On Signal Surveillance Analysis of Vibration Fault of Main Fan

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Abstract. The research idea of the coal mine main fan's fault diagnosis is generally the surveillance of the vibration state of the main fan's impeller and the drive motor's rotor. The vibration characteristics under different faults are obtained to distinguish the fault categories by analyzing the obtained vibration signals.

1. Introduction
Holographic spectrum analysis, Hilbert-Huang Transform (HHT), and other methods developed in recent years have shown superior performance in processing aperiodic and non-stationary fault signals. Hilbert-Huang transform (HHT) can effectively reflect the time-frequency information of signal locality characteristics by adaptively decomposing fault signals. Effective signal processing methods will continuously improve the real-time and accuracy of the main fan fault diagnosis system.

2. Determination of Sampling Frequency and Analysis Length of Vibration Signal of Main Fan
A sampling of the main fan's vibration signals refers to extracting a series of discrete values from continuous-time signals through sampling pulses. In order to obtain practical information in the original signal, the Shannon sampling theorem needs to be met when signal sampling, as shown in the formula:

\[ f_s \geq 2 f_{\text{max}} \]  

(1)

Where, \( f_{\text{max}} \) is the highest frequency component in the signal to be collected, and \( f_s \) is the sampling frequency.

After determining the sampling frequency, the number of sampling points selected for signal analysis is related to the frequency resolution. Set \( N \) as the number of sampling points for analysis and \( \Delta f \) as the frequency resolution. The corresponding formula is as follows:

\[ N = f_s / \Delta f \]  

(2)

In the vibration fault signals of the main fan, for the fault types such as rotor imbalance, rotor misalignment, surge, and component looseness in the rotating part, the fault characteristic information is mainly included in the frequency range of 10 times of the fault frequency, usually not higher than 2KHz. The characteristic frequency of fan bearing failure changes with the degree of failure, which is reflected in both the high-frequency and the low-frequency parts. The high-frequency part's analysis interval is generally within 5KHz; therefore, taking the sampling frequency of 12KHz can completely meet the analysis requirements. Due to the relatively large difference in characteristic frequencies
between fan faults, the condition can be met when the frequency resolution is 1Hz. According to formula (2), \(N = 12000\) can be obtained.

3. Hardware Design and Software Design of Vibration Signal Acquisition System for The Main Fan

3.1. Selection and Installation of Vibration Sensor for Main Fan

The vibration signal sensor of the mine's main fan adopts the vibration sensor produced by Shanghai Aviation Vibration Instrument Company: HZ834 piezoelectric acceleration sensor, which is integrated on a piece of polysilicon through micromachining technology and has the functions of measurement, conversion, and signal amplification. It uses microelectronic technology and capacitive measurement principle to realize excellent low-frequency response function and automatic calibration function of gravity acceleration. This kind of sensor has the characteristics of strong stability, high reliability, and strong anti-interference capability. Compared with common acceleration sensors, it is more convenient and straightforward to use. Its built-in self-checking system can also conveniently carry out self-checking on whether its performance is normal. See Table 1 for detailed parameters.

| Range  | Sensitivity | Frequency Response | Mounting Thread | Supply Voltage | Output |
|--------|-------------|--------------------|-----------------|----------------|--------|
| ±3g    | 100 mV/g    | 0.5~15kHz          | M8X1 Monolithic stud | 18~30VDC       | Three-wire voltage ±5V |

3.2. Signal Conditioner

According to the mine requirements, the CM4016TM16 channel multifunctional vibration signal conditioning module produced by Dataforth Company is selected. Some of its functional parameters are shown in Table 2.

| Input Channel | Input Range | Input Impedance | Input Protection Voltage | Computer Controlled Communication Interface | Filter Type |
|---------------|-------------|-----------------|--------------------------|---------------------------------------------|-------------|
| 16            | ±10mV~±40V  | 1MΩ             | ±40V                     | RS-232                                     | 8th order low-pass Elliptic filter |

3.3. Choice of Industrial Tablet Computer

Considering the data processing speed, Advantech PPC-157T industrial tablet computer meeting the explosion-proof standard is selected to complete the processing and analysis of collected data. Its main functional parameters are shown in Table 3 below.

| CPU                  | Intel® Core™2 Duo processor up to 2.16 GHz |
|----------------------|--------------------------------------------|
| Storage capacity     | 2GB Memory, 320G Disk Capacity             |
| System supports      | DOS, Windows, Linux (optional)             |
| Communication        | Supports Ethernet and RS232/485            |
| Input power supply   | 220V-AC                                    |
| Operating temperature| -10℃-55℃                                  |
| Dimension            | 315 x 240 x 87mm                           |

