Research on Feature Extraction Strategy Based on Improved Empirical Mode Decomposition Method

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Abstract: An improved empirical mode decomposition method is proposed to address the issues of modal aliasing and endpoint effects that affect the accuracy of fault diagnosis in traditional empirical mode decomposition methods. This method uses a median filter with a variable window when generating the intrinsic mode function (IMF). Compared with the traditional empirical mode decomposition method, the improved empirical mode decomposition method (IEMD) can reduce the mode aliasing and end effect, and improve the efficiency of feature extraction. In the IEMD method, the bearing vibration signals are decomposed by EMD, and the obtained IMF components are processed by a median filter with variable window values, in which the narrow window is used for the high frequency component and the wide window is used for the low frequency component. Then, the filtered internal model function is summed and subjected to a round of empirical mode decomposition to obtain an improved internal model function. The traditional EMD method and the IEMD method are compared by using the accelerated aging test equipment of induction motor bearings. The results show that the IEMD method can separate the characteristic frequency of the early fault of the motor and detect the early fault effectively.

Keywords: Empirical Mode Decomposition; Electric Machine; Early Fault Detection; Median Filter

1. Introduction

Empirical Mode Decomposition (EMD), as a nonlinear signal analysis method, has been widely applied in fields such as fault detection and data processing in recent years [1-3]. However, this method suffers from severe modal aliasing and endpoint effects during the signal decomposition process [4].

To solve the above problems, scholars have proposed a variety of methods, such as B-spline EMD[5], full set empirical mode decomposition and wavelet packet denoising to improve EMD, but the above methods have not fundamentally eliminated mode aliasing and end effects. Based on this, an IEMD method with median filter is proposed. The method can eliminate the effect of pulse noise and reduce the mode aliasing effect at the same time. The main idea of the proposed method is to first perform empirical mode decomposition on the signal to generate a series of internal mode functions. The obtained multiple IMFs are processed using a variable window size median filter, with a narrow window size for high-frequency components and a wide window size for low-frequency components. Then sum the filtered IMFs and reconstruct the signal. Perform EMD processing on the reconstructed signal again to obtain improved IMFs. The comparison with conventional empirical mode decomposition results shows that the new method (IEMD) improves the mode aliasing effect, resulting in better decomposition of each frequency component of each IMF.

Section 1 introduces the conventional EMD method, Section 2 introduces the median filtering method, and Section 2 also provides detailed instructions on how to set the variable window size and how to reconstruct the signal after filtering. Section 3 introduces the motor aging setting process. In Section 4, EMD method and IEMD method are used to process the data of normal and faulty motors, and the results are compared and discussed. Section 5 is the conclusion section, summarizing the advantages of the proposed method compared to the EMD method in handling early fault data.

2. Empirical Mode Decomposition

EMD is a nonlinear signal analysis method that decomposes vibration signals into a series of different frequency components. These components are called IMFs. The IMF needs to meet the following points[6]:

(1) The total zero crossing point and the total extreme point in the entire dataset should be equal or at most differ by 1.

(2) The average of the envelopes of the maximum and minimum values within any interval of the components should be equal to zero.

EMD can decompose signals into a series of IMFs. EMD is a screening process aimed at decomposing signals into narrowband signals. The specific process of the algorithm is as follows:

(1) Identify all local minima and maxima.

(2) Connect all local maximum/minimum values using a cubic spline to form an upper/lower envelope.

(3) Calculate the average of these envelope lines and subtract $h_1 = x(t) - m_1$ from the signal.

(4) Check if h_1 meets the two IMF standards. If not, repeat steps 1 to 3 until h meets IMF standards. Assuming that after i iterations, the following conditions are met:

$$h_{1(i-1)} - m_{1i} = h_{1i} \tag{1}$$

So $c_1 = h_{1i}$ is the first IMF. The widely used EMD termination criterion was proposed by Huang et al.[7], which is given through Cauchy convergence test.

