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Research on PD Signals Denoising Based on EMD Method

***Abstract**. Adaptive decomposition of complex data is realized and intrinsic mode function (IMF) components that reflect different scales information are gained through empirical mode decomposition (EMD) of partial discharge (PD) signals. The gained intrinsic mode function components are reconstructed after the wavelet threshold processing to reduce the interference of noise. This partial discharge signals denoising method has achieved good effect in the processing of simulation and measured data, which proves the effectiveness and superiority of the method.*

***Streszczenie.** Przedfstawionbo metode adaptacyjnej dekompozycji danych złożonych na przykładzie sygnału wyładowania niezupełnego. Do usunięcia wpływu szumów wykorzystano analizę falkową. (**Badania odszumiania sygnału wyładowania niezupełnego bazujące na metodzie empirycznej dekompozycji EMD**)*

Keywords: partial discharge, empirical mode decomposition, intrinsic mode function.
Słowa kluczowe: wyładowanie niezupełne, rozkłady empiryczne, wewnętrzna funkcja trybu.

Introduction

For large power equipment, partial discharge monitoring is an important means of early fault prediction. The partial discharge signals from the early malfunction of the internal power equipment are very weak. They are often surrounded by powerful noise source. How to eliminate the noise interference of partial discharge signals in power equipment is one of the most important issues of the current studies [1]. The traditional denoising method relies on the prior knowledge of source signal or the precise identification of transmission system, which often encounters difficulties in real applications [2-4]. Wavelet transformation has the features of low entropy, multiresolution, derelevance and flexible choice. It has unique effect especially in the information processing noise reduction. But the wavelet threshold noise reduction method can't better eliminate the pulse wave of pointed noise in magnetic circuit device. This is also one of the problems that restrict the signal processing of geomagnetic measurements.

Empirical mode decomposition [5] was first proposed in 1998 by Huang E of NASA. It is a time-frequency analysis method of processing a nonlinear non-stationary signal. Nunes et al applied the idea of one-dimension EMD to the field of image processing and proposed 2-dimensional empirical mode decomposition methods in 2003 [6]. The method is widely applied in the fields of nonlinear system analysis, earthquake engineering and structural nondestructive testing, geophysics, meteorology and biomechanics [7, 8], which completely changes the helpless dilemma in the nonlinear and unsteady signal processing. The paper uses the adaptive ability of EMD to decompose the partial noise signals, then analyzes each Intrinsic Mode Functions value generated after decomposition and proposes the wavelet threshold denoising method based on empirical mode decomposition. The experimental results show that the method not only increases the denoising ability but also can hold more characteristics of partial discharge signals.

Basic principle

EMD method is a brand-new processing method for non-stationary signal. Its starting point is to analyze the IMF from complex signals. Any complex signal is consisted of FA-AM. For non-stationary signal $x(t)$, if $x_k(t)$ represents the change of amplitude and frequency at the same time, it can be expressed in the following form [9]:

(1) $$x(t) = \sum_{k=1}^{K} X_k(t)$$

The gained IMF needs to meet the following two conditions: a) for the whole data analysis, the discrepancy of extremum points and zero points is less than 1, b) at any time, the average of envelope curve formed by partial maximum points and that formed by partial minimum points is zero, that is, the average value of IMF tends to be zero. The method essentially distinguishes the internal surge functions according to the features of scale and decomposes the data correspondingly [10]. The decomposed IMF components are ordered by frequency. The first separated IMF components have the highest frequency while the finally separated IMF components have the lowest frequency. The remained component is only a monotonic function with only one extreme point. The trend of original signal is represented. The up and down envelop curves are partially symmetric with the time axis and any two IMF are independent. Empirical mode decomposition method processes the data smoothly based on the scale characteristics of the signal itself. In theory, it can decompose signals of any type. Compared with Fourier analysis based on Prior function basis and wavelet analysis, EMD does not need to preset primary function. It is a multiscale time-frequency localization analysis method with adaptability [11].

Implementation

Empirical mode decomposition method decomposes complex signals into the sum of each IMF and decomposes any complex signal $x(t)$ through the following steps:

Determine all local extreme points of signal $x(t)$ and use three sample lines to connect all local maximum and local minimum point form the up and down envelop curves. The average of up and down envelop curves is recorded as m_1, then:

(2) $$x(t)m_1 = h_1$$

If h_1 cannot meet the condition of IMF, take h_1 as original signal and repeat the first step to get the average of up and down envelop curve, m_{11}: Then, judge whether $h_{11} = h_1 - m_{11}$ meets the condition of IMF, if it does not, repeat the step for K times to get $h_{1(k-1)}$-m_{1k}=h_{1k} and make h_{1k} meet the conditions of IMF. Take c_1=h_{1k}, then c_1 is the first components that meets the condition of IMF of signal $x(t)$.

