Remaining Life Predictions of Bearing Based on Relative Features and Support Vector Machine

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***Abstract*—A new prediction method is proposed based on relative features and support vector machine to estimate the bearing remaining life under limited data conditions. To eliminate the redundancy and relevance within features, principal component analysis (PCA) was applied to obtain the relative features, which could reflect the running states and degradation trends of bearings. Then, the relative features are input into the support vector machine. The bearing residual life prediction model is constructed based on the relative features and support vector machine. The field measured signals are used to verify the effective of the proposed method. The results show that the proposed prediction method can obtain accurate prediction results under small sample conditions.**

Keywords- PCA；SVM； bearing; Remaining Life Predictions

I. INTRODUCTION

Bearing is one of the most important parts of coal mining equipment. Its performance directly affects the health of the whole equipment. The actual service life of the bearing is much lower than the design life because of the special working environment such as dust, moisture and impact load. Once the running time exceeds the service life of the bearing, the vibration will increase, affecting the normal operation of coal mining equipment, and the bearing will get stuck in the heavy, or even cause serious accidents such as broken shaft failure. Therefore, it is necessary to monitor the health condition and predict the residual life of bearing. In addition, bearing residual life prediction is also a prerequisite for the equipment maintenance and repair.

Vibration signal analysis is one of the effective methods of bearing residual life prediction. The method is mainly divided into two steps. In the first step, the sequence of bearing degradation characteristics is constructed to describe the degradation process. The second step, the bearing residual life prediction model is established to predict the remaining life. The root means square value, kurtosis value, peak value, failure characteristic frequency, wavelet entropy, EMD entropy and other characteristic indexes [1-6] reflect the tendency of bearing degradation, which can be input into the residual life prediction model of bearing as the bearing degradation characteristic. However, these features are only sensitive to some stages of the bearing degradation process, and only one feature is used alone as the degradation feature of the bearing residual life prediction, resulting in a large prediction result error [7]. Therefore, the synthetic feature index is constructed by intelligent algorithm [8-9]. The synthetic characteristic index can describe the degradation process of bearing relative accurately, but increase the complexity of calculation [10].

In order to reduce the computational complexity and retain the relative comprehensive bearing degradation information, the principal component analysis (PCA) was used to obtain relative features (principal components), which reduce the number of degenerate feature quantities while retaining as much useful information as possible from the signals.

It is the most important that how to establish the model of residual life prediction. The traditional statistical model is to estimate the reliability life of the bearing by a set of reliability tests, but it cannot get the actual residual life. With the wide application of on-line monitoring system of coal mining equipment, the research of bearing life prediction based on the monitoring data of bearing health state is increasing gradually. Prediction models such as BP neural network model [11-13], similarity model [14] have been proposed and achieved good results. But these predictive models require more data samples. Failure data samples of bearing deterioration of coal machine equipment are very difficult to obtain. At the same time, the bearing data samples in the laboratory are quite different from the data samples of the actual working conditions of the coal machinery equipment. It cannot be used as an effective data sample for predicting the bearing residual life of coal machine equipment. How to establish a suitable prediction model under the condition of limited data samples is the key to accurately predict the bearing residual life. Support Vector Machine (SVM) is a machine learning algorithm to solve the classification and prediction of small samples [15-18]. It is widely used in wind power, rail transit and other fields. It can be used as a prediction model of bearing residual life under the condition of small samples.

In this paper, a new method for the bearing residual life prediction is presented and the frame is shown in figure 1. First, the vibration signal is collected to construct data samples, and feature extraction is performed, including characteristic values

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such as effective value, peak value, wavelet energy, and entropy. Then, these feature indicators are entered into the PCA model. Under the premise of retaining all kinds of characteristic information of the input signal, the input of degradation characteristics in the bearing life prediction model is reduced. The number of relative features in bearing life prediction model, that is, the number of principal components, is determined according to the cumulative contribution rate. Next, since the typical bearing data samples for coal machine equipment are scarce, the SVM prediction model is clearly applied. Finally，the bearing residual life prediction model based on PCA and SVM is constructed. On the one hand, many characteristic information in the signal is preserved, which ensures the accuracy of bearing residual life prediction. On the other hand, it effectively reduces the input of degradation feature in bearing life prediction model.

