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Fault Feature Extraction of Diesel Engine Based on Second Generation Wavelet and HHT

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Abstract. Aiming at difficulty of weak characteristics of the nonlinear and low signal-to-noise ratio signals measured from diesel engine, a novel method combining second generation wavelet denoising and Hilbert Huang Transform(HHT) is proposed, and is used for feature extraction and condition evaluation of vibration signals measured from diesel engine. Firstly, the original data is pre-processed using second generation wavelet to suppress abnormal interference of noise and obtain intrinsic mode functions(IMFs) by using EMD. Then the instantaneous frequency and amplitude are computed by Hilbert transform and Hilbert marginal spectrum is obtained, which can exactly provide the energy distribution of the signal with the change of instantaneous frequency. The vibration signals of diesel engine piston-liner wear are analyzed and the results show that the proposed method is feasible and effective in feature extraction and condition evaluation of diesel engine faults.

Introduction

The engine valve has long been recognized as an important influence on the performance of internal combustion engines which can cause the change of the vibration response of diesel engine [1-2]. When the piston-liner wear occurs, the vibration signals of the engine is non-stationary[3]. The spectrum based on Fourier transform represents the global rather than any local properties of the signals. Although non-stationary transient signals can have a spectrum by using Fast Fourier Transform(FFT), it resulted spectrum for such signals is broad band. For example, the spectrum of a single pulse has a similar spectrum to that of white noise. Consequently, the information provided by FFT for transient signals were limited.

In this paper, Hilbert Huang Transform(HHT) is introduced. Instead of relying on convolution methods, HHT is based on empirical mode decomposition (EMD) and the Hilbert transform [4]. For a non-stationary signal, the Hilbert marginal spectrum offers clearer frequency energy decomposition than the traditional Fourier spectrum[5]. However, the piston-liner wearing characteristics is always submerged in the background and noise signals, which will cause the mode mixture and generate undesirable intrinsic mode functions (IMFs). In order to decrease unnecessary noise influence on EMD, it is important to denoise before decomposing. In the denoising of traditional wavelet transform, the result of wavelet decomposing is related with wavelet basis function[6-7]. Moreover, an inappropriate wavelet will overwhelm the local characteristic of vibrating signal, and lost some useful detail information of original signal. To circumvent these difficulties, we present a lifting scheme to construct adaptive wavelets by the design of prediction operator and update operator. The experiment analysis results show that the proposed method is feasible and effective.

HHT

HHT is based on empirical mode decomposition (EMD) and the Hilbert transform [4]. HHT is performed into two steps. First, EMD decomposes the time-series into a set of functions designated as IMFs, then applying the Hilbert transform to those IMFs for generation of the Hilbert spectrum. For any signal, to get a meaningful instantaneous frequency using Hilbert transform, the signal has to decompose a time-series into IMFs which must satisfy two conditions:(1) In the entire data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one; (2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

A practical procedure, known as sifting process, is employed for this purpose. Details are given in [4]. Any signal x(t) can be decomposed into IMFs $c_1(t)$, $c_2(t)$, . . . , $c_n(t)$, and a residue $r_n(t)$,

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

Applying the Hilbert transform to each IMFs, the original data can be expressed as,

$$x(t)=\mathrm{Re}\sum_{j=1}^{n}\mathrm{a}_{\mathrm{j}}(\mathrm{t})\mathrm{e}^{i\varphi_{\mathrm{j}}(\mathrm{t})} \tag{2}$$

This frequency–time distribution of the amplitude is designated as Hilbert time– frequency spectrum,

$$H(\omega,t)=\mathrm{Re}\sum_{j=1}^{n}\mathrm{a}_{\mathrm{j}}(\mathrm{t})\mathrm{e}^{\mathrm{i}\int\omega_{\mathrm{j}}(\mathrm{t})\mathrm{dt}} \tag{3}$$

We can also define Hilbert marginal spectrum,

$$h(\omega)=\int_0^T H(\omega,t)dt \tag{4}$$

where T is the total data length. The Hilbert marginal spectrum offers a measure of the total amplitude distribution from instantaneous frequency.

Second Generation Wavelet

The lifting scheme can be used to construct adaptive wavelets by the design of prediction operator and update operator [8-10]. It does not rely on the Fourier transform. The principle of lifting scheme wavelet transform is described as,

(1)Split: Split the original signal X(k) with the length of L into even sets Xe(k) ={x(2k)， $k\in Z$ } and odd sets Xo(k)={x(2k+1)， $k\in Z$ }.

(2)Update: Using a one-point update filter, the approximation signal is computed, c(k)=(Xe(k)+Xo(k))/2.