The first IMF contains high-frequency oscillations in the signal.

$$x(t) - c_1 = r_1 \tag{2}$$

The residual contains all remaining frequency information of the data, and another filtering process is applied to generate a second IMF, and so on.

$$\begin{cases} r_1 - c_2 = r_3 \\ r_{n-1} - c_n = r_n \end{cases} \tag{3}$$

When r_n is a monotonic function or a function with only one extreme value, the process stops; Therefore, the process can be expressed by the following formula:

$$x(t) = \sum_{i=1}^{I} (x_i(t) + r_I(t)) \tag{4}$$

Where $c_i(t)$ is the i th IMF and $r_I(t)$ is the residual component.

3. Improved Empirical Mode Decomposition

In the IMDE method proposed in this paper, the signal is decomposed into a series of IMFs, and then the variable window size median filter is applied to each IMF component. Sum the processed IMF again to recombine the signal. The recombined signal is decomposed by EMD again, and an improved IMF is generated. Sum the processed IMFs again to recombine the signals. The recombined signals are decomposed by EMD again, and improved IMFs are generated.

3.1 Median Filter

The nonlinear median filter can remove noise and smooth the signal. The median filter function is as follows:

$$y(t) = median[x(t-l), x(t-l+1)\cdots x(n)\cdots x(t+l)] \tag{5}$$

Where $x(t)$ is the input signal and $y(t)$ is the output signal. The filter passes through the signal point by point and replaces each input with its adjacent median. The concept of adjacency can be defined as a sliding "window" that slides on each input signal. The median filter with small window can eliminate most of the noise, but it will also cause some information loss, while the median filter with large window is on the contrary, and the information loss is small.

3.2 IMDE with Median Filter

Firstly, EMD is used to process the original signal, and the signal is decomposed into a series of IMFs (different frequency components). For high-frequency IMFs, a median filter with a smaller window is applied, while for low-frequency IMFs, the window size is increased. The variable window median filter can eliminate the noise in the high-frequency component and keep the information integrity of the low-frequency component. The window size of median filter increases with the order of IMF. The smaller the order of IMF, the smaller the window size selected. The choice of window size will be explained later in this section. After generating a series of IMFs, median filtering is applied to each IMF, and the IMFs after median filtering are superimposed to generate the filtered version of the original data. At this point, the EMD method is applied to the filtered version of the original data again, and a new IMFs is generated. This process includes the following steps.

Step 1: apply EMD algorithm to signal $x(t)$ to obtain IMF component $c_l(t)$ and residual $r(t)$, $l=1,2,\cdots,L$ is the number of IMFs, and initialize all IMFs.

Step 2: use window size hf for IMF defined as high frequency, and use window size lf for other IMF to generate median filtered IMFs $c_{med,l}(t)$.

Step 3, sum the IMFs $c_{med,l}(t)$ of all median filters to create the filtered version of the original signal, i.e. $x_{filtered}(t)$.

Step 4, apply EMD algorithm to generate improved $d_m(t)$ on $x_{filtered}(t)$, where $m=1,2,\cdots,M$ is the number of improved IMF.

The window size of median filter increases with the order of IMFs. Select a smaller window size for the initial IMF, and then the window size of each IMF will increase. To achieve the above objectives, two adaptive windows are defined, in which the "high frequency" IMFs are filtered with a smaller window, and the remaining IMFs are filtered with a larger window size.

Once the initial EMD process is completed and a series of IMFs are generated, the dominant frequency of each IMF is checked. Let L be the number of IMFs, then:

$$f_{IMF1}, f_{IMF2}, \cdots, f_{IMFL} \tag{6}$$

If the fundamental frequency of the i th IMF is higher than half of the highest frequency IMF plus the lowest frequency IMF, the IMF is considered as high frequency. High frequency and low frequency are defined as:

$$\begin{cases} f_{IMFi} \le \dfrac{f_{IMF1}}{2} + f_{IMFL} : low\ frequency \\ f_{IMFi} > \dfrac{f_{IMF1}}{2} + f_{IMFL} : high\ frequency \end{cases} \tag{7}$$

On this basis, the internal model filters are divided into high frequency and low frequency. All IMFs from i to L (including i) are low frequency, while all IMFs from 1 to i are high frequency. The following window sizes apply to each IMF.

The high frequency window size of the i th IMF can be given by the following formula:

$$hf = round\left(\frac{i}{L} * H(IMF_i)\right) \tag{8}$$

The low frequency window size of the i th IMF can be given by the following formula:

$$lf = round\left(\frac{i}{L} * (H(IMF_i))^2\right) \tag{9}$$

Where L is the number of IMFs. $H(IMF_i)$ is the Shannon entropy of IMFi, the IMF's Shannon entropy is defined as:

$$H(p) = -\sum_{i=1}^{k} p(i)\log(p(i)) \tag{10}$$

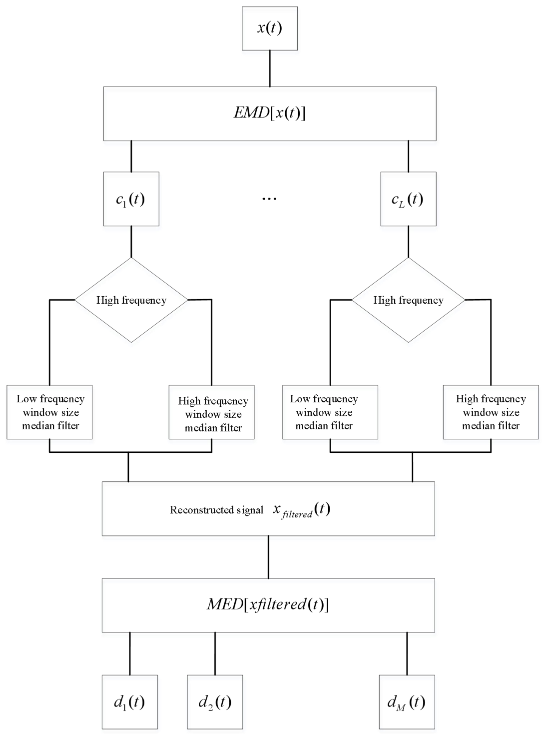

Figure 1. Algorithm flow Chart

The above criteria for calculating the window size of median filters allow the creation of median filters with unique window sizes for each IMF. This method relates the size of each window to the whole data by the number of IMFs. In addition, the window size is associated with each IMF by giving the entropy of IMF. The fixed window of each IMF can also remove impulse noise as much as possible, and this new method applied in iemd also establishes a direct relationship between the entropy of each IMF and the window size of the median filter. As part of the experiment and analysis, this paper will further explain this point. This new method is helpful to eliminate noise and improve mode mixing. The flow chart of the whole process is shown in Figure 1.

4. Accelerated Aging Device Settings

This article designs an experimental device to simulate the discharge from the shaft to the bearing. The experimental discharge device (Electrical Discharge Machining EDM) is shown in Figure 2. The motor operates without load for 30 minutes, with an external shaft current of 27 amperes and an AC voltage of 30 volts per cycle. The aging process is accelerated by thermal aging after each EDM aging cycle. The aging of the motor is achieved through multiple cycles, each of which includes EDM and thermal aging processes. After each accelerated aging cycle, the motor runs on a performance testing platform. During performance testing, collect current, voltage, rotor speed, torque, and vibration data from the motor at a sampling frequency of 12 kHz.

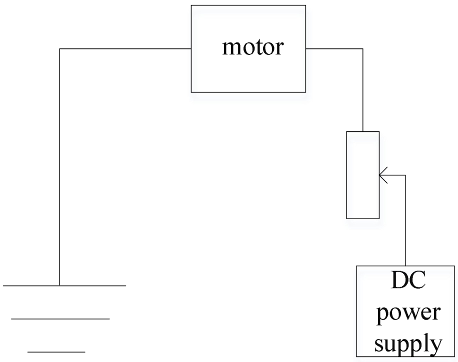

Figure 2. EDM Device Diagram

There are a total of 8 cycles, with cycle 0 being the normal operating state of the motor and cycle 7 being the fault state.

Figure 3 shows the performance test settings used after each accelerated aging process, where the data on the motor has been collected. There are a total of six accelerometers used for vibration measurement. Sensors S1 and S2 (in plane A-B) are the same, so sensor S1 is selected for analysis. It is known that the frequency component of 2.5kHz is the characteristic of the fault. In order to analyze the data, a power spectral density (PSD) graph was introduced, where the PSD of the signal displayed the power distribution of each frequency component of the signal[8]. Figure 4 and Figure 5 show the PSD of motor health and fault states. The PSD of the motor in normal state in Figure 4 shows a frequency component of 2.5 kHz, with very low amplitude. The PSD of the motor fault state in Figure 5 shows a significant increase in the amplitude of the frequency component at around 2.5 kHz.

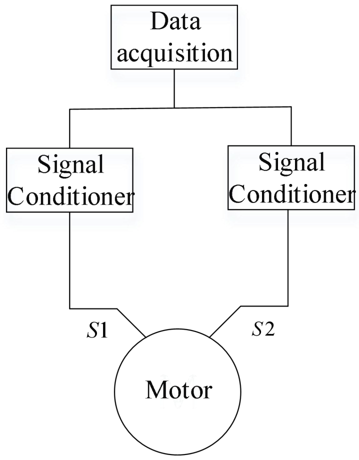

Figure 3. Motor Performance Testing and Data Collection Settings

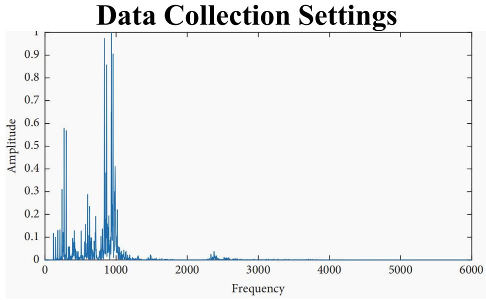

Figure 4. Normal State Motor PSD

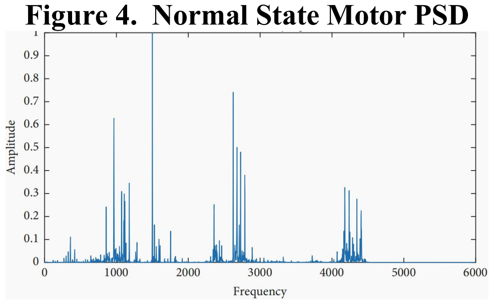

Figure 5. Fault State Motor PSD

5. IEMD Method for Early Fault Detection

The EMD and IEMD methods were used to analyze the operating states data of the motor, and the results are shown in Figure 6 and Figure 7. From Figure 6 and Figure 7, it can be seen that there is a significant difference between the first IMF of EMD and the first IMF of IEMD. In IEMD, the high-frequency component near 2.5 kHz is filtered as a separate component. The IEMD method displays components with a frequency range of 1kHz as the second IMF. However, the EMD method mixes the 2.5 kHz component with the 1 kHz frequency band component, and cannot distinguish between these two different frequency components. This will greatly affect the identification of early weak faults in the motor.

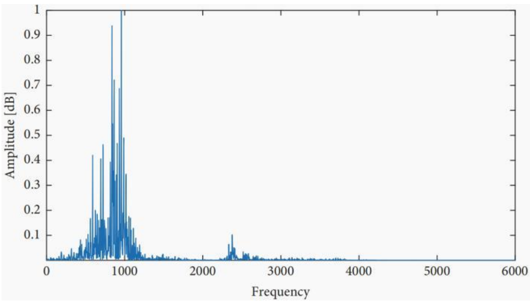

Figure 6. The first IMF of a Normal Motor Using the EMD Method

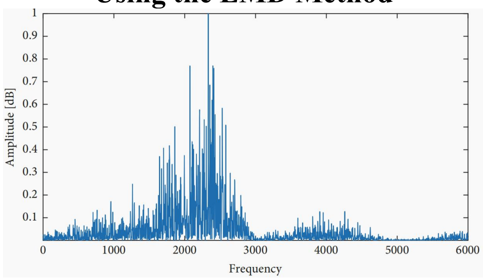

Figure 7. The first IMF of a Normal Motor Using the IEMD Method

Figure 8 shows the second IMF for normal motors using the EMD method. By comparing the first and second IMF of the EMD method (Figure 6 and Figure 8), it can be seen that there is a significant amount of mode mixing in the 1 kHz frequency range, which makes it impossible to monitor the fault feature frequency.

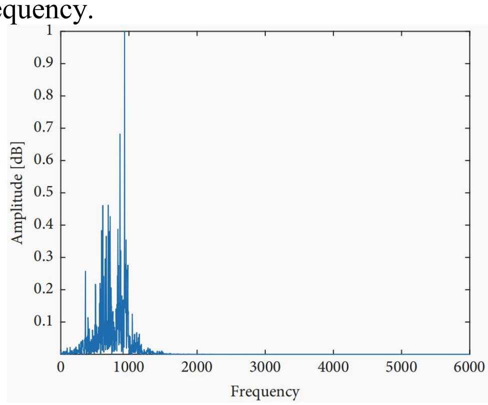

Figure 8. Second IMF Using EMD Method for Normal Motors

As shown in Figure 9, the second IMF of the IEMD method successfully represents a frequency component of 1 kHz. According to Figure 7 and Figure 9, it can be seen that the first IMF of the IEMD method represents the fault frequency, which means that this method can effectively achieve the separation of fault feature frequencies and achieve early fault diagnosis.

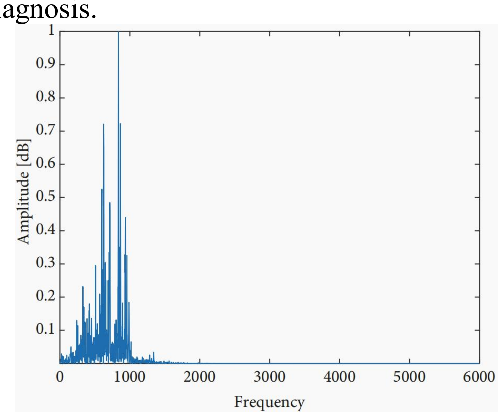

Figure 9. Second IMF for Normal Motors Using IEMD Method

In summary, the first and second IMFs of the conventional EMD method exhibit significant modal aliasing (in the 1 kHz range and 2.5 kHz range), while the proposed IEMD method clearly separates these two different components into two different IMFs. Therefore, the proposed IEMD method can effectively distinguish fault frequency components with physical significance and very low amplitude in health state detection, while conventional EMD methods have significant modal aliasing effects.

6.Conclusion

This article proposes an IEMD method based on median filtering and compares it with the EMD method. The results indicate that the IEMD method with adaptive window size median filtering can effectively improve the mode mixing problem. Using induction motor fault data, IEMD and EMD methods were compared. The IEMD method can successfully identify extremely low amplitude frequencies related to faults under normal conditions.

The first IMF component of the traditional EMD method represents the fault related frequency, which is mixed with the motor operating frequency and cannot be distinguished. The proposed improved IEMD method can effectively separate the fault related frequency from the operating frequency. The results indicate that the improved IEMD method can effectively separate the frequency components of fault features and achieve early fault diagnosis.

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