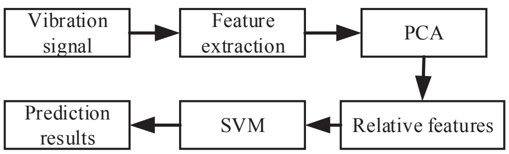


Figure1 Technical Framework of Bearing Residual Life Prediction

II. PRINCIPAL COMPONENT ANALYSIS（PCA）

It is assumed that the data matrix $X_{n\times m}$, each row corresponds to data sample x_i , each column corresponds to the characteristic amount of an observed sample ξ_i . Since different characteristic quantities have different dimensions, and different dimensions will cause differences in variable dispersion degree. It is necessary to standardize the obtained different characteristic quantities to obtain the matrix $\widehat{X}_{n\times m}$.

$$\widehat{\xi}_i = \frac{\xi_i - E(\xi_i)}{Std(\xi_i)} \tag{1}$$

where

$\widehat{\xi}_i$: Standardized characteristic quantity

$E(\xi_i)$: mean value

$Std(\xi_i)$: standard deviation

The covariance matrix C of the matrix $\widehat{X}_{n\times m}$ is calculated.

$$C = \mathrm{cov}(\widehat{X}_{n\times m}) \tag{2}$$

The eigenvalues and eigenvectors of the covariance matrix are calculated. Arrange eigenvalues in order from large to small. The corresponding eigenvectors constitute the corresponding eigenmatrix K.

$$K = \begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1m} \\ k_{21} & k_{22} & \cdots & k_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ k_{m1} & k_{m2} & \cdots & k_{mm} \end{bmatrix} \tag{3}$$

The cumulative contribution rate is used to determine the number of principal components. The contribution rate is based on the following formula:

$$\text{contribution rate:}\quad \frac{\lambda_i}{\sum_{k=1}^{k=m} \lambda_k} \quad (i = 1,2,\cdots,m)$$

The principal components whose cumulative contribution rate is greater than 85% are taken as the Relative multi-feature degradation feature quantity [19], which is calculated according to the following formula.

$$p_j = \widehat{X}_{n\times m} \cdot \begin{bmatrix} k_{1j} \\ k_{2j} \\ \vdots \\ k_{mj} \end{bmatrix} \tag{4}$$

where

$j = 1,2,\cdots,U$ (U - Principal component number）

III. SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine is one of the machine learning algorithms that effectively handle small sample problems. Given sample set $S = \{(x_i, y_i)|_{i=1}^{n}, x_i \in X \subseteq R^n, y_i \in Y \subseteq R\}$, x_i - Input variable, y_i - Predictive value, then the regression function:

$$f(x) = \langle w \bullet x \rangle + b \tag{5}$$

Where $w \in R^n$ is weight vector, $b \in R$, is offset threshold, $w \bullet x$ denotes the point product of w and x . w and b are obtained by solving the following optimal problems.

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \tag{6}$$

St.

$$\langle w \bullet x_i \rangle + b - y_i \le \zeta_i + \varepsilon$$

$$y_i - \langle w \bullet x_i \rangle - b \le \zeta_i^* + \varepsilon \quad i = 1,2,\cdots,n$$

$$\zeta_i, \zeta_i^* \ge 0$$

Where：C is the penalty factor, ζ_i and ζ_i^* is relaxation factor and non-sensitive factor. When the data are nonlinear, the kernel function is introduced into the SVM, the original data is mapped to the high dimensional space, and the nonlinear problem is transformed into the linear problem. The RBF kernel function is the most commonly used kernel function, and its expression is:

$$K(x,y)=\exp(-\frac{\|x-y\|^2}{p^2}) \tag{7}$$

where p is Kernel function index. The Lagrangian function is introduced to transform the optimization problem into a convex quadratic programming problem.

$$\max W(a_i,a_i^*)=-\frac{1}{2}\sum_{i,j}^{n}(a_i-a_i^*)(a_j-a_j^*)K(x_i,x_j)- \\ \varepsilon\sum_{1}^{n}(a_i-a_i^*)+\sum_{i=1}^{n}y_i(a_i-a_i^*) \tag{8}$$

$S.t.$

$$\sum_{i=1}^{n}(a_i-a_i^*)=0$$

$$0<a_i<C \quad i=1,2,\cdots,n$$

$$0<a_i^*<C$$

where a_i and a_i^* are Lagrangian operators.

