Acoustic Diagnosis Method for Engine Failure

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Abstract. The engine is an important equipment in modern society, and its failure diagnosis method has always been valued and continuously developed. As a non-contact method, the failure acoustic diagnosis method has advantages that are unmatched by other methods. This thesis introduces the current development of acoustic diagnosis technology for engine failure, and introduces the commonly used methods: wavelet analysis, empirical mode decomposition and acoustic imaging, and summarizes the development trend of future engine failure acoustic diagnosis technology.

1. Engine failure acoustic diagnosis
The sound signal is generated during the working process of the engine. As the operating state changes (failure occurs), it will be mutated and distorted. It contains information on the vibration and deformation of the engine and is an important signal for analyzing the operating state.

The collection of sound signals is not limited by the working environment of the engine and the installation location, and sound signal contains various state information. Acoustic diagnostics typically collect sound signal from a microphone or microphone array, and compare them to background noise, and then use sophisticated algorithms and database screening to diagnose the engine to detect suspected failure.

2. Research on Failure Diagnosis Based on Sound Signal
The time domain waveform of the engine sound signal without any treatment is confusing, and the periodic characteristics of the signal are obvious, but it cannot be directly used for failure diagnosis analysis. In recent years, the commonly used methods for failure diagnosis of sound signals include wavelet analysis, empirical mode decomposition and acoustic imaging.

2.1. Wavelet analysis
Wavelet analysis is a typical time-frequency analysis which is suitable for the uncharacteristic signal and time-frequency localization analysis. It inherits and develops the idea of short-time Fourier transform localization, and overcomes the disadvantage that the window size does not change with frequency. S. Mallat introduced the idea of multi-scale analysis in the field of computer vision into wavelet analysis and proposed the concept of wavelet multi-resolution analysis. Multi-resolution analysis (MRA) is a theory based on the concept of function space. In the time domain, the scale changes from large to small, the corresponding frequency domain scale changing from small to large. Large-scale information, that is, signal contour information, can be obtained by a low-pass filter; small-scale information, that is, noise and mutation information, can be obtained by a high-pass filter. The wavelet decomposition tree for multiresolution analysis is shown in Figure 1.
Wavelet multi-resolution analysis is mature in the field of failure diagnosis and is widely used. Such as Wang Xiaolong et al.[1] applied it to the processing of rolling bearing failure acoustic signals; Pan Zhengrong et al.[2] improve the signal-to-noise ratio of acoustic signals through multi-scale decomposition; Zeng Rong et al.[3] used wavelet to extract sound feature parameters and construct BP neural network for pattern recognition; Li Zengfang et al.[4] performed wavelet analysis on the sound intensity signal to obtain the band energy characteristics; Pagi V B et al.[5] diagnosed multiple failure categories using the acoustic signal energy distribution of motorcycles as the feature object; Sun Kuanlei et al.[6] used the wavelet analysis single subband reconstruction algorithm to extract the signal characteristic frequency to process the acoustic signal.

Wavelet multi-resolution analysis can well represent a large class of signals with low frequency information as the main component, but it can not well decompose and represents signals that contain a lot of detail (small edges or textures) [7]. In order to overcome this shortcoming, wavelet packet analysis is proposed. It performs finer decomposition on the high-frequency part of the signal that is not subdivided by wavelet multi-resolution analysis, thereby improving the frequency resolution of the high-frequency part. Moreover, it introduces the concept of optimal basis selection that is, after the frequency band is divided into multiple levels, self-adaptively selecting the corresponding frequency band according to the characteristics of the analyzed signal to match it and the signal spectrum, thereby further improving the time-frequency resolution. Therefore, wavelet packet analysis has a wide range of applications. In recent years, many scholars have applied it to failure diagnosis. For example, Lan Huili et al.[8] used the wavelet packet sensitive band energy as the recognition feature, and performed fuzzy clustering on the recognition feature to realize the correct recognition of the failure; Fu Jinsong[9] constructed the energy feature vector of the sound signal using wavelet packet, and developed non-stationary sound signal analysis software; Mo Huifang et al.[10] used the relative wavelet energy spectrum as a feature to classify failure; Li Chunlei et al.[11] combined wavelet packet analysis technology, BP neural network pattern recognition technology and traditional failure acoustic diagnosis technology for failure detection.

Summarizing the existing failure acoustic diagnosis method of wavelet multi-resolution analysis and wavelet packet analysis, the mainstream has the following five steps [12-17]:

1) Wavelet multiresolution analysis or wavelet packet analysis is performed on the sound signal;
2) The energy of each band signal is calculated;
3) Constructing an energy feature vector composed of relative energy of each frequency band, and normalizing the feature vector;
4) Taking the characteristic band energy as the characteristic parameter of the sound signal, according to the variation law of the energy of each frequency band after processing, the sensitive sub-band energy which can reflect the essential characteristics of the sound signal is extracted as the characteristic parameter for identifying the failure;
5) The fuzzy c-means clustering algorithm, energy tolerance, expert system, BP neural network and other methods are used to identify the characteristic band energy and complete failure diagnosis.

2.2. Empirical mode decomposition
Empirical mode decomposition (EMD) is a new self-adaptive signal time-frequency processing method that Norden E. Huang and others creatively proposed in 1998 at NASA. The Hilbert-Huang Transform (HHT) is formed by performing a Hilbert transform on the EMD-processed signal. EMD performs signal decomposition based on the time scale characteristics of the data itself, without any pre-set basis function. Because of this feature, EMD can theoretically be applied to the decomposition of any type of signal. Therefore, it has a obvious advantage in dealing with non-stationary and nonlinear data, and has a high signal-to-noise ratio.

