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Research on Early Fault Self-Recovery Monitoring of Aero-Engine Rotor System

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Abstract

In order to increase robustness of the AERS (Aero-engine Rotor System) and to solve the problem of lacking fault samples in fault diagnosis and the difficulty in identifying early weak fault, we proposed a new method that it not only can identify the early fault of AERS but also it can do self-recovery monitoring of fault. Our method is based on the analysis of the early fault features on AERS, and it combined the SVM (Support Vector Machine) with the stochastic resonance theory and the wavelet packet decomposition and fault self-recovery. First, we zoom the early fault feature signals by using the stochastic resonance theory. Second, we extract the feature vectors of early fault using the multi-resolution analysis of the wavelet packet. Third, we input the feature vectors to a fault classifier, which can be used to identify the early fault of AERS and carry out self-recovery monitoring of fault. In this paper, features of early fault on AERS, the zoom of early fault characteristics, the extraction method of early fault characteristics, the construction of multi-fault classifier and way of fault self-recovery monitoring are studied. Results show that our method can effectively identify the early fault of AERS, especially for identifying of fault with small samples, and it can carry on self-recovery monitoring of fault.

Keywords: AERS, Early Fault, Support Vector Machine, Classification Identification of Fault, Self-Recovery Monitoring of Fault

1. Introduction

With the development of the modern aviation industry, the safety of aircraft and reliability are more and more attracted. The engine is heart of aircraft and AERS is central part of engine. If AERS has fault in flight, the aircraft would be severely threatened in safety. Because the structure of AERS is complex, load is bigger and the change of operation conditions is frequency, it will be the more difficult in the fault identification. Especially in the early failures occurred, if we can catch timely the fault information, and can effectively identify it and carry on self-recovery monitoring of fault, it will have important significance to eradicate or eliminate the potential fault caused of an accident. Fault identification on AERS is widely studied and many results are obtained [1−3]. At present now, effective identification of early fault has more difficulty. In particular, obtaining of the early fault information is more difficulty, and effectiveness of fault

identification is not satisfactory. Because operation of AERS is in strong noise density, the early fault information is very weak and signals are easily flooded in noises, satisfactory results are very difficult by general methods. Our method can not only fast identify the early fault of the AERS but also carry on self-recovery monitory of fault.

2. Features of Early Fault on AERS

In the flight, the wear, deformation, corrosion and fracture of structure components and effects of work stress, external environment and human factors will lead to faults of AERS. The early fault of AERS often shows a form in micro-cracks, micro-creeping, micro-corrosion and micro-wear. These faults, with the exception of little sudden faults, the majority have a development process from nothing to fault, minor to general, evolution to fast. In this process, the structure of system, properties and internal energy will change. We can monitor the early faults through catching these fault information in time,

and it can be identified and be self-recovery. These early faults of AERS have the following features:

1) Fault signal is very weak. When fault is at early stage or just sprouted, the changes of the fault signal is very weak in amplitude, phase and time-frequency characteristics, and the little fault characterization is often difficult to detect.

2) Fault signal will be drowned by noise signal. During the flight, the noise signal is usually among the fault signal. When the fault signal is very weak and the noise signal is very strong, the early fault signal will be drowned by noise signal. In order to detect the early fault, we must reduce noise or extracted early fault information from the noise signal.

3) Fault signal is often a transient one. The damage structure components of aircraft is generated by impact loading, and this fault is manifested by transient signal, such as expansion of early cracks, is a process from gradual to mutation.

4) Fault occurred in the area of stress concentration. When area of stress concentration is acted by strong regional load, the fault of structural part is easy occurrence in the creeping. For the ferromagnetic metal part, the magnetic memory method can be used for the early fault detection and localization [4].

5) Fault has volatile. That means sometimes we can not find the fault trace in fault condition. But with the change of action or time, the system can recover automatically. Volatile fault can be shown by eventuality fault, transient fault and interruption fault.