According to the KKT condition, the regression function of support vector machine is [16-18]:

$$f(x)=\sum_{i=1}^{n}(a_i-a_i^*)\cdot K(x_i,x)+b \tag{9}$$

IV. Applications

In the engineering application, the data samples come from the roller bearing vibration signals of a main belt conveyor in a mine. The vibration acceleration sensors are installed on the roller bearing. The signals are collected by data acquisition system and stored in the computer.

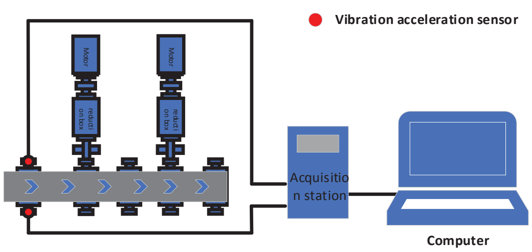


Figure2 Schematic diagram of the on-line data acquisition system

The roller speed is 69r/min, the bearing type is 23144, the sampling frequency is 4000Hz, and the sampling number is 8000. YHZ18 data acquisition instrument produced by Beijing tiandi longyue company was used for data collection. The computer is used as the server here.

From the data recorded by the monitoring system, it can be found that the amplitude of vibration on the left side of the tension drum increases slightly from August 1 to August 23. The roller bearing was replaced on September 19. The vibration data of the initial deterioration stage of the roller bearing from August 1 to August 23 was selected as a data sample to predict the bearing remaining life. The data sample interval was 0.5 days.

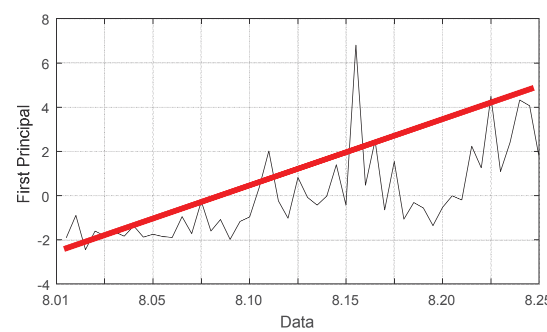
Firstly, the characteristic quantities of data samples are extracted, including: effective value index, peak value index, kurtosis index, waveform index, wavelet energy index, wavelet entropy index, etc.

The extracted feature indicators are input into the PCA model to perform feature fusion, and the redundancy and correlation among features are removed. The obtained principal component contribution rate and its cumulative contribution rate are shown in Table 1.

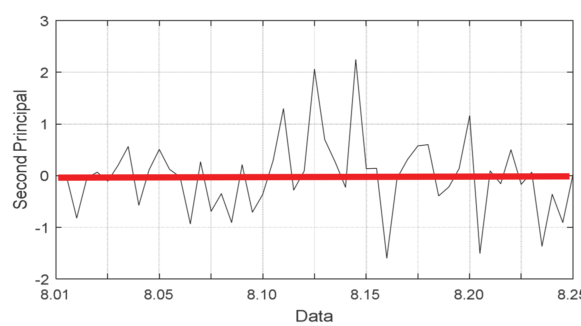
Table 1 Principal contribution rate and cumulative contribution rate

Principal	1	2	3	4	5	6	7
contribution rate	0.55	0.32	0.10	0.03	0.00	0.00	0.00
cumulative contribution rate	0.55	0.87	0.97	1	1	1	1

In this paper, the method of cumulative contribution rate is used to extract principal components, and the threshold of cumulative contribution rate of principal component extraction is set to 0.85[18-19]. As can be seen from Table 1, the first and second principal components (Relative features) contain most of the information in the signal, therefore, the first and second features are selected as the degenerate feature variables.