Separate $x(t)$ from c_1 to get:

(3) $$r_1 = x(t) - c_1$$

Take r_1 as original date to repeat the second and third step to get the second component c_2 that meets the condition of IMF. Repeat the steps for n times to get n components that need the IMF condition of signal $x(t)$. So, there will be:

$$\left.\begin{array}{c} r_1 - c_2 = r_2 \\ \vdots \\ r_{n-1} - c_n = r_n \end{array}\right\} \tag{4}$$

When r_n becomes a monotone function which can't extract components that meet IMF conditions, the loop ends. So it can be gained from (3) and (4):

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{5}$$

where: r_n– residual component which represents average trend of signals.

From the above process, it can be seen that the decomposition process EMD is actually a *screening* process. In the process of *screening*, the partial high-frequency signals are extracted. It has the characteristics of multiresolution.

The termination conditions of empirical mode decompositions are still not very clear. According to decomposition threshold standard of the scanning stop determined by Huang E, it can be realized by the limit of standard deviation (SD):

$$SD^2 = \sum_{x=0}^{X}\sum_{y=0}^{Y}\left[\frac{\left|(h_{k-1}(x,y) - h_k(x,y))\right|^2}{h_{k-1}^2(x,y)}\right] \tag{6}$$

There is no fixed standard for SD value which is usually between 0.2-0.3.

Reconstruction of Intrinsic Mode Functions

From the previous EMD principles, the gained IMF is shown as the hierarchy filtering from high frequency to low frequency. If the original signal $x(t)$ is in Gaussian distribution and its IMF is also in Gaussian distribution [12]. Noise signals mainly concentrated in the first few layers of IMF components so signals can be extracted from the details construction from the bottom to the top. EMD method starts from the time scale features. It first separates the characteristic time scale in the signals from the smallest modal and then separates the bigger modal of characteristic time scale and finally the biggest characteristic time scale. Therefore EMD method can be seen as a set of high-pass filters [13, 14]. Figure 1 offers the flow chart of IMF details construction.

For the interference suppression of partial discharge signals, the information of partial discharge signals can be clear seen by the way of IMF reconstruction. But due to the lack of threshold value, the amplitude of the reconstructed partial discharge signal will be reduced, which can not represent the real information of the signals. Therefore, the paper adopts the method of reconstructing IMF after the threshold. The noise concentrates in the front layers of IMF components after EMD decomposition. So the adaptive selection method of using threshold to treat layers and then reconstructing is adopted, which can extract precisely the partial discharge signals. Its specific algorithms are as follows:

Get the IMF component in response to EMD. Set threshold processing layer as m. The value of m ranges from 1 to the total layers of IMF.

Make threshhold process to the value from imf(1) to imf(m), its specific threshold value is selected by wavelet threshold.

Reconstruct the IMF component IMF after processing to get all signals.

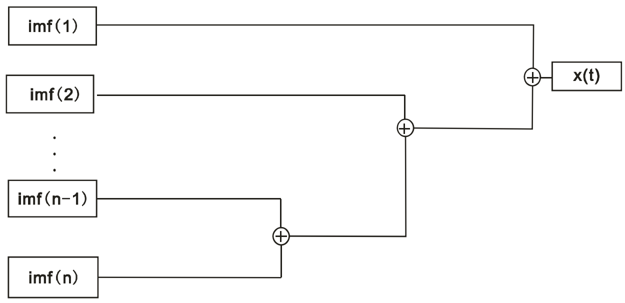

Fig.1. Reconstruction of IMF

Selection of Wavelet Threshold

Wavelet changes all have good local characteristics in both time and domain frequency and at the same time can change frequency resolution and time resolution. Suppose the signal f_i with the length of N is polluted by e_i then the measured signal with noise is:

$$X_i = f_i + e_i \quad i=1,2,\ldots,N \tag{7}$$

where: e_i – the Gaussian white noise that follows N $(0, \sigma^2)$.

After the signal X_i with noise is decomposed with wavelet, the energy of partial discharge signals mainly concentrate in limited groups of coefficients. After wavelet transformation, the maximum value of modules increases with the increase of scale. The energy of interference signal is distributed throughout wavelet domain. After wavelet transformation, the maximum value of modules decreases with the increase of scale. The wavelet coefficients of noise mainly concentrate in small scale while the wavelet coefficients of original signal concentrate in large scale. Wavelet denoising is to estimate the wavelet change coefficient of original signals and then reconstruct.

The Benchmark of Processing Technology Comparison

To compare the effects of EMD and wavelet de-noising, 2 evaluation indexes are adopted here.

The mean square error (MSE) [15]:

$$e_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x(i) - \hat{x}(i))^2 \tag{8}$$

where: N– the total length of signal, $x(i)$– the original signal without noise, $\hat{x}(i)$ – the estimated value of reference signal that is, signals denoised.

