradation features in early failure stage

| Feature | Relevance (C) | Monotonicity (M) | Robustness (R) | Comprehensive |
|---------|---------------|------------------|----------------|---------------|
| Feature $T_{16}$ | 0.991 | 0.134 | 0.930 | 0.685 |
| Feature $T_{11}$ | 0.875 | 0.122 | 0.930 | 0.642 |
| Feature $T_{19}$ | 0.906 | 0.095 | 0.905 | 0.635 |
| Feature $T_{14}$ | 0.925 | 0.076 | 0.894 | 0.632 |
| Feature $T_{11}$ | 0.908 | 0.080 | 0.907 | 0.632 |

Table 4. Five optimal degradation features in fault development stage

| Feature | Relevance (C) | Monotonicity (M) | Robustness (R) | Comprehensive |
|---------|---------------|------------------|----------------|---------------|
| Feature $T_{20}$ | 0.991 | 0.083 | 0.857 | 0.644 |
| Feature $T_{16}$ | 0.855 | 0.073 | 0.925 | 0.618 |
| Feature $T_{18}$ | 0.861 | 0.030 | 0.872 | 0.588 |
| Feature $T_{15}$ | 0.545 | 0.081 | 0.940 | 0.522 |
| Feature $T_{5}$ | 0.542 | 0.079 | 0.941 | 0.520 |

correlation evaluation score and robustness score. The reason is that although the extracted degraded features have a certain trend on the whole, they have strong volatility, and their trend curve is not smooth curve. So it is difficult to maintain absolute monotonicity. At the same time, the monotonicity evaluation criterion is analysed. The expression is a cumulative function based on step function, so all the data of the whole degradation characteristics are accumulated, resulting in the low evaluation of monotonicity criterion.

5. Conclusion

The AdaBoost regression model is analysed and studied, and applied to the evaluation of bearing degradation characteristics, and a new comprehensive evaluation system is obtained. The process is as follow. Based on the root mean square value, the bearing degradation process is divided into different degradation stages, aiming at three degradation stages, such as, normal operation stage, early fault stage and fault development stage. Three kinds of degradation features with excellent characterization are selected as a high-dimensional degradation feature set constructed by fusing degradation features. Finally, the analysis of accelerated life experimental data shows that the degradation feature evaluation method can effectively select the degradation features based on AdaBoost regression with good characterization.

Although the degradation feature evaluation method based on AdaBoost regression is successful, the selection of training features depends on human experience. This leads to a certain degree of subjectivity.
Therefore, in the follow-up work, the AdaBoost regression model will be further improved to remove the influence of artificial experience.

Acknowledgments
This work is supported by Special fund for technological innovation guidance of Shaanxi Province of China (No. 2021CGBX-12).

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