3. Extraction of Early Fault Characreristic

Because the vibration of engine is larger in operation, fault characteristics of the AERS will be submerged in the strong background noise in the early. In order to extract characteristics of early fault from being submerged signals by noise, we use the stochastic resonance theory to zoom characteristic signals of early fault [5].

In the failure, the energy of AERS will change in all frequency bands and different faults have different effects to the signal energy in each frequency band. So, we can use wavelet packet to decompose the output signal in stochastic resonance and select signal energy in the characteristics frequency band as a feature vector.

If the data length of original signal $x(t)$ is N, the data length of discrete signals $x^{k,m}(i)$ is reduced to $2^{-k}N$ by decomposition of wavelet packet and its energy can be expressed as:

$$E_n\left(x^{k,m}\right) = \frac{1}{2^{-k}N-1} \sum_{i=1}^{2^{-k}N} \left(x^{k,m}(i)\right)^2 \qquad (1)$$

where, N = the length of original data, k = layer number by wavelet packet decomposition, m = the serial number of decomposition frequency band location = 0, 1, 2, ... $2^k - 1$.

The energy within the each frequency band can be calculated by Equation (1) and the feature vector can be constructed by the energy.

4. Classification Identification of Fault

The SVM can do the classification very well in the few numbers of fault samples and it can solve the identification problems on nonlinear and high-dimensional pattern.

The fault identification of the AERS belongs to problem of multi-classification and it needs to construct multi-fault classifier. In this paper, we adopt improved classification algorithm of the "one-to-many".

To the classification of K type, way of "one-to-many" is need to construct K two classifiers. In this way constructing every two classifiers, all n training samples of K type should be operated. In the testing and classification, the scale of classifiers is larger and speed is slower.

An improved the "one-to-many" classification algorithm is to construct two classifiers of K, and the training sample of m type in the K classifiers is $y_i^m = 1$ and other types marking is $y_i^m = -1$. Established output function in M classifiers can be expressed as:

$$f^m(x) = \text{sgn}\left\{ \sum_{SVM} \alpha_i^m y_i^m K(x_i \cdot x) + b^m \right\} \qquad (2)$$

The algorithm overcomes defects that "one-on-one" approach needs to establish many number classifiers and it can control the training samples number in traditional "one-to-many". Its operate speed is fast and effect of fault classification is well.

5. Self-Recovery Monitoring of Fault

Fault monitor process of AERS is shown in Figure 1.

Fault self-recovery database consist of many intelligent models. It can carry on self-recovery monitoring based on different fault sources and fault characteristics.

Self-recovery monitoring of fault can be realized by smart structure [6], affixing magnetic field [7], regenerating materials [8], etc.

When AERS has fault, the system can not work normally. Self-recovery model based on the fault compensation can restore original function of system by means of the fault self-recovery compensator. If system equations under normal condition are

$$\dot{x}(t) = Ax(t) + Bu(t) \qquad (3)$$

$$y(t) = Cx(t) \qquad (4)$$
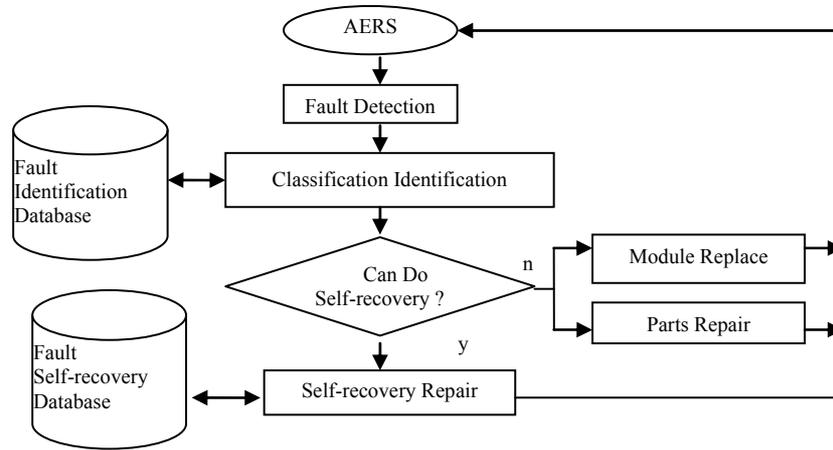
Compensator equations are

Figure 1. Fault self-recovery monitor process of AERS.

$$\dot{z}(t) = Dz(t) + Ey(t) \qquad (5)$$

$$u(t) = Fz(t) + Hy(t) \qquad (6)$$

The system loop equations depicted in (3) and (4) are

$$\dot{x}(t) = (A + BHC)x(t) + BFz(t) \qquad (7)$$

$$\dot{z}(t) = ECx(t) + Dz(t) \qquad (8)$$

When fault of component or sub-system occurred during the flight, the loop feedback equations are

$$\dot{x}(t) = (A_f + B_f \overline{H} C_f)x(t) + B_f \overline{F} z(t) \qquad (9)$$

$$\dot{z}(t) = \overline{E} C_f x(t) + \overline{D} z(t) \qquad (10)$$

To make the performance of fault system as close as possible to the performance of the original system, we can design the appropriate self-recovery compensator $\{\overline{D},$ $\overline{E}, \overline{F}, \overline{H}\}$ to achieve the fault self-recovery compensation. During flight, when the aircraft cockpit, wings and other important components have severe vibration or chatter, distributed piezoelectric driver compensator can weaken or offset the impact of vibration by vibration control and active vibration absorber.

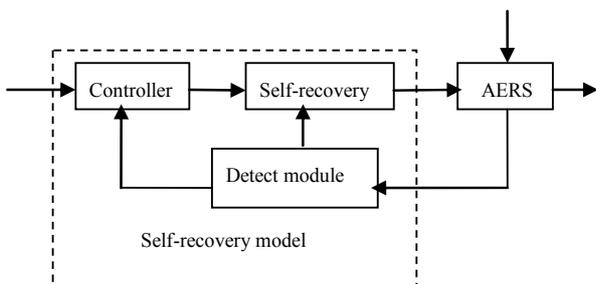Self-recovery monitoring based on intelligent structure is shown in Figure 2.

Figure 2. Self-recovery monitoring based on smart structure.

When the sensor module detects the fault information, the signals will transmit to self-recovery module and act to the controller. Fault of AERS will be restored by smart structure. It is based on different fault sources and fault feature, and the fault self-recovery tactics is adopted.

6. Experimental Results and Its Analysis

In order to verify the usefulness of the method, we choose the four conditions of the AERS. They are normal condition, early rotor misalignment, early rotor unbalance and early rotor crack. These signals are preprocessed and the fault features are extracted. Fault is identified by the multi-fault classifiers and fault is monitored by self-recovery module.

In the experiment, according to the character of AERS, we collected 10 group data by the acceleration sensor. They respectively correspond to the over four conditions in the 1800 rpm. The sampling frequency is 256 Hz and the rotation frequency is 30 Hz. The characteristic frequency of fault and its concomitant frequency are shown in Table 1.

Figure 3 shows the output waveform of the stochastic resonance system and its spectrum. The frequency component in 30 Hz is obvious in Figure 2. Because the fundamental frequency is 30 Hz, the rotor misalignment fault is often accompanied by $1x\omega$ (30 Hz), $2 x\omega$ (60 Hz) and $3x\omega$ (90 Hz).

Table 1. $2x\omega$ (60Hz) crossed concomitant frequency and unbalance.

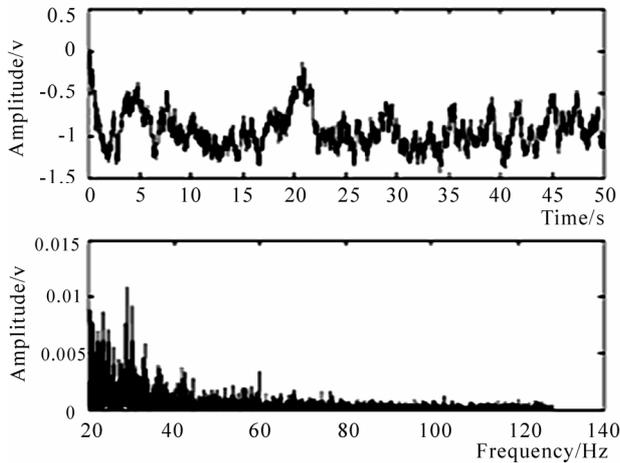| Type	Misalignment	Unbalance	Crack
Characteristic frequency	$1x\omega$ (30Hz), $2 x\omega$ (60Hz)	$1x\omega$ (30Hz)	$2x\omega$ (60Hz)
Concomitant frequency	$3 x\omega$ (90Hz)		$4x\omega$ (120Hz)

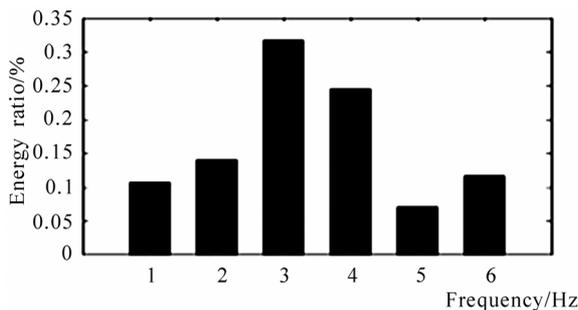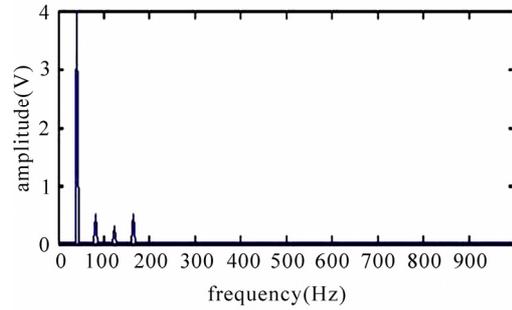**Figure 3. The output waveform of stochastic resonance system and its spectrum.**
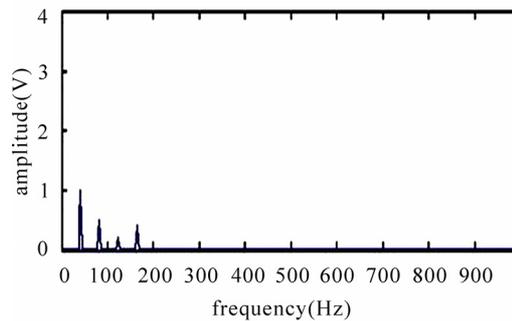

Figure 4. Energy distribution of rotor misalignment.

(a) Waveform before monitoring

(b) Waveform after monitoring

Figure 5. Frequency domain waveform of rotor misalignment.

Table 2. Test results of stochastic resonance system.

Fault type	Misjudgment samples	Diagnosis samples	Diagnosis rate
Misalignment	1	40	97.5 %
Unbalance	0	40	100 %
Crack	2	40	95 %

The energy feature extraction is done by the wavelet packet analysis. It is based on the signal waveform of stochastic resonance system. Seven-layer wavelet packet is resolved in the db3 wavelet and we obtained 64 frequency bands. In order to reduce the amount of computation, we divide the frequency bands as 6 segments: 0 ~ 0.4X, 0.4 ~ 0.8X, 0.8 ~ 1.2 X, 1.8 ~ 2.2X, 2.8 ~ 3.2X and greater than 3.6X. Thus 64 frequency bands will be composed of the 6 groups: 1 ~ 4 bands, 5 ~ 8 bands, 9 ~ 11 bands, 12 ~ 15 bands, 16 ~ 30 bands and 55 ~ 64 bands. Energy value of each group is added together and they are processed on the normalization. The energy distribution of rotor misalignment fault will be acquired. It is shown in Figure 4.

Repeated the above process, the energy distribution of each condition can be obtained and it is taken as training samples of SVM.

According to the training samples obtained from four conditions, we take 40 groups energy distributions from each condition as training samples and input to the improved fault classifier of "one-to-many". We choose Gaussian RBF kernel function as a classification function and make the parameters $\sigma = 0.01$, punishment factor C = 100. The classification results are shown in Table 2.

We can see that classification results by the stochastic resonance system are significantly high than classification result by direct wavelet packet feature extraction. The classification time of the each testing samples is smaller (in 0.05s, 1.8 GHZ computers). Its accuracy is higher and speed is quick in early fault identification.

In order to monitor misalignment, we adopt a principle of the electromagnetic effect [9]. The number of misalignment is detected by four acceleration sensors, and four electromagnetic sets are controlled by the output signal of four sensor. When misalignment occurred, the misalignment force F by rotor produced can be adjusted by alignment force F' of electromagnet produced. The alignment force F' is equal to the misalignment force F in number and they are contrary in direction. Figure 5 shows the result of self-recovery monitoring on rotor misalignment.

We can find out that vibration of rotor is obviously reduced in Figure 5(a) and Figure 5(b). Because of the misalignment fault of rotor is counteracted by the electromagnet force, the rotor misalignment is inhibited and the normal operation condition is restored well.

7. Conclusions

1) Our method can effectively extract the early fault feature of the AERS by combination the stochastic resonance with the wavelet packet resolving. Energy eigenvectors of constructed by this methods can accurately reflect the condition changes of AERS.

2) Multi-fault classifier based on the SVM has characteristics that its algorithm is simpler, the classification effect is well and identification efficiency is higher. It particularly suits to the classification identification of small sample and self-recovery monitoring of early fault on AERS.

3) The fault diagnosis is aimed at finding failure in time and to ensure safe operation of plant. The method of fault self-recovery monitoring provides an effective way.

8. References

[1]   D. Simon, "A comparison of filtering approaches for aircraft engine health estimation," Aerospace Science and Technology, Vol. 12, No. 4, pp. 276–284, 2008.

[2]   S. Borguet and O. Léonard, "Coupling principal component analysis and Kalman filtering algorithms for on-line aircraft engine diagnostics," Control Engineering Practice, Vol. 17, No. 4, pp. 494–502, 2009.

[3]   T. Ramesh Babu and A. S. Sekhar, "Detection of two cracks in a rotor-bearing system using amplitude deviation curve," Journal of Sound and Vibration, Vol. 314, No. 3–5, pp. 457–464, 2008.

[4]   A. Dubov and S. Kolokoinikov, "Review of welding problems and allied processes and their solution using the metal magnetic memory effect," Welding in the World, Vol. 49, No .9, pp. 306–313, 2005.

[5]   K. Tanaka and M. Kawakatsu, "Stochastic resonance in auditory steady-state responses in a magnetoencephalogram," Clinical Neurophysiology, Vol. 119, No. 9, pp. 2104–2110, 2008.

[6]   S. Hurlebaus and L. Gaul, "Smart structure dynamics," Mechanical Systems and Signal Processing, Vol. 20, No. 2, pp. 255–281, 2006.

[7]   A. Ignatios and B. Alexey, "Anomaly induced effects in a magnetic field," Nuclear Physics B, Vol. 793, No. 1–2, pp. 246–259, 2008.

[8]   Mueller and S. N. Sokolova, "Characteristics of lightweight aggregate from primary and recycled raw materials," Construction and Building Materials, Vol. 22, No. 4, pp. 703–712, 2008.

[9]   Y. Asher, P. Yosef, and L. Yuri, "Spectral and variational principles of electromagnetic field excitation in wave guides," Physics Letters A, Vol. 344, No. 1, pp. 18–28, 2005.