EMD is defined by an algorithmic process and is not defined by a defined theoretical formula. The purpose is to decompose the signal into a set of well-performing intrinsic mode functions (IMF), and the decomposed IMF components contain local characteristic signals of different time scales of the original signal.

Summarizing the existing failure acoustic diagnosis method of EMD, the mainstream has the following steps:
1) Empirical mode decomposition is performed to obtain IMF to make the non-stationary data tranquilization
2) Hilbert transform is performed on each IMF to get the Hilbert spectrum, obtaining the frequency with physical meaning to achieve the identification of failure.

EMD is very common in the field of failure diagnosis. For example, Ma Chao et al.[18] used the kurtosis and energy of the EEMD signal as the evaluation index to extract the IMF signal containing the failure information, and narrow-band filtered the decomposition signal to realize the failure type identification through the Hilbert envelope spectrum; Tang Fuqiang [19] proposed a failure diagnosis method that first performs EMD and then uses Laplace wavelet correlation filtering analysis; Li Hui et al. [20] decomposed the time series signal and extracted the IMF component representing the bearing failure for envelope spectrum analysis to obtain the characteristics of the failure signal; Zhang Zhanyi et al.[21] used the EMD to decompose the light vibration test signal, and finded the rubbing component after comparing the boundary spectrum of the IMF component with the bearing acceleration signal and the rotor radial displacement signal.

2.3. Acoustic imaging
Acoustic imaging is based on the microphone array measurement technology. By measuring the phase difference of the sound waves reaching the microphones in a certain space, the position of the sound source is determined according to the phased array principle, the amplitude of the sound source is measured, and the distribution in space of sound source is displayed as an image. It can completely reproduce the surface vibration and the radiated sound field of the sound source, and is suitable for the coherent sound field. It can overcome the shortcomings of difficult to select the measuring point of traditional acoustic failure diagnosis, and the measured sound source position is also more accurate.
Acoustic imaging technology also can depict the sound field information of the whole sound source, which contains more mechanical state information than a limited number of measure points. Acoustic imaging technology mainly includes far-field beamforming and near-field acoustic holography according to the measurement distance.

Beamforming measures the sound source distribution on the surface of the object, and finds the main noise source position, and obtains the main characteristics of the radiated sound field and the physical mechanism of the sound source. It takes into account sound source identification and the characteristics of frequency domain analysis. Beamforming is more suitable for the identification and localization of mid-high frequency, discrete and large-structured sound sources in the far field. The resolution is limited by the Rayleigh criterion. At the same time, due to the loss of the “evanescent wave” component by far-field measurement, only the relative size distribution of the sound pressure on the surface of the sound source can be reconstructed. The resolution of Beamforming is not high, but the algorithm is simple and practical, and has high engineering application value.

Near-field acoustic holography (NAH) is a new sound field imaging technology developed on the basis of traditional acoustic holography. By performing sound pressure holographic measurement on the holographic measuring surface surrounding the source, and then by means of the spatial field transformation relationship between the source surface and the holographic surface, the sound field of the source surface can be reconstructed from the holographic surface sound pressure, and many acoustic quantities can be reconstructed from the sound source to the two-dimensional surface parallel to the holographic measurement surface in the far field. It is convenient to obtain the acoustic energy flow pattern of the spatial sound field acoustic radiation, revealing the law of structural acoustic-vibration coupling, and realizing the sound field visualization. NAH can not only record the wave component, but also record the "evanescent wave" component. NAH makes the reconstruction accuracy of the sound field greatly exceeds the Rayleigh resolution criterion, reaching a few one-tenth to a few percent of the normal wavelength.

Summarizing the existing failure acoustic diagnosis methods based on far-field beamforming and near-field acoustic holography, the mainstream has the following three steps [22, 23]:

1) Using far-field beamforming or near-field acoustic holography to process the sound field information from the microphone array to obtain a source image reconstruction matrix;

2) Feature extraction is performed by using singular value decomposition or texture statistical features based on gray level co-occurrence matrix to obtain feature vectors;

3) Identify by using methods such as SVM to perform state diagnosis.
3. Summary and prospect

Failure acoustic diagnosis technology is an important means to improve engine reliability and safety. This thesis introduces several common methods for current failure acoustic diagnosis, including wavelet analysis, empirical mode decomposition, and acoustic imaging, and refines the main diagnostic steps of these methods. In recent years, due to the increasingly complex, intelligent and mechatronic engines, the failure diagnosis technology is urgent to further develop failure acoustic diagnosis technology.

1) Deep learning learns, interprets and analyzes input data by establishing a deep neural network, and acquires the ability to interpret data knowledge. At the same time, it automatically adjusts and updates network weights according to the characteristics of input data, improves the ability to feature extraction and learns new knowledge. Therefore, combining failure acoustic diagnosis with deep learning methods will be an important idea for failure diagnosis in the future.

2) The traditional failure acoustic diagnosis is to extract a certain parameter or a certain type of parameter by a certain method, and judge according to the change of the parameter. This method has great limitations. Starting from different methods, using multiple types of parameters for failure diagnosis, and modular approach will be adopted to comprehensively analyze the various features, so that the conclusion will be more reliable.

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