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Applying empirical mode decomposition (EMD) and entropy to diagnose circuit breaker faults

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ABSTRACT

In this paper, a new method to extract characteristic parameters from vibration signal of HV (high voltage) CB (circuit breakers) is proposed based on the empirical mode decomposition (EMD)-entropy. First, the normal signal and several fault signals are decomposed with empirical mode, and then extraction and selection the IMF function. Second, calculating the signal envelope after selection in IMF using Hilbert method. Finally, on each envelope signals using time integral of entropy, acquiring the EMD-characteristic entropy vector. The fault signal characteristic entropy vector and normal signal's comparison determine fault types. In practice, this method is very convenient, and can be applied directly to diagnose the fault signals and its species.

1. Introduction

Empirical mode decomposition, first proposed by Huang et al. [1], is a kind of adaptive signal decomposition technique using the Hilbert–Huang transform (HHT) and can be applied with nonlinear and non-stationary time series. Recently, it has been successfully applied in biomedicine, geophysics, equipment fault diagnosis and other fields, and good results have been achieved [2–6].

During the past decade, research on fault diagnosis of mechanical equipment was increasingly rising; especially the study on vibration signals that based on Fault Diagnosis has become a hot spot [7–10]. Using wavelet packet analysis method of vibration signal processing circuit breaker action, Chen and co-workers [7] extracted vibration signal in the characteristic energy entropy of each frequency band, and established the diagnosis model of neural network for fault diagnosis that based on vibration signal of circuit breaker. Using Hilbert Huang transform processing of bearing vibration signals. Xiong [8] obtained the time frequency energy three-dimensional Hilbert spectrum, and the experiments proved that as a powerful tool for bearing fault, the characteristic spectrum can reveal the bearing time-frequency characteristics under different conditions. According to the energy distribution of high frequency components extracted from the empirical mode decomposition. Li [9] proposed a method of fault feature extraction based on the energy entropy of intrinsic mode functions. Experimental results show the effectiveness of circuit breaker fault diagnosis.

As a consequence, this paper presents a method based on EMD and information entropy. The signal envelope of the intrinsic mode function of empirical mode decomposition is segmented according to time principle, then calculating energy entropy of each section, finally, the energy entropy is used as a feature vector to Fault diagnosis. At the same time, the simulation and experiment results are also been proposed.

The paper unfolds as follows. Section 2 describes related works about EMD, end effect and end condition methods, indicating how end effect occurs and why it is important. Sections 3 and 4 briefly review extraction of signal envelopes and information entropy. Section 5 illustrates the research design on data source, preprocessing, input selection, methodologies implementation, and experimental procedure in details. Following that, in Section 6, the experimental results are discussed. Finally, Section 7 summarizes this work and come to conclusion.

2. Empirical mode decomposition

Intrinsic-mode functions (IMF) and the sifting process are the two key parts of the EMD technique. The term "intrinsic-mode function" is used because it represents the oscillation mode embedded in the data. An intrinsic-mode function is a function that satisfies two conditions [4,10]:

1) The number of extrema and the number of zero crossings should be equal or keep the difference no more than one.

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Table 1
the Process of EMD.

	IMF_1	IMF_2	IMF_3	...	IMF_n
	$X(t)$	$X(t)-c_1=r_1$	$r_1-c_2=r_2$	...	$r_{n-2}-c_{n-1}=r_{n-1}$
0	$X(t)-m_1=h_1$	$r_1-m_2=h_2$	$r_2-m_3=h_3$	...	$r_{n-1}-m_n=h_n$
1	$h_1-m_{11}=h_{11}$	$h_2-m_{21}=h_{21}$	$h_3-m_{31}=h_{31}$	...	$h_n-m_{n1}=h_{n1}$
2	$h_{11}-m_{12}=h_{12}$	$h_{21}-m_{22}=h_{22}$	$h_{31}-m_{32}=h_{32}$	...	$h_{n1}-m_{n2}=h_{n2}$
3	$h_{12}-m_{13}=h_{13}$	$h_{22}-m_{23}=h_{23}$	$h_{32}-m_{33}=h_{33}$	...	$h_{n2}-m_{n3}=h_{n3}$
...	...	...	...	...	...
k	$h_{1(k-1)}-m_{1k}=h_{1k}$	$h_{2(k-1)}-m_{2k}=h_{2k}$	$h_{3(k-1)}-m_{3k}=h_{3k}$	...	$h_{n(k-1)}-m_{nk}=h_{nk}$
IMF	$h_{1k}=c_1$	$h_{2k}=c_2$	$h_{3k}=c_3$	...	$h_{nk}=c_n$

2) The local average defined by the average of the maximum and minimum envelopes is zero, i.e., both envelopes are locally symmetric around the envelope mean.