(3)Select prediction operator: Design three different prediction operators.

N=l: d(k) =Xo(k)-c(k) (5)

N=3: d(k) =Xo(k)-[-c(k-1)/8+c(k)+ c(k+1)/8] (6)

N=5: d(k) =Xo(k)-{3[c(k-2)- c(k+2)]/128+c(k) -11[c(k-1)- c(k+1)]/64-c(k+2)} (7)

Where, N is the number of neighboring c(k) while applying the prediction operator , k=1~L/2. An optimal prediction operator is selected for a transforming sample according to minimizing the $[d(k)]^2$.

(4) Predict**:** Compute the detail signal d(k) by using the optimal prediction operator.

Because we update first and the transform is only iterated on the low pass coefficients c(k), all c(k) depend on the data and are not affected by the nonlinear predictor. Then reuse these low-pass coefficients to predict the odd samples, which gives the high-pass coefficients d(k). We use a linear update filter and let only the choice of predictor depend on the data. The selection criterion of minimizing the squared error, an optimal prediction operator is selected for a transforming sample so that the used wavelet function can fit the transient features of the original signal.

In the signal denoising, apply various thresholds to modify the wavelet coefficients at each level. The wavelet coefficients are modified via soft-thresholding with universal threshold at each level.

Application

The proposed method is applied to extract feature of the diesel engine piston-liner wear fault. According to the fundamentals of diesel engines, vibrations have a close relationship with the impact of the piston-liner. The characteristics of vibrations generated by a 6 cylinders diesel engine were measured by accelerometer mounted on the cylinder body of cylinder 3 correspond to the top dead center, we collected three kind vibration signals from the same cylinder, which represent the engine no wearing, slightly wearing, and serious wearing states. All data were sampled at 25.6 kHz, and the analyzing frequency is 10 kHz. The rotating speed of the diesel engine is 1100 r /min around. Fig.1 a) ~ c) show the vibration signals of the engine no wearing, slightly wearing, and serious wearing situation. From the comparison in the time domain, we can see that the amplitude peaks of no wearing and slightly wearing signals are about the same in the time domain, no distinctness features. But the serious wearing signal's is the highest.

From the Hilbert marginal spectrum shown in Fig.1 d) ~ f). we can see that the marginal spectrum offers a measure of the amplitude distribution from each instantaneous frequency. For no wearing cylinder, the energy of the signal obvious distributes in a lower frequency area which is limited to a range of 2kHz. For slightly wearing cylinder, the lower frequency energy content is low due to leakage of combustion, and much energy distributes in a higher frequency area (5kHz~7kHz) generated by the occurrence of piston slap. For serious wearing cylinder, the peaks of energy of the signal are concentrated on the higher frequency area due to increasing the strength of piston slap generated by the piston-liner wearing, whereas the lower frequency energy content decrease due to increasing the leakage of combustion.

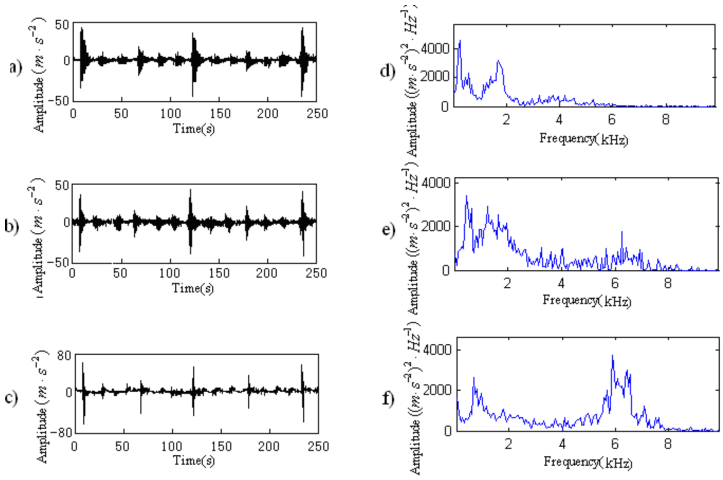

Fig. 1. Vibration signals of diesel engines and Hilbert marginal spectrum. a)~c) vibration signals of no wearing、slightly wearing、Serious wearing, d)~f) Hilbert marginal spectrum of corresponding a)~c).

Conclusion

The second generation Wavelet transform can overcome the denoising disadvantage of traditional wavelet transform and is adopted to remove noise. It can reduce the mode mixture in EMD, improve the quality of decomposition and obtain a much better decomposition performance. The proposed method can be applied to extract the fault characteristic information of the piston-liner wearing vibration signal effectively.

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