Study on fault feature extraction of ECS turbine bearing by combination of EEMD and HMM

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Abstract. According to nonstationary characteristics of aircraft environment control system turbine bearings, the objective in the paper is to present EEMD and HMM method to extract characteristic quantities. Firstly, vibration signals under different operating conditions, such as normal bearing and cage fracture under partial load condition, are decomposed by EEMD to filter noise signal and advance signal-to-noise. Then HMM of those signals is calculated, contrasted and analyzed after space reconstruction. The experimental result show that the HMM can be used as the characteristic quantity of ECS turbine bearing on running state. Moreover, this method can accurately and effectively identify the running state of the bearing.

1. Introduction

The environmental control system (ECS) of an aircraft can guarantee comfort in the engine compartment and safety of the whole flight process [1]. The ECS turbine is the power source that drives the air flow in the whole system, and its working state will directly affect the normal operation of the ECS of the aircraft, thus affecting the flight safety of the aircraft. Bearing, as a key component of ECS turbine, plays a vital role in the normal operation of the whole system. Therefore, accurate and timely fault diagnosis of ECS turbine bearing is of great significance.

The vibration signal generated during the operation of ECS turbine bearing contains a lot of information. Its operation state can be known through the extraction and analysis of the eigenvalue of the vibration signal, so as to further predict the state change trend and find and eliminate faults in time [2]. The traditional fault diagnosis method is to extract the eigenvalue and identify the fault of the bearing in time and frequency domain. The vibration signal of rolling bearing under different fault conditions has the characteristics of time-varying and periodic pulse [3]. High frequency resonance analysis, i.e. envelope analysis, two factor analysis and other frequency domain analysis methods, can identify these features. Some time-frequency analysis methods such as wavelet transform, neural network, Hidden Markov Model (HMM) and Kalman filtering can be used to analyze the state of rolling bearing vibration signal [4,5]. For some typical fault modes of bearing, such as spalling fault, it is necessary to model the historical data and current data in real time, and predict the fault on the basis of time series model or other types of control model or intelligent model. HMM is an intelligent state identification and prediction model with strong state description and prediction ability, which can be used to establish typical fault prediction algorithm of rolling bearing [6,7].

Because the vibration signal contains a large amount of background noise, noise reduction processing needs to be carried out before HMM prediction. Overall empirical mode decomposition
(EEMD) is an improved method based on Empirical Mode Decomposition (EMD). It not only does not need to consider the pre selection of basis function, but also can adaptively decompose the nonlinear and non-stationary signals, but also can effectively solve the problem of mode aliasing in EMD [8]. Based on this, firstly, EEMD is used to decompose the bearing vibration signal into basic mode component (IMF) containing fault characteristic information to remove noise interference, and then HMM prediction is carried out according to the denoised signal to make up for the shortcomings of traditional analysis methods. This method is used to verify the fracture failure of cage under eccentric load.

2. EEMD principle

In 1998, Huang[9] proposed a completely data-driven adaptive decomposition Empirical Mode Decomposition (EMD) method, which greatly improved the analysis effect of nonlinear and non-stationary signals. However, in practical application, this method generally has the problem of mode aliasing, that is, a single IMF contains characteristic signals with greatly different frequencies, or signals with similar frequencies are decomposed into different IMF. The main reason for mode aliasing is that abnormal events in the signal have an adverse impact on the selection of extreme points, resulting in uneven distribution of extreme points, resulting in "overshoot" and "undershoot" in the EMD process[10,11]. In order to solve this problem, Wu [8] proposed the overall empirical mode decomposition (EEMD) method. This method adds the Gaussian white noise with limited amplitude to the signal to be decomposed, and uses the characteristics of uniform distribution of Gaussian white noise in time and frequency domain to smooth abnormal events, so as to reduce the adverse impact of abnormal events on the selection of extreme points in the process of EMD. To achieve the purpose of uniform signal extreme point distribution. Finally, using the zero mean characteristic of white noise, the noise is offset by multiple averaging.

The decomposition steps of EEMD are summarized as follows:

1. In the original signal \( x(t) \), Gaussian white noise with the mean value of 0 and constant amplitude standard deviation are added respectively.

\[
x_i(t) = x(t) + n_i(t)
\]

among it, \( i = 1\sim N \)

2. EMD decomposition is carried out respectively in \( x_i(t) \), and K of IMF components and a remainder \( r_i(t) \) are obtained each time.

\[
x_i(t) = \sum_{j=1}^{K} c_{ij}(t) + r_i(t)
\]

among it, \( c_{ij}(t) \) is the j-th IMF obtained by decomposition after adding Gaussian white noise for the i-th time. \( j = 1\sim k \)

3. Based on the principle that the statistical mean value of uncorrelated random sequence is 0, the IMF corresponding to the above steps is overall averaged to eliminate the impact of multiple Gaussian white noise on the real IMF, and the IMF and remainder \( r(t) \) after EEMD decomposition are

\[
c_j(t) = \frac{1}{N} \sum_{i=1}^{N} c_{ij}(t)
\]

\[
r(t) = \frac{1}{N} \sum_{i=1}^{N} r_i(t)
\]

among it, \( c_j(t) \) is the j-th IMF obtained after EEMD decomposition of the original signal. Finally, K IMF components and a remainder \( r(t) \) are

\[
x(t) = \sum_{j=1}^{K} c_j(t) + r(t)
\]
3. Fault prediction principle of ECS turbine bearing based on HMM

Hidden Markov model (HMM) is a probabilistic model expressed by parameters and used to describe the statistical characteristics of stochastic processes. Hidden Markov process is a double stochastic process: one potential process is called "state" process, and the other observable process is called "observation sequence". The observation sequence is determined by the implicit state process. The HMM model is used to establish the prediction algorithm of typical bearing faults, which can be divided into the following steps:

Firstly, the HMM model is trained using historical data. According to different bearing States, the historical data of vibration signals are extracted respectively, and several training sequences are cut out; Vector quantize the training sequence according to K-means algorithm, train the HMM model corresponding to each bearing state according to F-B algorithm, and obtain the HMM model parameters that can accurately reflect each bearing state; Then, the ARMA model about likelihood probability is established. The current measured vibration signal is introduced into the established HMM model to identify the current bearing state and calculate the maximum likelihood probability of the bearing in a certain state; Taking the likelihood probability as the characteristic parameter, the characteristic parameter time series with time interval is established; Carry out model identification and parameter calibration, calculate the order and parameters of ARMA model, and establish ARMA model considering white noise. Finally, based on the established HMM model, the subsequent characteristic parameters at each time are predicted, and the values of the characteristic parameters at each time are predicted and compared with the given decision thresholds A1 and A2; The judgment conditions of bearing failure and failure are respectively, so as to obtain the time T1 and T2 when the bearing reaches the failure and failure state, and the corresponding time T1 and T2 when the bearing fails and fails.

4. Fracture experiment of rolling bearing cage under eccentric load

The experimental platform of this experiment (as shown in Figure 1) consists of rotor system and data acquisition system. The rotor system is mainly composed of drive system module, spindle system module, tooling, test piece module and lubrication system module, which can simulate the mechanism characteristics of the actual environmental control system. The drive system module is composed of asynchronous motor with rated speed of 2800r / min and rated power of 750W. The spindle system is connected with the motor and the tested piece module. In the experiment, the rolling bearings under different working conditions are placed in the test piece module, and the vibration signals are measured by the acceleration sensor.

![Figure 1. rotor system of experimental platform.](image)

In this experiment, the normal state of the bearing and the common working conditions of cage fracture are selected. The cage fracture is shown in Figure 2. Set the rotating speed of the motor as
2400r/min (working frequency as 40Hz) and the sampling frequency of the data acquisition system as 4000Hz. Collect 8 groups of data for different working conditions, and the sampling time of each group is 1s. Firstly, taking the first group of data as an example, the time domain diagram and corresponding spectrum diagram of the collected vibration signal are shown in Figure 3, and they are preliminarily compared and analyzed. The fracture fault test of rolling bearing cage under eccentric load is carried out, and the test data are used to test the prediction effect of fault prediction algorithm on cage fracture fault. The vibration signal of rolling bearing with broken cage under eccentric load is shown in Figure 3.

![Figure 2. Fracture diagram of cage.](image1)

![Figure 3. Vibration signal of rolling bearing.](image2)

As can be seen from Figure 3, a large number of vibration signals are generated during bearing operation, and these signals can be accurately collected by the acceleration sensor. It can be seen from the time domain diagram that under normal working conditions, the change of vibration signal is relatively stable and the amplitude is very small; Under the condition of eccentric load, when the cage breaks, the vibration amplitude increases obviously, and the impact amplitude shows obvious
periodicity, and the complexity of the signal increases. It can be seen from the spectrum diagram that under normal working conditions, except for individual frequency peaks, the change is very stable on the whole; When the cage is cut open, the frequency peak is concentrated in the low-frequency part, and the overall frequency fluctuation is more obvious than that under normal working conditions. From the above characteristics, we can preliminarily judge the working state of the bearing, but there are some limitations to diagnose more accurately.

In order to further distinguish the different working conditions of the bearing, the method mentioned above is used for processing and calculation. Firstly, in order to eliminate the influence of environmental noise on the internal essential characteristics of the signal, EEMD decomposition is carried out for all 8 groups of vibration signals under 2 different working conditions. Taking the signals in the first group under normal state as an example and the signals in the cage fracture fault state as an example, the decomposition results are shown in Figure 4.

![EEMD decomposition](image)

**Figure 4.** EEMD decomposition of rolling bearing vibration signal

### 5. HMM model training of bearing vibration signal after denoising

Since EEMD decomposition is essentially a principal component separation method, that is, the most important information contained in the original signal is extracted first, it can be seen from Figure 5 that the main components of the bearing vibration signal are concentrated in the first four IMF, and the environmental noise is separated to the low-frequency part. The vibration signal after denoising can be obtained by recombining the first four IMF. Similarly, for other data, the IMF containing the main information of the original signal is selected for combination, and then the denoised signal is predicted by HMM.

#### 5.1. Characteristic parameter threshold of bearing fault

The noise reduced data of the bearing are introduced into the two HMM models after training for state identification, and the maximum likelihood probability of each sequence belonging to two types of bearing States is calculated. The results are shown in Fig. 5. In order to more clearly reflect the change of state in the fracture process of rolling bearing cage under eccentric load, the average value series is processed. Sum every 2S (i.e. 8 probability values) and take the average value, and take the calculation result as the characteristic parameter; Then, push back one average value, recalculate and save, and the results are shown in Figure 6. As shown in Figure 6, the maximum likelihood probability after sorting
is 197.4s, and the maximum value is equal to 32.61. The experimental data signal shows that the bearing vibration is very intense at this time, and the fault characteristics are very obvious. Therefore, the determination threshold A2 of the bearing fault state is set to 32.

Figure 5. calculation results of likelihood probability of cage fracture bearing vibration signal under eccentric load.

Figure 6. likelihood probability value of bearing vibration signal after average cage fracture under eccentric load.
5.2. Fault state identification of bearing based on HMM

Analyze the measured vibration data of the environmental control turbine bearing after noise reduction, and iteratively calculate the characteristic parameters. If the characteristic parameters are greater than the judgment threshold $A_2$ of the fault state, the time $T_2$ when the bearing reaches the fault state can be predicted. The calculated results of the predicted values of the characteristic parameters are compared with the actual values, as shown in Figure 7. It can be found that the predicted value of characteristic parameters fits well with the actual value, which shows that the HMM model can accurately reflect the actual change law of characteristic parameters. The prediction results are shown in Fig. 7. The actual value of $T_2$ at the time of bearing failure is 196s and the predicted value is 190.4s; The actual value of time $T_2$ from bearing failure is 157.2003s, the predicted value is 151.6102s, the prediction error is 5.5901s, and the confidence is 96.44%.

6. Conclusion

Combined with EEMD denoising technology and HMM model method, this paper realizes the detection method of monitoring the fault vibration signal of rolling bearing. The calculated results of the predicted values of characteristic parameters are compared with the actual values. Compared with the traditional time-domain and frequency-domain analysis methods, fractal theory, as a nonlinear dynamic analysis method, has the advantages of high precision and high reliability, and can clearly distinguish the fault states with similar characteristics in time-frequency domain. Aiming at the non-stationary characteristics of rolling bearing fault signal, a bearing fault diagnosis method based on HMM model is proposed. In this method, HMM model is used to establish an accurate model for the decomposed dynamic data, and the fracture fault of rolling bearing cage under eccentric load is identified.

![Figure 7. test of HMM prediction effect of cage fracture bearing vibration signal under eccentric load.](image)

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