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Analysis of the partial discharge of ultrasonic signals in large motor based on Hilbert-Huang transform

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ABSTRACT

Partial discharge (PD) is one of the main diagnosis methods for the insulation aging of large motors. A data compression denoising method based on the empirical mode decomposition (EMD) algorithm is proposed according to the weak and large disturbances of large motor PD signals. A simulation model is constructed to verify the effectiveness of the proposed algorithm. Furthermore, the denoising effect of the proposed algorithm is compared with that of the db2 and db8 wavelets in the experiments. The simulation and experimental results show that a data compression denoising algorithm based on EMD can achieve the same denoising effect with those based on db2 and db8 wavelets. The proposed algorithm is even better in terms of relative error and mean square error. For actual signal processing, the data compression denoising algorithm is better than the other algorithms and does not lose the original signal energy. The PD ultrasonic signals are spectrally analyzed by using HHT, and signal energy distribution in time and frequency can be clearly described. The main PD ultrasonic signal characteristics can be extracted currently from the marginal and Hilbert spectra. The results of this study will be helpful for the diagnosis of PD faults in large motors.

1. Introduction

Large electric machines play a key role in electric power systems and in every industrial production department. Thus, the safe operation of this machine has received increasing attention from researchers. The motor of these machines is influenced by thermal, electrical, and mechanical stresses and the external environment; thus, a weak insulation produces partial discharge (PD) in the local field. A long discharge duration will eventually cause insulation breakdown, thus leading to motor damage. According to Japanese and European statistics, 15–35% of motor faults are related to stator winding insulation [1]. To date, the PD method is used locally and abroad to diagnose the aging state of the main insulation of high-voltage motor windings. This method has been used for more than 70 years and has become a common monitoring technique [2,3]. However, the operation environment of a motor has weak PD signals with great interference. A PD monitoring system does not only include a highly sensitive sensor and signal processor but also an algorithm that efficiently eliminates noise in the software to obtain a real PD signal.

The wavelet analysis method is usually used in algorithms to eliminate noise for PD in the last few decades [4–7]. Considerable research works have been conducted on eliminating noise from PD signals [4–12]. Not only wavelet and complex wavelet transforms but also a direct notch filter is applied to suppress PD signal interferences. The results show a significantly improved signal–to–noise ratio (SNR) [8–12]. Signal processing algorithms have changed rapidly in recent years. In particular, Hilbert–Huang transform (HHT) theory is proposed and applied. This theory is a major breakthrough in non-stationary signal processing. Local and foreign researchers have used HHT as a new signal processing tool in fields such as sound analysis [13], time-series analysis of financial data [14], low-frequency oscillations of power systems [15], mechanical fault diagnosis [16], seismic signal analysis [17], and medical signal processing [18].

PD ultrasonic signals in large motors are typical non-stationary signals. Furthermore, HHT depends on the signal itself. Therefore, the decomposition of signal data has real physical meaning and high time–frequency resolution. This study proposes a data compression method that uses HHT to eliminate noise in PD ultrasonic signals. Furthermore, HHT is used to analyze two types of PD signals. This analysis is the preliminary preparation for the fault feature extraction and diagnosis of large motor insulation faults.

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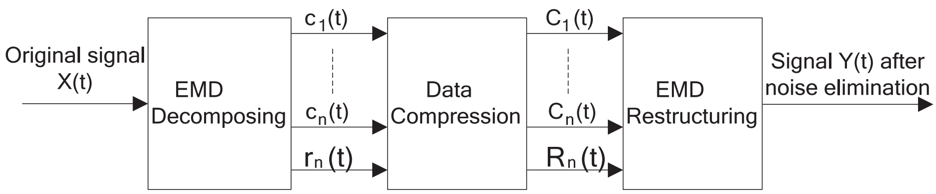

Fig. 1. Structure diagram of EMD data compression de-noising.

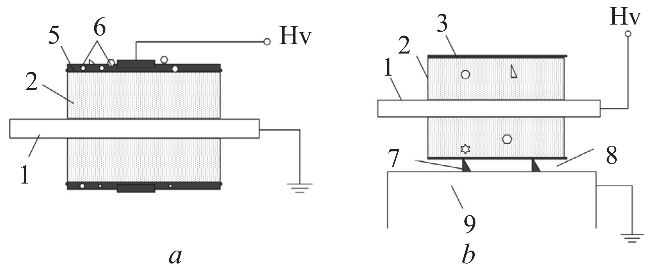

Fig. 2. Experimental PD model. 1 – Copper conductor; 2 – main insulation layer; 3 – low-resistance corona-preventing layer; 4 – cavity; 5 – high-resistance corona-preventing layer; 6 – oil-contaminated or damaged corona-preventing layer; 7 – point contact; 8 – gap; and 9 – stator core. (a) Experimental model of surface PD; (b) Experimental model of slot PD.