3.4. Software Design of Vibration Signal Acquisition System for The Main Fan

Matlab's own data acquisition toolbox (DA toolbox) contains a dynamic connection library of M files and MEX files integrated by Matlab, which can communicate interactively with data acquisition equipment in real-time to obtain acceleration signal data of vibration. The signal acquisition process is shown in Figure 1.
4. Application Advantages of HHT Theoretical Basis in Vibration Surveillance of Main Fan

4.1. Application Advantages of HHT Theory
Hilbert-Huang Transform (HHT) is a new signal processing method, which can decompose the signal with extremely high time-frequency resolution by empirical mode decomposition according to the local time-varying characteristics of the signal to be analyzed.

4.2. Brief Introduction of HHT Theory
HHT mainly includes empirical mode decomposition technology and Hilbert-Huang transform, of which the former is the key part.IMF Definition: A standard eigenmode function needs to meet the following two constraints at the same time:

4.2.1. In the time region of the decomposed signal, the sum of the number of maximum points and minimum points must be equal to the number of intersection points of the signal function through the zero axes, or the difference between the two is not more than one.

4.2.2. At any time point, the upper and lower intrinsic modal function envelopes' average value is zero. The screening of the IMF can be stopped when the following conditions are met:

$$0.2 \leq \frac{\sum_{j=0}^{T} |h_{i,k-1}(t) - h_{i,k}(t)|^2}{\sum_{j=0}^{T} |h_{i,k-1}(t)|^2} \leq 0.3$$

(3)
4.2.3. **Treatment of Modal Aliasing Problem**

At present, the relatively mature solution to the problem of mode aliasing is the Ensemble Empirical Mode Decomposition (EEMD) proposed by Huang. The general process of EEMD decomposing the signal is as follows:

4.2.3.1. **On the basis of the original signal** \( x(t) \) **data, a zero-mean Gaussian white noise sequence** \( z(t) \) **is added:**

\[
y(t) = x(t) + z(t)
\]

(4)

4.2.3.2. **Initial empirical mode decomposition is performed on the integrated signal** \( y(t) \) :

\[
y(t) = \sum_{j=1}^{n} c_j + r_n
\]

(5)

4.2.3.3. **Combined with the principle of EMD decomposition**, white noise sequence should be added in the decomposition process of each cycle, assuming that the cycle ends after \( k \) times:

\[
y_k(t) = \sum_{j=1}^{n} c_{jk} + r_{nk}
\]

(6)

4.2.3.4. **Calculate the IMF obtained after EEMD processing:**

\[
c_j = \frac{1}{N} \sum_{k=1}^{N} c_{jk}
\]

(7)

The rule of the influence of adding Gaussian white noise to EEMD on the effect accuracy meets the following formula:

\[
\sigma = \frac{\varepsilon}{\sqrt{N}}
\]

(8)

Where, \( N \) is the total number, which is consistent with Formulas (7), the standard deviation \( \sigma \) is the error between the original signal and the decomposed IMF, and \( \varepsilon \) is the amplitude of the added noise. From Formula (8), it can be seen that the smaller \( \varepsilon \) is selected, the larger \( N \) is obtained, and the more accurate the decomposition result is. However, when \( \varepsilon \) is taken too small, the noise is difficult to affect selecting extreme points, thus losing the supplementary scale function. According to previous analysis experience, this paper selects the total number \( N \) as 100 and \( \varepsilon \) as 0.2. By taking the bearing inner race fault signal as an example, the EMD decomposition and EEMD decomposition results are compared as follows:
Figures 2 and 4 respectively show the first eight principal components of EMD and EEMD decomposition results of bearing inner race fault signals, and Figures 3 and 5 respectively show a Fourier spectrum of corresponding decomposition components. Compared with Figure 3 and Figure 5, it is self-evident on the whole that the spectrum of IMF components obtained by EEMD decomposition is more straightforward and more transparent, the noise influence is further weakened,
and the fault characteristic information in low-frequency signals is much more obvious. In Figure 3, the frequency spectrum mode aliasing phenomenon of the 5th component is relatively serious, and the frequency spectrum information of the 4th and 6th components is mixed at the same time. Although the 6th component in Figure 5 contains a small part of the leaked energy of the 5th component, and the 5th component has effectively improved the mode aliasing degree in Figure 3 and hardly contains the energy information of the 4th component. Therefore, EEMD, as an effective noise-assisted signal analysis method, is a further improvement of the EMD analysis method and improves the accuracy of signal analysis.

5. Decomposition of Fan Vibration Signal Based on EEMD

According to the analysis of the acquisition parameters, the sampling frequency is 12KHz, and the number of sampling points is 16384. The main fan in the mine is a single cyclone. The rated speed of the fan is high, which is 1450 r/min. Due to the high probability of bearing faults occurring in the coal mine fan system and the relatively complex state characteristics, this paper selects the typical fault signals of the inner and outer races of the fan bearing from the seven types of faults analyzed, such as the inner race, outer race, rolling body, imbalance, misalignment, surge, and loose parts, for EEMD decomposition. Under the rated rotation speed, the time domain waveforms of the normal signal of the fan and the fault signal of the bearing outer race at the non-drive end are shown in Figures 6, 7, and 8, respectively:

![Figure 6. Normal Signal Time Domain Waveform](image1)

![Figure 7. Time Domain Waveform of Inner Race Fault Signal](image2)
According to the EEMD decomposition parameters set in this paper: The N value of the total number is 100, and the value of $\varepsilon$ is 0.2, the normal signal of fan bearing, inner race fault signal, and outer race fault signal are decomposed, and the decomposition results are shown in Figures 9, 10, and 11, respectively. In the later part of this paper, the extraction of fault characteristic quantities is mainly concentrated in the front part of IMF components; therefore, the EEMD decomposition results of fan fault signals in this paper only take the first eight IMF components.

Figure 8. Time Domain Waveform of Outer Race Fault Signal

Figure 9. Normal Signal EEMD Decomposition (First 8 Components)

Figure 10. Decomposition Results of Inner Race Fault Signals (First 8 Components)
5.1. Analysis of Spectrum Characteristics of IMF

The spectrum characteristics corresponding to IMF components of fan normal signals, inner race fault signals, and outer race fault signals are shown in Figures 9, 10, and 11, respectively. The first nine IMF components’ spectral characteristics are selected for analysis corresponding to the IMF main component selected.

Figure 11. Decomposition Results of Bearing Outer Race Fault Signals (First 8 Components)

Figure 12. Spectrum of IMF Components of Normal Signals (First 9 Components)

Figure 13. Spectrum of IMF Components of Inner Race Fault Signal (First 9 Components)

Figure 14. Spectrum of IMF Components of Outer Race Fault Signal (First 9 Components)
The main fan motor’s driving end bearing dimensions are as follows: Bearing pitch diameter $D = 4.01$ cm; The average diameter of the rolling body $d = 1.04$ cm; The number of rolling bodies $Z = 10$; Contact angle $a = 0^\circ$.

Fault frequency of the outer ring part of the bearing
\[ f_o = \frac{Z}{2} \left(1 - \frac{d}{D} \cos a\right) f_r \] (9)

Failure frequency of bearing inner ring part:
\[ f_i = \frac{Z}{2} \left(1 + \frac{d}{D} \cos a\right) f_r \] (10)

Fault frequency of bearing rolling body:
\[ f_b = \frac{1}{2} \frac{D}{d} \left(1 - \frac{d^2}{D^2} \cos^2 a\right) f_r \] (11)

Bearing cage rotation failure frequency:
\[ f_c = \frac{1}{2} \left(1 - \frac{d}{D} \cos a\right) f_r \] (12)

Relative rotation frequency of inner and outer rings, $f_r$, is the rotation frequency of the shaft, and $N$ is the rotational speed of the shaft.

\[ f_r = \frac{N}{60} \] (13)

Under the rated rotational speed, the rotation frequency of the motor shaft $f_r = 1450/60 = 24.17$ Hz. According to Formula 9 and 10, it can be theoretically calculated that the fault characteristic frequency of the bearing outer race is $f_o = 89.4$ Hz, and that of the inner race is $f_i = 152.1$ Hz.

Because the bearing’s geometric size will have certain errors, the fan’s actual rotating speed will also have certain fluctuations, the actual characteristic frequency and the calculated theoretical frequency will often produce errors. From the IMF component spectrum of Figure 10 and 11, it can be found that the actual inner race fault frequency is $f_i = 146.3$ Hz, and the outer race fault frequency is $f_o = 88.03$ Hz. In Figure 10, the IMF’s c4 and c5 components can be found the characteristic frequency of inner race fault and its 3, 4, and 5 frequency doublings, of which three frequency doubles have modulation phenomenon. In Figure 11, the IMF’s c4 and c5 components can be found the characteristic frequency of outer race fault and its 2, 3, and 4 frequency doublings successively. In the fan’s normal vibration signal, the vibration frequency of 88.03 Hz is obvious in the low-frequency amplitude c5. This is because the number of rollers carried by the bearing part is different during the fan’s operation, which causes the change of the bearing stiffness and causes the fluctuation of the shaft center. At this time, the vibration frequency contains the same component as the outer race’s characteristic frequency.

Comparing the IMF component spectrum of normal fan signal, bearing inner race fault signal and outer race fault signal, it can be obviously found that the main energy part of inner race fault signal is concentrated between 2500-5500Hz, and the energy of inner race is higher than that of the outer race. This part is the natural frequency generated by the bearing elements excited by local damage of bearing and is also an essential basis for extracting fault diagnosis features.
5.2. Extraction of Fan Fault Characteristics Based on Intrinsic Modal Energy Entropy

There are many types of fan faults considered in this paper, including seven types of faults such as the motor drive end bearing, the inner and outer races of the bearings at both ends of the fan impeller, the rolling body, and rotor imbalance, misalignment, surge, and loose support. Based on the EEMD analysis results of various fault types, this paper focuses on analyzing the first six intrinsic modal functions containing more fault information. By extracting their intrinsic modal energy entropy values, the fan fault diagnosis is analyzed. The formula for extracting intrinsic modal energy entropy is as follows:

$$E_i = \int_{-\infty}^{+\infty} |c_i(t)|^2 dt, i = 1, 2, \cdots 6$$ (14)

Due to the different values of the extracted intrinsic modal energy entropy, it is necessary to normalize it in order to facilitate the later analysis by BP neural network. The fault characteristic vectors $T$ constructed with energy values as elements are as follows:

$$T = \begin{bmatrix} E_1 & E_2 & E_3 & E_4 & E_5 & E_6 \end{bmatrix}$$ (15)

Summarized as follows:

$$E = \sqrt{\sum_{i=1}^{6} |E_i|^2}$$ (16)

$$T' = \begin{bmatrix} \frac{E_1}{E} & \frac{E_2}{E} & \frac{E_3}{E} & \frac{E_4}{E} & \frac{E_5}{E} & \frac{E_6}{E} \end{bmatrix}$$ (17)

According to the above method, on the basis of the rated fan speed of 1450 r/min, the frequency is reduced to 45Hz successively, and the corresponding fan speed is changed to 1305 r/min. The vibration fault characteristic values of 1450, 1392, 1334, and 1305 types of fan speeds are extracted, respectively, and the fault data samples are determined by comparative analysis. Corresponding to the eight types of fan faults (including normal conditions) analyzed, at each rotating speed, four typical representative data groups are selected for each fault type, with a total sample number of 128. One set of fault characteristic values of the bearing part and the fan’s rotating part at the rated speed are shown in Table 4 in turn.

| Fault Type          | Energy Entropy | Energy Entropy |
|---------------------|----------------|----------------|
|                     | 1              | 2              | 3              | 4              | 5              | 6              |
| Normal              | 0.5172         | 0.6650         | 0.1674         | 0.3255         | 0.3775         | 0.1179         |
| Inner Race Fault    | 0.9917         | 0.1104         | 0.0633         | 0.0171         | 0.0045         | 0.0012         |
| Outer Race Fault    | 0.8891         | 0.4464         | 0.0907         | 0.0218         | 0.0379         | 0.0055         |
| Roller Fault        | 0.6247         | 0.7530         | 0.1850         | 0.0903         | 0.0190         | 0.0048         |
| Unbalance           | 0.9032         | 0.7201         | 0.5628         | 0.2589         | 0.0165         | 0.0032         |
| Misalignment        | 0.6740         | 0.5150         | 0.4326         | 0.1675         | 0.0502         | 0.0546         |
| Surge               | 0.5236         | 0.3491         | 0.2962         | 0.1543         | 0.0176         | 0.0041         |
| Loose Parts         | 0.9481         | 0.4682         | 0.3121         | 0.3675         | 0.1003         | 0.0261         |

6. Conclusions

According to the fault signal characteristics of the main fan in the mine, this paper systematically analyzes the signals of typical vibration fault types of the main fan and introduces in detail the advantages of HHT in analyzing vibration signals for the purpose of extracting the corresponding fault characteristic values. The problem of the modal aliasing effect in HHT application is improved. Finally, according to the EEMD decomposition results, the intrinsic mode function energy entropy method is used to extract the fault eigenvalues, laying a data foundation for the main fan's research of common vibration faults.
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