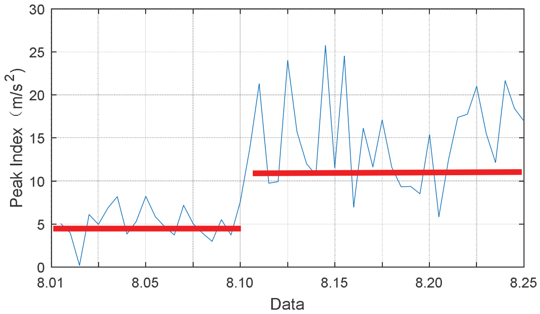
(a) First feature trend change



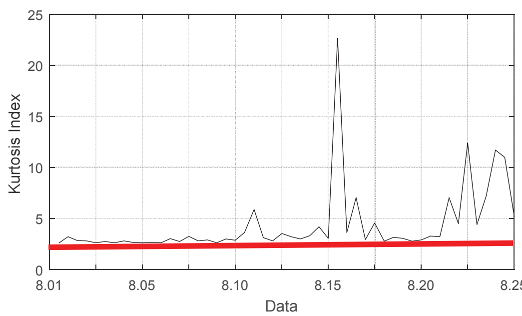
(b) Second feature trend change

Figure3 Trend Change of Degraded Characteristic Output of PCA Model

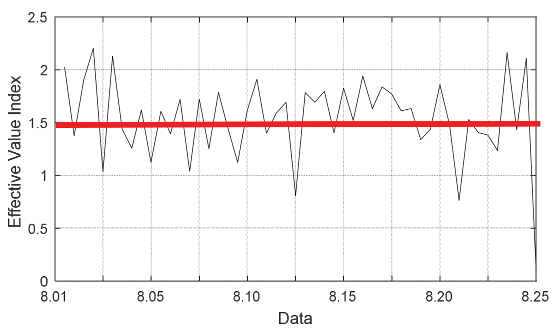
Limited to space, the trend curves of the effective value index, the peak value index and the kurtosis index are given here, as shown in Figure 4.



(a) Peak trend curve



(b) Kurtosis index curve



(c) Effective value index curve

Figure4 Trend Curves of different Indices

From Figures 3 and 4, it can be concluded that the first relative feature has a significant upward trend, reflecting the deterioration process of bearings. The second Relative feature represents the influence of working conditions and bearing itself on the bearing deterioration process. Peak value index, kurtosis index and effective value index are the most commonly used indexes for bearing life prediction in laboratory environment. However, in the analysis of the field measured data, it is found that: If these indexes are simply used as the degradation characteristic quantity of bearing life prediction, it is difficult to meet the requirements of practical engineering application. The peak index showed a step rise on August 10. Before and after the jump, the peak index fluctuated around the stable state. From August 15th to August 22nd to August 25th, the kurtosis index showed a large jump, and there was no noticeable change in other time. The effective value index cannot represent any deterioration information of the bearing.

Taking the first and second relative features as the degenerate characteristic variables, a prediction model was established to predict the residual life of the bearing.

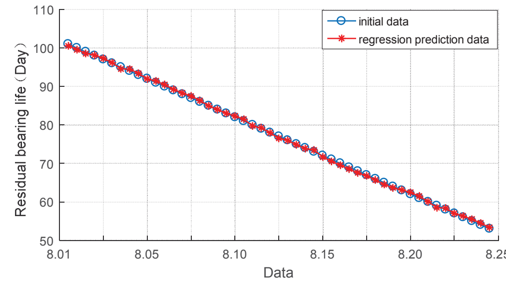


Figure5 Residual Life Prediction Model of Tension Cylinder Bearing

The mean square error of the prediction model is 0.00005677. The prediction method based on Relative feature and support vector machine has a good overall prediction effect, and the prediction curve almost coincides with the real-life curve, as shown in figure 5.

The predicted sample data is from August 1-23. The predicted results show that the remaining life of the bearing is 27($54\times0.5=27$) days. That is, the bearing can continue to be used for 27 days. On September 19, the ending time of the service life of the roller bearing is taken as the maintenance of the roller bearing. The obvious pitting and spalling can be found during maintenance, as shown in figure 6. The results are in good agreement with the predicted results.

Figure6 Photographs of Bearing Damage

□. CONCLUSIONS

(1) In this paper, the PCA method is used to obtain the relative features, which can greatly reduce the number of degenerate feature quantities while retaining as much useful information as possible from the signals.

(2)A bearing life prediction model based on relative feature and support vector machine is constructed to realize accurate prediction of bearing residual life under the condition of small samples.

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REFERENCES

[1] Chong Feiyun, Chen Jin, Dong Guangming. Spectral Kurtousis and AR Model Based Method for Fault Diagnosis of Rolling Bearrings[J]. Journal of Vibration, Measurement & Diagnosis, 2012, 32(4): 538-541.

[2] Xu Dong, Xu Yongcheng, Chen Xun. et al. Residual Fatigue Life Prediction Based on Grey Model and EMD[J]. Journal of Vibration Engineering, 2011, 24(1): 104-110.

[3] Ma Jiaju, Liang Wenmei. Analysis of Statistical Characteristics of Rolling Bearing Vibration[J]. Bear, 1994(1): 33-37.

[4] Shi Linshuo, Shen Jinwei, Zhang Yazhou, et al. Fault Diagnosis of a Rolling Element Bearing Based on AR Model and Spectral Kurtosis[J]. Vibration and Shock, 2011, 30(12): 257-260.

[5] Feng Fuzhou, Si Aiwei, Jiang Pengcheng. Application of Wavelet Correlation Permutation Entropy and Hidden Markov Model to Fault Prognostic[J]. Journal of Vibration Engineering, 2013, 26(2): 269-276.

[6] Li Bin, Hu Leigang, Xiao Mingqing. Analysis of Fault Tolerance of the Acquisition Technology Based on Beams Scanning of Laser Satellite Communication[J]. Journal of Air Force Engineering University (Natural Science Edition), 2011, 12(2): 6-11.

[7] Miao Xuewen, Wang Dawei, Hong Jie. .Progress of Life Theory of Rolling Bearings[J]. Bear, 2008(3): 47-52.

[8] Shen Zhongjie, Chen Xuefeng, He Zhengjia, et al. Remaining Life Predictions of Rolling Bearing Based on Relative Features and Multivariable Support Vector Machine[J]. Journal of Mechanical Engineering, 2013, 49(2): 183-189.

[9] Chen Chang. Reliability Assessment Method for Space Rolling Bearing Based on Condition Vibration Feature[D], Chongqing University, 2014

[10] Wang Fuguang, Li Wei, Zheng Jinde, Prediction of Remaining Life of Rolling Bearings Based on Multi-frequency Scale Fuzzy Entropy and ELM[J], Noise and Vibration Control, 2018, 38(1): 188-192.

[11] Xi Lifeng, Huang Runqing, Li Xinglin, et al. Residual Life Predictions for Ball Bearing Based on Neural Networks[J], Journal of Mechanical Engineering, 2007, 43(10): 137-143.

[12] Fan Gaofeng, Liu Weisheng, Liu Cun, et al. Wind Power Prediction Based on Artificial Neural Network[J]. Proceedings of the Csee, 2008, 28(34): 118-123.

[13] Pan Ziwei, Wu Chaoying. The Bearing Life method Based on Neural networks[J]. Mechanical Science and Technology, 1999(4): 584-586.

[14] Wu Bin, Li Lu, Song Jiancheng, et al. Approach for remaining useful life prediction for mechanical equipment based on similarity[J]. Industry and Mine Automation, 2016, 42(6): 52-56.

[15] Xu Jiya, Wang Yan, Yan Dahu, et al. SVM Prediction of Performance of Rolling Bearings with Fusion of KPCA and Information Granulation[J], Journal of System Simulation, , 2018(6): 2345-2350.

[16] Hao Ying. Research on Fault Diagnosis and Life Prediction of Civil Aviation Engine Based on Intelligent Technology[D]. Nanjing University of Aeronautics and Astronautics, 2006.

[17] Feng Guangbin, Wu Zhenyu, Yuan Huiqun. Model Construction of Serpentine Belt Drive Systems with Multi-Ribbed Belt Damping and Belt Slipping Control[J]. Jounrual of Vibration, Measurement & Diagnosis, 2011, 31(1): 64-69.

[18] Bie Fengfeng, Liu Chang, Zhou Guoqiang, et al. Research on Fault Prediction Approach for Reciprocating Machinery Based on Local Wave Method and SVM Prediction Model[J], China Mechanical Engineering, 2011, 22(6): 687-691.

[19] Wang Haiqing, Song Zhihuang, Li Ping. Improved PCA with Application to Process Monitoring and Fault Diagnosis[J]. Journal of Chemical Industry and Engineering, 2001, 52(6): 471-475.