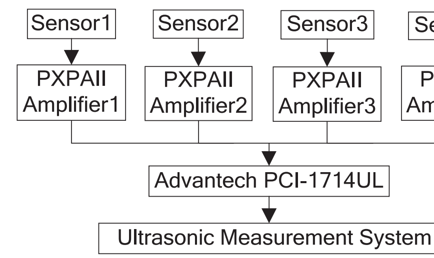

Fig. 3. System framework.

2. HHT and signal processing methods

2.1. Basic HHT theory

HHT is a novel analysis method for non-linear and non-stationary data [19]. Empirical mode decomposition (EMD) is a key part of the HHT method. In EMD, any complicated data set can be decomposed into a finite number of intrinsic mode functions (IMFs) that admit well-behaved Hilbert transforms. An IMF is as a function that satisfies the following conditions [20]: (1) the number of extrema and zero crossings in a whole data set is equal or should differ by one at most; (2) the mean value of an envelope defined by using local maxima and local minima is zero at any data point.

Huang [19,20] states that the Hilbert transform of these functions are “well-behaved” and can be used to calculate instantaneous frequencies. The EMD algorithm is based on a recursive structure called sifting. The careful application of sifting produces physically plausible IMFs. Given any signal X(t), IMFs are obtained by the following steps [19,21,22]:

(1) $i = j = 1$ is initialized.
(2) All of the local extrema of X(t) is identified and categorized into two sets: the maxima and minima.
(3) All local maxima is connected by a cubic spine line to form an upper envelope $X_{upper}(t)$. The procedure for local minima is repeated to form a lower envelope $X_{lower}(t)$. Both upper and lower envelopes should encompass all data between the envelopes.
(4) The mean signal $M_{i,j}(t) = (X_{upper}(t) + X_{lower}(t))/2$ is calculated.
(5) The mean $M_{i,j}(t)$ is subtracted from X(t) to obtain the first candidate to IMF $H_{i,j}(t)$: $H_{i,j}(t) = X(t) - M_{i,j}(t)$.
(6) Sifting conditions are compared: if $H_{i,j}(t)$ satisfies the definition of an IMF, the process is halted; otherwise, $H_{i,j}(t)$ is considered the signal for the next round of sifting and $j = j + 1$. The algorithm then restarts from Step 2. After resifting up to k times, the first IMF is denoted by $c_i(t)$ if $H_{i,k}(t)$ becomes an IMF.
(7) The criteria is stopped: residue $r_i(t) = X(t) - c_i(t)$ is set; if $r_i(t)$ is less than a certain predetermined value or becomes non-oscillatory, then the number of IMFs depends on the signal and is not fixed, thus indicating that the sifting process can be stopped. Otherwise, $r_i(t)$ is considered the signal in the subsequent sifting process and $i = i + 1$. The algorithm then restarts from Step 2. The process ends when $r_n(t)$ has one extrema at most after n times of repetition.

Table 1
Operating specifications of ultrasonic sensor.

Item	Parameter
Operating frequency range	30–140 kHz
Resonant frequency	95 kHz
Sensitivity	> 80 dB

In summary, the following is obtained:

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

Thus, the original signal X(t) is decomposed into n IMFs and residue $r_n(t)$, which can be either an adaptive trend or a constant.

2.2. EMD-based denoising

IMFs and a residual function are obtained after the original signal is decomposed by the EMD algorithm. IMFs comprise several different frequency segments. These segments serve as bases for a spatial–temporal filter of the original signal, which is composed of different noise and target signal frequencies [23,24]. A spatial–temporal filter is constructed on the basis of the frequency of IMF components to set the filter parameters, the IMF components of noise can then be directly eliminated to obtain a useful target signal only. However, the actual original signals collected in the field often include noise signals that cover the whole frequency range of a target signal. Therefore, realizing ideal noise elimination by using only temporal and spatial filters is impossible. Furthermore, a target signal is sometimes removed, thus resulting in the loss of the original signal energy.

For the wavelet denoising principle, the high-frequency part of a signal will be compressed when wavelets decompose the original signal. By setting the data compression ratio, the high-frequency part of signal wavelet decomposition is assumed to be less than a set value and the subsequent high-frequency parts are expressed as noise. Thus, high-frequency term is set to zero. Similarly, for the EMD data compression algorithm, the EMD of the original signal is decomposed into numerous different frequency segments of the IMF and residual function. At this point, noise is decomposed into different frequency segments of the IMF and residual amount, and less noise occurs in IMF decomposition than in the original signal. Therefore, each IMF component that is less than a set data compression value is considered noise and is set to zero. Finally, each IMF is reconstructed by using EMD after data compression to eliminate noise in the original signal. The principle block diagram is shown in Fig. 1. Therefore, reconstructed signal Y(t) can be expressed as