Application of PCA+CHMM in Equipment Performance Degradation State Recognition Postprint

Authors: Zhong Fei, Ning Qian, Zhou Xinzhi, Zhao Chengping

Date: 2018-05-20T00:00:00+00:00

Abstract

A performance degradation state recognition method based on the combination of PCA (Principal Component Analysis) and CHMM (Continuous Hidden Markov Model) is proposed to accurately identify the current degradation state of mechanical equipment. First, features in the time domain, frequency domain, and time-frequency domain are extracted from the equipment's vibration signals over the full life cycle; after preliminary screening, these are combined to form a new feature set, which is then subjected to dimensionality reduction using PCA. Subsequently, the dimensionality-reduced data is utilized to train a full-life-cycle CHMM to determine the number of degradation states, followed by training a separate CHMM for each degradation state; the current degradation state of the equipment is determined by comparing the likelihood probability values of the observation sequence under each model. Finally, experimental comparisons are conducted between PCA+CHMM and PCA+SVM, PCA+KNN, PCA+CART methods regarding their respective degradation state recognition accuracies; the results demonstrate that PCA+CHMM achieves the highest average recognition accuracy with favorable recognition performance, making it suitable for equipment degradation state recognition.

Full Text

Preamble

Title: Application of PCA+CHMM in Equipment Performance Degradation State Recognition

Authors: Zhong Fei[1], Ning Qian[1,2], Zhou Xinzhi[1,2], Zhao Chengping[1]
[1]College of Electronics & Information Engineering, Sichuan University, Chengdu 610065, China

[2]Science & Technology on Electronic Information Control Laboratory, Chengdu 610036, China

Abstract: To accurately identify the degradation state of mechanical equipment, this paper proposes a performance degradation state recognition method based on the combination of PCA (Principal Component Analysis) and CHMM (Continuous Hidden Markov Model). First, time-domain, frequency-domain, and time-frequency-domain features are extracted from the vibration signals of the equipment' s full life cycle. After preliminary screening, these features form a new feature set, which is then subjected to dimensionality reduction using PCA. Next, a full life cycle CHMM is trained using the reduced-dimension data to determine the number of degradation states. Subsequently, a separate CHMM is trained for each degradation state, and the current degradation state of the equipment is determined by comparing the likelihood probabilities of the observation sequence under each model. Finally, experiments compare the recognition accuracy of each degradation state among PCA+CHMM, PCA+SVM, PCA+KNN, and PCA+CART methods. The results demonstrate that PCA+CHMM achieves the highest average recognition accuracy and exhibits superior recognition performance, making it suitable for equipment degradation state identification.

Keywords: performance degradation; principal component analysis; continuous hidden Markov model; feature dimensionality reduction; degradation state recognition

---

0 Introduction

The primary process of equipment performance degradation state recognition involves feature extraction from raw data and the selection and establishment of recognition models. During the feature extraction stage, single performance indicators suffer from limited information content, poor anti-interference capability, low fault sensitivity, and information redundancy. Consequently, multiple feature parameters are typically extracted simultaneously for equipment performance degradation assessment. However, when the dimensionality of feature parameters is high, redundant information and noise are inevitably introduced, leading to overfitting during model training. Therefore, feature dimensionality reduction methods must be employed. Dimensionality reduction can be achieved through feature selection or feature extraction. Feature selection simply chooses a subset from the original feature set, whereas feature extraction involves a mapping transformation of the original features. PCA is a commonly used feature extraction algorithm that replaces the original variables with fewer uncorrelated comprehensive variables while minimizing information loss.

The IMS (Intelligent Maintenance Systems) concept was first proposed by Professor Lee from the University of Wisconsin. The evaluation and prediction of equipment performance degradation processes constitute the core technology of

IMS. Correctly identifying the current performance degradation state of equipment is a prerequisite for predictive maintenance. Applying degradation state recognition technology to actual industrial production can significantly reduce equipment maintenance time, prevent catastrophic accidents caused by equipment failures, and is of great importance for reducing maintenance costs and improving production efficiency.

Hidden Markov Model (HMM) is a temporal probability model with extensive applications in speech recognition, natural language processing, and pattern recognition. Given the similarities between equipment fault diagnosis and speech recognition in pattern classification and recognition, HMM can be applied to model equipment performance degradation processes. However, HMM defines observation data as discrete values, requiring vector quantization of continuous feature data before modeling, which inevitably leads to information loss and affects recognition accuracy. CHMM uses a mixture of Gaussian density functions to describe the distribution of continuous observation values, enabling direct training with continuous observations and avoiding information loss from vector quantization.

Related research includes: literature [5] applied PCA and DHMM (Discrete Hidden Markov Model) to engine fault diagnosis; literature [6] introduced a state conditional probability vector to improve HMM for uncertainty assessment of airborne equipment health states; literature [7] proposed a bearing performance degradation assessment method based on wavelet packet transform and HMM; literature [8] extracted wavelet packet entropy from equipment vibration signals as feature vectors and combined them with Gaussian mixture models for bearing performance degradation assessment; literature [9] successfully applied EEMD and SVM to rolling bearing degradation state recognition; literature [10] used membership functions and CHMM to model bearing performance degradation processes with good results. This paper investigates a method combining PCA feature dimensionality reduction and CHMM for equipment performance degradation state recognition and demonstrates its effectiveness through analysis of full life cycle bearing data.

1.1 PCA Introduction

PCA (Principal Component Analysis), proposed by Pearson in 1901, is a commonly used feature dimensionality reduction method. Its fundamental principle transforms the original random vector with correlated components into a new random vector with uncorrelated components through an orthogonal linear transformation. The components of the new random vector are ordered as the first, second, third principal components, etc., based on their variance contribution rates. Generally, selecting principal components whose cumulative contribution rate exceeds 85% can replace the original random variables and achieve data dimensionality reduction. PCA eliminates correlations between feature parameters while preserving the maximum amount of original information. The computational procedure is as follows: (a) Construct a sample matrix X by treating each feature of the original feature set as a column vector, where M is the feature length and N is the number of features; (b) Center the matrix X by subtracting the corresponding mean from each column vector; (c) Calculate the covariance matrix C of the centered matrix; (d) Solve for the eigenvalues and eigenvectors of covariance matrix C; (e) Arrange the eigenvalues obtained in step (d) in descending order to form a column vector, and combine the corresponding eigenvectors as column vectors to form the eigenvector matrix; (f) Multiply matrix X by the eigenvector matrix to obtain the principal components. Calculate the contribution rate of each principal component (contribution rate = individual eigenvalue / sum of eigenvalues) and select a subset of principal components as needed.

1.2 CHMM Definition

HMM (Hidden Markov Model) was initially proposed by Baum et al. as a temporal probability model with strong temporal pattern classification capabilities. HMM is a dual stochastic process: one is the hidden Markov chain state transition process, and the other is the observation process describing the relationship between hidden states and observation sequences. Unlike HMM, CHMM's observation sequences are continuous values, and the observation probability matrix consists of a mixture of Gaussian density functions.

CHMM can be described by four parameters [12]: (a) The number of hidden states N, denoted as S, S, S, ⋯, S, with the state at time t denoted as q, where q $\{S, S, \cdots, S\}$; (b) The initial state distribution probability vector $=$ $(\ , \ , \cdots, \ )$, where $= P(q = S)$ and $1 \quad i \quad N$; (c) The hidden state transition probability matrix $A = \{a\} N\times N$, where $a = P(q = S \mid q = S)$ and $1 \quad i, j \quad N$; (d) The observation probability matrix $B = \{b(O)\} N\times M$, where $b(O) = \Sigma \quad c \quad N(O, \quad, U)$, M represents the number of Gaussian mixture components, c is the weight of the m-th Gaussian mixture component, is the mean vector, and U is the covariance matrix, satisfying $\Sigma \quad c = 1$ and $c \quad 0$. In summary, CHMM can be represented as $= (\ , A, B)$. CHMM includes three fundamental problems: the evaluation problem, the decoding problem, and the learning problem, with corresponding algorithms known as the forward-backward algorithm, Viterbi algorithm, and Baum-Welch algorithm. Detailed derivations of these algorithms can be found in reference [12].

---

2 PCA+CHMM Degradation State Recognition Method

Equipment health status undergoes a series of degradation states from normal operation to failure. Degradation state recognition is essentially a pattern recognition problem, with common algorithms including KNN, Naive Bayes, decision trees, and SVM. If the current operating state of equipment can be correctly identified, appropriate preventive or corrective measures can be taken before failure occurs, thereby avoiding major failures and reducing maintenance costs. The combination of PCA and CHMM can achieve accurate identification of equipment performance states.

Before conducting equipment degradation state recognition, it is necessary to collect equipment operation data. Sensor-acquired raw signals contain large amounts of data and noise, making preprocessing essential. The proposed degradation state recognition method proceeds as follows: (a) Preprocess the raw equipment data. To ensure comprehensive and effective feature extraction, features are extracted from three aspects: time domain, frequency domain, and time-frequency domain. Time-domain features are divided into dimensional and dimensionless types. Dimensional features include mean, RMS, square root amplitude, absolute mean, skewness, kurtosis, variance, maximum, minimum, and peak-to-peak value (10 types). Dimensionless features include waveform index, peak index, impulse index, margin index, kurtosis index, and skewness index (6 types). For frequency-domain features, the raw signal undergoes fast Fourier transform first, then 13 features are constructed using the spectrum and frequency component values, numbered as frequency features 1-13. Time-frequency domain features represent nonlinear characteristics of the raw data. EMD (Empirical Mode Decomposition) can extract weak features from the original signal. The raw signal is decomposed into 6 IMF (Intrinsic Mode Function) components using EMD, and the energy values of each IMF component form 6 time-frequency domain features. The above features total 35 types, forming the feature set. Definitions of each feature parameter can be found in reference [13]. (b) Perform PCA feature dimensionality reduction. From the feature set obtained in the previous step, select features that clearly reflect equipment degradation trends to form a new feature set. Apply PCA dimensionality reduction to this new feature set following the procedure described in Section 1.1, calculate the contribution rate of each principal component, and select principal components whose cumulative contribution rate exceeds a certain threshold to form the final sample data. (c) Determine the number of equipment degradation states. Specifically, train a full-cycle CHMM using all feature sequences obtained in the previous step, with the number of hidden states set to [4, 10]. Then use the Viterbi algorithm for decoding and select the state number that yields small degradation state partition error and conforms to the temporal transition 规律 of equipment degradation states as the final number of degradation states. (d) Train different CHMMs for different degradation states, totaling N models. By calculating the likelihood probability values of the current observation sequence under these N models, the model with the highest likelihood probability value indicates the current degradation state of the equipment.

[Figure 1: see original paper]

3.2 Feature Extraction and PCA Dimensionality Reduction

The experiment utilizes the full life cycle accelerated fatigue vibration data of Bearing 1 from the second group of the Intelligent Maintenance Systems (IMS) at the University of Cincinnati. The bearing model is ZA-2115, with a rotational speed of 2000 min/r, radial load of 26.6 kN, sampling frequency of 20 kHz, sampling once every 10 minutes, with each sampling lasting 1 second. The bearing failed after the 984th sampling, as shown in [Figure 2: see original paper]. The raw data does not clearly reflect the bearing' s performance degradation trend.

Thirty-five features are extracted from the time domain, frequency domain, and time-frequency domain of the raw signal, and features sensitive to degradation state changes are selected to form the feature set. For example, the RMS value in the time domain shows a certain trend over time, while the skewness feature shows almost no change before equipment failure and should obviously be excluded during feature selection.

[Figure 3: see original paper]

Using the same method, features in the frequency domain and time-frequency domain are screened. Finally, 20 features are selected: mean, RMS, square root amplitude, absolute mean, maximum, minimum, peak-to-peak value, waveform index, skewness index, kurtosis index, frequency features 1, 2, 6, 10, 13, and IMF1, IMF3, IMF4, IMF5, IMF6 energy values. At this point, the feature dimensionality remains high. If used directly as sample data, it would be inconvenient due to large data volume, and many features exhibit very similar trends, resulting in information redundancy.

[Figure 4: see original paper]

Applying PCA dimensionality reduction to these 20 features yields a first principal component contribution rate of 99.33%, second principal component of 0.63%, and third principal component of 0.02%. The cumulative contribution rate of the first two principal components reaches 99.96%, so the first and second principal components are selected as the final sample data (feature set).

[Figure 5: see original paper]

3.3 CHMM Modeling and Testing

The full-cycle sample data obtained from PCA dimensionality reduction in the previous section serves as the training sequence. The number of hidden states is set from 4 to 10, and different full-cycle CHMMs are trained using the Baum-Welch algorithm. The Viterbi algorithm is then used to decode the sample sequence, and the number of degradation states is determined by comparing the degradation state partition effects.

[Figure 6: see original paper] [Figure 7: see original paper]

As shown in the figures, when the state number is set to 5, 6, or 7, the last state contains only one data point, which is clearly unrealistic. When set to 8, 9, or 10, the partition results show interleaving phenomena, which also do not conform to equipment performance degradation patterns. Only when the state number is set to 4 does the partition result relatively conform to the temporal variation 规律 of performance degradation. Therefore, the number of equipment degradation states is set to 4, with partition intervals shown in .

The full-cycle sample data is divided into four state intervals. Sample data in each interval is partitioned into training and test sequences at a 7:3 ratio. Four CHMMs corresponding to different degradation states are trained, and equipment degradation state identification is achieved by comparing the likelihood probability values of the current observation sequence under each degradation state model.

As shown in [Figure 8: see original paper]-[11], the test sequences of each state are input into the four models, yielding comparisons of the four likelihood probability outputs.

[Figure 8: see original paper] [Figure 9: see original paper] [Figure 10: see original paper] [Figure 11: see original paper]

Similarly, the full life cycle sample data (feature set) is partitioned into training and test sets at a 7:3 ratio to train KNN, CART, and SVM (multi-class) models for bearing performance degradation state recognition. The recognition accuracy comparison among CHMM, KNN, CART, and SVM is presented in .

In , PCA+CHMM achieves the highest average recognition accuracy among the four methods, with each state' s recognition accuracy exceeding 96%, showing balanced performance. PCA+CART has the lowest average recognition accuracy, with particularly poor performance in recognizing severe degradation states. PCA+SVM and PCA+KNN both achieve average recognition accuracies above 90%, but their recognition accuracies for individual degradation states are not well-balanced. Unlike KNN, SVM, and CART, CHMM can train a separate model for each degradation state and possesses strong temporal pattern recognition capability, which 恰好符合设备退化状态在时间上分布不均衡的情形. The combination of PCA and CHMM achieves high recognition accuracy in equipment performance degradation state identification, and experiments prove this method is feasible and effective.

---

4 Conclusion

This paper proposes a method combining PCA and CHMM for equipment performance degradation state recognition. PCA removes information redundancy and reduces data dimensionality, while CHMM not only possesses strong temporal pattern recognition capability but also avoids information loss from vector quantization. Using bearing data provided by the University of Cincinnati, experimental comparisons demonstrate that this method is suitable for equipment degradation performance state identification with high recognition accuracy. Since this method can only identify the current degradation state of equipment, future work may focus on combining regression algorithms with CHMM to achieve predictive capabilities for equipment performance degradation states.

References

[1] Lee J, Kramer B M. Analysis of machine degradation using a neural network based pattern discrimination model [J]. Journal of Manufacturing Systems, 1993, 12 (5): 379–387.

[2] Wang Jianli. Research on performance degradation assessment and trend prediction of rolling bearings [D]. Dalian: Dalian University of Technology, 2013.

[3] Wang Wanzi. Research on interactive features and adaptive clustering algorithms [D]. Xi' an: Shaanxi Normal University, 2011.

[4] Xia Lisha, Fang Huajing, Luo Zhen. A survey on fault diagnosis and prognosis based on hidden Markov models [C]// Proceedings of the Chinese Control and Decision Conference. 2013: 4881-4884.

[5] Huang Jiashan, Zhang Pingjun. Research on engine fault diagnosis based on PCA and DHMM [J]. Journal of Xiamen University: Natural Science, 2010, 49 (5): 617-621.

[6] Zhang Jinchun, Zhang Jijun, Cao Biao. Research on health assessment method for airborne equipment based on HMM [J]. Computer Measurement & Control, 2015, 23 (2): 491-493.

[7] Xiao Wenbin, Chen Jin, Zhou Yu, et al. Application of wavelet packet transform and hidden Markov model in bearing performance degradation assessment [J]. Journal of Vibration and Shock, 2011, 30 (8): 32-35.

[8] Li Weihua, Dai Bingxiong, Zhang Shaohui. Bearing performance degradation assessment based on wavelet packet entropy and Gaussian mixture model [J]. Journal of Vibration and Shock, 2013, 32 (21): 35-40.

[9] Wei Yonghe, Wang Minghua. Rolling bearing degradation state identification based on EEMD and SVM [J]. Computer Integrated Manufacturing Systems, 2015, 21 (9): 2475-2483.

[10] Jiang Wanlu, Yang Kai, Dong Keyan, et al. Research on comprehensive assessment method for bearing performance degradation degree based on CHMM [J]. Chinese Journal of Scientific Instrument, 2016, 37 (9): 2014-2021.

[11] Karl P LIII. On lines and planes of closest fit to systems of points in space [J]. Philosophical Magazine Series 6, 1901, 2 (11): 559-572.

[12] Rabiner L R. A tutorial on Hidden Markov Models and Selected Applications in Speech Recognition [J]. Readings in Speech Recognition, 1990, 77 (2): 267-296.

[13] Dong Shaojiang. Research on life prediction method for space rolling bearings based on optimized support vector machine [D]. Chongqing: Chongqing University, 2012.

Note: Figure translations are in progress. See original paper for figures.