Cross correlation coefficient [16]:

$$R(m) = \sum_{i=0}^{N-|m|-1} x(i)\hat{x}(i+m) \tag{9}$$

where: $R(m)$– the denoised signal which is similar to waveform of the original reference. In the follow-up of calculation, take m=0 and all results are normalized.

Simulation Signal Analysis

In theory studies, partial discharge pulse can normally use four mathematical models to simulate: single index attenuation model, single exponential oscillation attenuation model, double exponential decay model and double exponential oscillation attenuation model. The actual partial discharge signals are often shown in the form of index attenuation oscillation, so the following partial discharge signals expression is adopted [17]:

Single exponential decay oscillation form:

$$S_1(t) = Ae^{-t/\tau}\sin(2\pi f_c t) \tag{10}$$

Double exponential decay oscillation form:

$$S_2(t) = A(e^{-1.3t/\tau} - e^{-2.2t/\tau})\sin(2\pi f_c t) \tag{11}$$

where: A– pulse strength parameters, τ– attenuation constant, f_c– oscillation frequency which is 1MHz.

Residual noise is simulated with white noise during simulation. Figure 2 gives simulation signal with sampling frequency of 10MHz. Figure 2 is the ideal partial discharge signals with the amplitude A of 0.2mV.

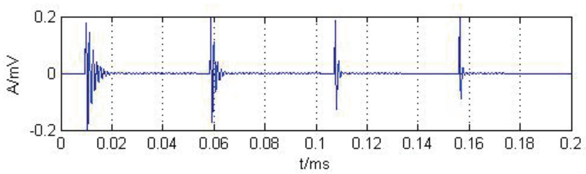

Fig.2. Ideal discharge signals

The added white noise $e(t)$ is the Gaussian random number with the amplitude of (-0.05, 0.05). The waveform is shown in Figure 3.

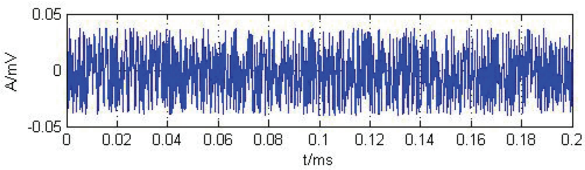

Fig.3. White noise signals

Obviously, narrowband interference and white noise have submerged the signal completely. Discharge signals and the specific discharge type can not be told. Effective data can be gained with denoising processing.

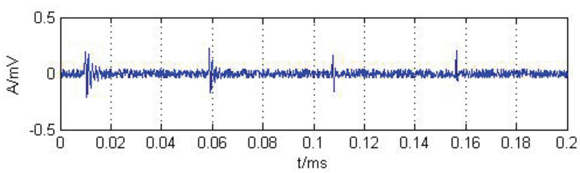

Fig.4. Partial discharge signals with noise

9 IMF and 1 Residual component are gained through the EMD of the above partial discharge signals with noise as is shown in Figure 5. Among them, the first IMF component represents the feature of noise with high frequency. The second and third IMF represents the main features of partial discharge signals.

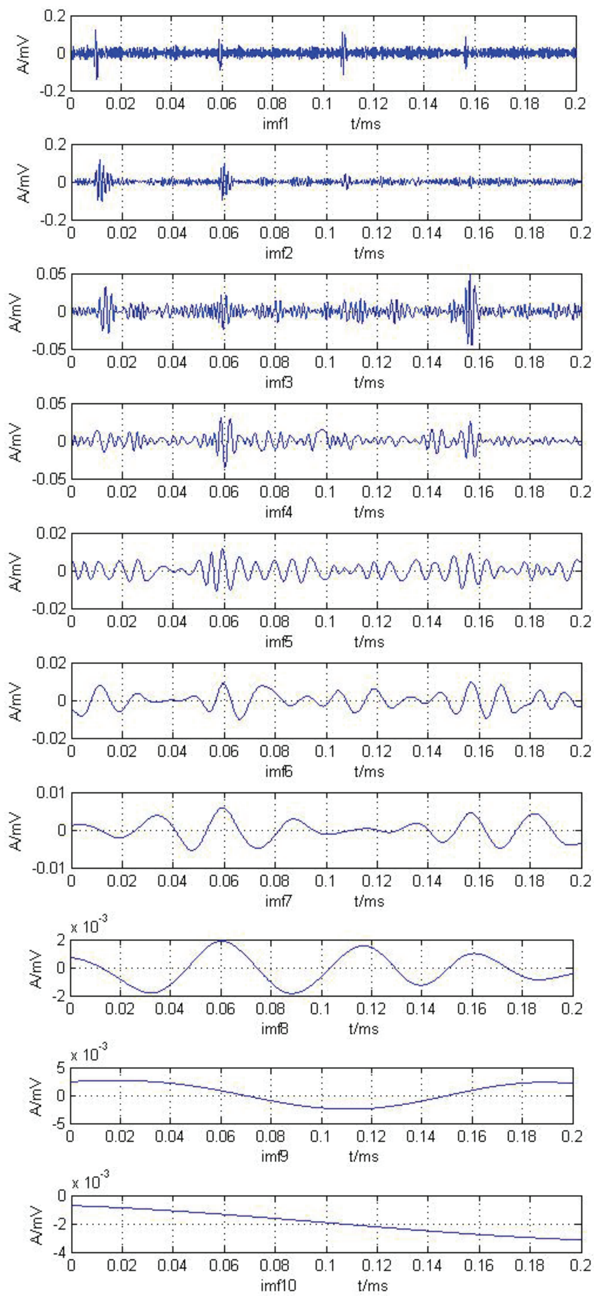

Fig.5. Decomposition of signal by EMD

Denoising Performance Comparison

To illustrate the superiority of the method in the paper in the aspect of denoising, the paper analyzes the simulation signal with the method of empirical mode decomposition, wavelet threshold denoising and wavelet threshold denoising based on empirical mode decomposition. The waveform after the denoising is shown in Figure 7 to Figure 9. Among them, Figure 7 is the signal figure that is to EMD to decompose the noise signal and filter it with soft threshold for the first 3 IMF and then directly sum the filtered signals. In Figure 8, select dB8 wavelet as wavelet section to do 5 layers decomposition. Soft threshold is used for processing. Figure 9 is the signal waveform with the new denoising method. When the three methods of denoising are compared, the extracted signal with the EMD denosing method contains more information about the original partial discharge signal and keep a great amount of noise information, which is not beneficial for the further processing. Figure 8 uses the method of wavelet threshold denoising. The noise is filter but at the same time useful partial discharge signals are filtered. Confused partial discharge signals are also produced. Figure 7 uses the new method of wavelet threshold denoising based on empirical mode decomposition.

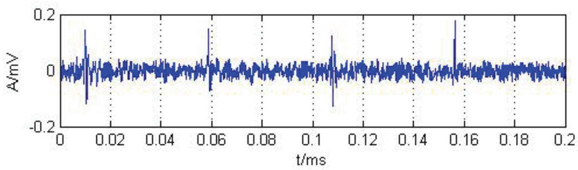
Fig.6. Partial discharge signals after EMD denoising

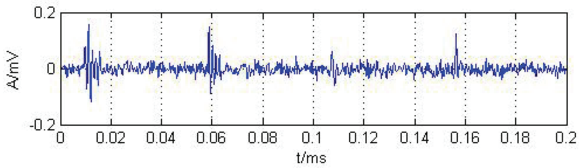
Fig.7. Partial discharge signals after wavelet threshold denoising

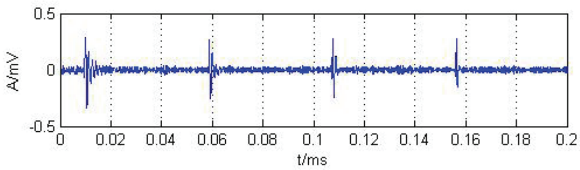
Fig.8. Partial discharge signals based on the wavelet threshold denoising of EMD

The results show that the wavelet threshold denoising based on empirical mode decomposition is better in effect than empirical mode decomposition. It is close to wavelet threshold denoising. Specific index can be seen in Table 1.

Table 1. Denoising performance of wavelet and EMD

Algorithm	e_{MSE}	R
EMD combined with wavelet	1.7308×10^{-4}	0.8034
Db8	2.1642×10^{-4}	0.7573
EMD	2.3674×10^{-4}	0.7206

Conclusion

EMD is a recent analysis method for nonlinear and no stationary signals. It can divides frequency according to the physical forms of the signals. The paper combines it and threshold value denoising. EMD is used in the decomposition of partial discharge signal. The result of the simulation and field data processing of partial discharge signals show that compared with traditional denoising methods, empirical mode decomposition based on wavelet threshold denoising algorithm can eliminate noise more effectively with less signal distortion. It is suitable for the application of engineering. In the partial discharge denoising, compared with wavelet transform, the EMD has the following features: a) the algorithm is simple and quick, IMF is gained through the direct separation from original signal. Its physical meaning is obvious; b) it is not based on Fourier transform, and is not affected by Fourier transform and the limit of uncertainty principle; c) it is not based on the waveform matching principle. The decomposition effect is not affected by the wavelet function selection.

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REFERENCES

[1] Guo J., Wu G.N., Zhang X.Q., The Actuality and Perspective of Partial Discharge Detection Techniques, *Transaction of China Electrotechnical Society*., 20(2005), No. 2, 29-35
[2] Xiao Y., Yu W.Y., