Data processing of pulsation signals based on local wave decomposition and teager energy

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Abstract. Nonstationary and nonlinear signals are often encountered in the research and development of turbomachinery. One such example is the pulsating strain signal measured during engine ramping to find the maximum resonant strain in the application. Because the pulse signal may come from different interference sources, it is difficult to detect weak useful signal in the background of noise. In order to solve this problem, a new method based on local wave decomposition (LWD) and Teager energy is proposed. According to the local characteristics of the vibration signal, the optimal prediction operator of the transformed sample is constructed by selecting the appropriate square error minimization criterion, so that the second generation wavelet basis function can fit the local characteristics of the vibration signal. The adaptive second generation wavelet is used as the prefilter to improve the effect of LWD decomposition. Then the correlation kurtosis is used to select the sensitive internal model function (IMFs). Finally, the Teager energy operator algorithm is applied to the selected sensitive IMF to identify the characteristic frequency. The validity of the method is verified by the measured strain signal of a turbocharger turbine as an example.

1. Introduction

Nonstationary and nonlinear signals are often encountered in the research and development of turbomachinery. Sometimes the frequency of these signals changes with time. An example of this is the measurement of a pulsating strain signal in an engine ramp to find the maximum resonance of a turbomachinery blade. Because the signal frequency is proportional to the engine speed, it changes when the speed changes.

Traditionally, these signals are analyzed by FFT method [1]. But for the non-stationary signal which changes with time, Fourier transform is powerless. In view of the nonstationarity and nonlinearity of these signals, several advanced time-frequency analysis techniques are introduced and applied to the analysis of these signals. Local wave decomposition (LWD) is one of the most effective time-frequency analysis methods [2]. It is an adaptive time-frequency signal processing method. LWD decomposes the original signal into a series of band limited intrinsic mode functions (IMFs). Each IMFs component can be modulated or modulated according to the characteristics of the signal. It can well reveal the nonlinear and non-stationary information of the vibration signal. It has been successfully applied to the fault diagnosis and structural health monitoring of rotating machinery [3].
However, due to the problem of pattern mixing, LWD cannot extract fault features accurately. In order to reduce mode mixing, it is important to eliminate noise before decomposition. Wavelet transform is widely used in signal denoising. The result of wavelet decomposition is related to wavelet basis function. In addition, improper wavelet transform will cover up the local characteristics of vibration signal and lose some useful original signal details. In order to overcome the above limitations, this paper introduces lifting algorithm to design adaptive wavelet function for signal denoising [4-5].

Because of the different sources of the fluctuating strain signal, it is difficult to detect the weak useful signal in the noise background if the signal processing error interferes. This paper reports the results of this investigation.

2. New method

2.1. Local wave decomposition

The local wave decomposition (LWD) method is developed under the simple assumption that any signal contains different simple intrinsic oscillation modes. Any signal can be decomposed into a finite number of IMF [2]. By definition, any signal \( x(t) \) can be decomposed as follows:

Firstly, all the local extremum of the signal is obtained, and the local mean \( m(t) \) is fitted by cubic spline, and the detail \( h(t) = x(t) - m(t) \) is extracted. \( H(t) \) is regarded as a new \( x(t) \), and the above operations are repeated until \( h(t) \) satisfies the IMF condition, and then the first IMF \( c_1(t) = h(t) \) is obtained. Let the residual \( r_1(t) = x(t) - h(t) \) be a new signal, repeat the above process, and get other order IMFs. Therefore, we can decompose the signal into IMFs \( c_1(t), c_2(t), \ldots, c_n(t) \), and a residue, which is the average trend of:

\[
x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t)
\]

For each IMF in Eq. (1), we can always have its Hilbert transform,

\[
H[c_i(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau
\]

According to this definition, we can get an analytic signal,

\[
x_i(t) = c_i(t) + jH_i(t) = a_i(t)e^{j\phi_i(t)}
\]

After Hilbert transformation of each IMF component, the original signal can be expressed as,

\[
x(t) = \Re \sum_{i=1}^{n} a_i(t)e^{j\phi_i(t)}
\]

2.2. Second generation wavelet

Sweldens introduces lifting scheme as a powerful tool to construct second generation wavelets [4-5]. By choosing the criterion of least square error, we get the optimal prediction operator of the transform sample, which makes the constructed wavelet function fit the transient characteristics of the original signal. The stage of the second generation wavelet transform is described as [4-6].

In the process of wavelet threshold denoising, the selection of threshold is the key, which is directly related to the denoising effect. In order to obtain the best denoising effect, this paper adopts the threshold selection scheme proposed by Pan [7].

2.3. The improved LWD

In order to overcome the shortcomings of LWD, the adaptive second generation wavelet is used as the pre-filter bank program as follows:
(1) Using lifting scheme to construct self-adaptive second generation wavelet to denoise the original signal.

(2) After wavelet de-noising, the second generation wavelet is used to reconstruct the original signal, and then the original signal is decomposed into a small number of IMFs by LWD.

Here we consider a noisy nonstationary signal with amplitude modulation,

\[ x(t) = 1.2(1 + 0.2 \sin(2\pi \times 7.5t)) \cos(2\pi \times 30t) + 2.5 \sin(2\pi \times 10t) + 0.25 \text{randn} \]  

where \text{randn} is a random number vector of normal distribution, with an average value of 0 and a standard deviation of 1.

The simulated signal in Figure 1 is analysed using LWD. The decomposition results are shown in Figure 2(a). Due to the interference of noise, the mode mixture occurs between IMFs. Thus, the decomposition results of LMD fail to represent the real characteristics of the simulated signal. To improve the results, the simulated signal is decomposed by the improved LWD, and the results are shown in Figure 2(b). It can be seen that the first IMF \( c_1(t) \) has the obvious amplitude-modulated characteristic, the second IMF \( c_2(t) \) is sinusoidal component.

![Figure 1. Waveform of simulated signal](image1.png)

![Figure 2. Decomposition results of the simulated signal](image2.png)
2.4. Teager energy operator

The Teager energy operator of time-varying signal is defined as [8],

\[ J[x(t)] = [\dot{x}(t)]^2 + x(t) \ddot{x}(t) \]  \hspace{1cm} (6)

where \( \dot{x}(t) \) and \( \ddot{x}(t) \) are the first and second derivatives of signal with respect to time \( t \) respectively.

For discrete-time signals, the Teager energy operator is transformed into discrete-time signals.

\[ J[x(n)] = [x(n)]^2 - x(n-1)x(n+1) \]  \hspace{1cm} (7)

The Teager energy operator is only suitable for narrow band signals. For complex multicomponent signals, the improved LWD algorithm can decompose the signals into IMFs.

2.5. Correlation kurtosis

Correlation kurtosis not only retains the characteristics of kurtosis, but also has the characteristics of correlation function. It is a parameter reflecting the strength of periodic pulse signal in fault signal [9]. When applied to turbine blade signal, if there is interference in the pressure distribution introduced by rotating blade, the interference is similar to the impact signal with obvious period, and the kurtosis is larger, while the correlation kurtosis of other impact signals is smaller. The correlation kurtosis is calculated as,

\[ CK_k(T) = \frac{\sum_{n=1}^{N} \left( \prod_{m=0}^{y} x_{n-mT} \right)^2}{\sum_{n=1}^{N} x_{n}^{2y+1}} \]  \hspace{1cm} (8)

where \( x_n \) is the signal sequence, \( N \) is the number of samples in the original signal, \( T \) is the period of the pulse signal, and \( M \) is the period of shift.

3. Experimental analysis

The turbine involved is a small turbocharger installed in a gas station test unit. The output flap mode of turbine blade is a problem worthy of attention. Under the static and room temperature conditions, the natural frequency of strain measuring blade is measured as 12670Hz. The turbocharger is running on the engine, and its speed is rising and falling constantly. In this way, the recorded signal of turbine blade strain can be obtained from the excitation Figure 3 (a), which is the standardized Figure 3 (b) The peak frequency of FFT spectrum of blade strain is 13650 Hz. This is an unexpected result: the natural frequency of the first blade mode is 12670 Hz, and the expected maximum strain of the blade at room temperature and static state should appear near or on the frequency. Because of the combined use of the centrifugal stiffness and Young's modulus reduction of the turbine blade material at hot state, the order of the engine is 7, so the exciting force is relatively small, and the small strain of blade is expected to be obtained. However, the occurrence of peak strain at 13650 Hz is puzzling and requires an explanation.

(a) Waveform of blade strain signal  \hspace{1cm} (b) FFT spectrum of the blade strain signal

**Figure 3.** Measured turbine blade strain signal
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Figure 4. Decomposition results of blade strain signal

Figure 5. Envelope spectrum analysis

The strain signal was decomposed by LWD, and the first four IMF decomposition results are shown in Figure 4 (a). The second IMF contains the pulse characteristic signal whose marginal spectrum is shown in Fig. 5 (a). The circular mark corresponds to 12650 Hz, and the rectangular mark corresponds to the peak value of 13070 Hz and 12650 Hz. This may be the vibration mode pursued by the blade. A higher frequency peak value of 13070 Hz is also given. The reason for this is not clear.

Therefore, the proposed method is applied to strain signal processing. Figure 4 (b) shows the results of the improved LWD decomposition. The correlation kurtosis of each IMF component is calculated according to the period of detection component. According to the maximum correlation kurtosis criterion, IMF1 was selected as the sensitive component. Then the Teager envelope analysis is applied to the IMF1, and the Teager envelope spectrum is shown in Figure 5(b). The circular mark corresponds to 12650 Hz, and the rectangular mark corresponds to 13070 Hz. It can be seen clearly that there is an obvious peak value at 12650 Hz compared with the LWD result in Figure 5(a), which further proves the value of the new method.

4. Conclusions

In order to overcome the difficulties of traditional FFT methods, a new signal processing method is proposed in this paper. In this method, a self-adaptive second generation wavelet is used to reduce the influence of noise and improve the effect of LWD decomposition. The LWD method is used to extract feature components from the original signal and separate them from the background noise and irrelevant components. The correlation kurtosis is used to screen out sensitive feature components, effectively eliminate the interference components and capture the feature information. Teager energy
enhances the detection of the characteristic frequency of weak impact. Experiments are carried out on a turbine wheel to verify the effectiveness of the FFT method. The results show that this method can identify the first vibratory mode of the blade from the weak strain gauge signal, which is difficult for the traditional FFT method.

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