In essence, the EMD method is how to determine the instantaneous equilibrium position based on time series, the average of the upper and lower envelope. And then the non-stationary signal is decomposed into a set of linear and stationary IMF. The Process of EMD as shown in Table 1.

Given a signal $x(t)$, the starting point of the EMD is the identification of all the local maxima and minima. All the local maxima are then connected by a cubic spline curve as the upper envelope $e_u(t)$. Similarly, all the local minima are connected by a spline curve as the lower envelope $e_l(t)$. The mean of the two envelopes is denoted as $\mathrm{m}_l(t)=[e_u(t)+e_l(t)]/2$ and is subtracted from the signal. Thus, the first proto-IMF $h_1(t)$ is obtained as:

$$h_1(t)=x(t)-m_1(t) \tag{1}$$

The above procedure for extracting the IMF is referred to as the sifting process. Since $h_1(t)$ still contains multiple extrema in between zero crossings, the sifting process is performed again on $h_1(t)$. This process is applied repetitively to the proto-IMF $h_k(t)$ until the first IMF $c_1(t)$, which satisfies the IMF condition, is obtained. Some stopping criteria are used to terminate the sifting process. A commonly used criterion is the sum of difference (SD) [11].

$$SD=\frac{\sum_{t=0}^{T}\left|h_{k-1}(t)-h_k(t)\right|^2}{\sum_{t=0}^{T}{h_{k-1}}^2} \tag{2}$$

When the SD is smaller than a threshold, the first IMF $c_1(t)$ is obtained, which is written as

$$x(t)-c_1(t)=r_1(t) \tag{3}$$

Note that the residue $r_1(t)$ still contains some useful information. We can therefore treat the residue as a new signal and apply the above procedure to obtain the equation below:

$$r_{i-1}(t)-c_i(t)=r_i(t) \qquad i=1,\ldots,N \tag{4}$$

The whole procedure is terminated when the residue $r_N(t)$ is either a constant, a monotonic slope, or a function with only one extremum. Combining Eqs. (3) and (4) yields the EMD of the original signal:

$$x(t)=\sum_{n=1}^{N}c_n(t)+r_N(t) \tag{5}$$

The result of the EMD produces N IMFs and a residue signal. For convenience, we refer to $c_n(t)$ as the nth-order IMF. By this convention, lower-order IMFs reflect fast oscillation modes, while higher-order IMFs typically represent slow oscillation modes. If we interpret the EMD as a time scale analysis method, lower-order IMFs and higher-order of IMFs correspond to the fine and coarse scales, respectively.

3. Extraction of signal envelopes

A lot of mutation information in signals is often embodied in the envelopes of signals, and the high-frequency components in vibration signals are the carrier wave of envelopes. Hilbert method is often used to extract the envelopes of signals in mechanical fault diagnosis [12,13].

For a real signal, this is defined as the Hilbert transform:

$$\hat{x}(t)=\frac{1}{\pi t}\cdot x(t)=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}d\tau \tag{6}$$

The analytic signal of a signal is defined as:

$$g(t)=x(t)+j\hat{x}(t) \tag{7}$$

where $\hat{x}(t)$ is Hilbert transform of $x(t)$, then the amplitude of $g(t)$is:

$$A(t)=\sqrt{x^2(t)+\hat{x}^2(t)} \tag{8}$$

which is the envelope of $x(t)$.

4. Application of entropy

The uniformity of probability distribution of system information is reflected by information entropy. The greater the entropy value H is, the more uniform information distribution is, and the greater the disorder degree of the information is. Therefore, it can also be used to describe the uncertainty degree of the system [14,15].

Let an information system has N random information sources $x_1,x_2,\ldots,x_N$, and the probability that each information source appears in the whole system is $p_1,p_2,\ldots,p_N$, respectively. Then its information entropy is defined as follows

$$H=-\sum_{i=1}^{N}p_i\log p_i \tag{9}$$

Fault diagnosis of circuit breaker is essential for normal state and fault state to distinguish. The fault can be regarded as different mutations in the normal state. According to this property, we can use the piecewise approach to achieve entropy extraction. This is in this paper according to characteristic entropy time segmented [16–18] extraction method, the principle as shown in Fig. 1.

In Fig. 1, *Signal*1 as normal signal envelope, *Signal*2 as the fault signal envelope. On the *Signal*1, *Signal*2 were segmented according to time period principle, each of them has three segments *Seg*1, *Seg*2, *Seg*3. Because the *Signal*2 relative to the *Signal*1 state is changed, so the *Signal*2 *Seg*1, *Seg*2, *Seg*3 energy relative to the *Signal*1 *Seg*1, *Seg*2, *Seg*3 energy has also changed, namely energy distribution changes. So we will change *Signal*1, *Signal*2 corresponding to each segment of the transformation of the change of energy distribution uniformity.

5. Methodologies

The steps of fault diagnosis with EMD-feature entropy fault diagnosis are as follows: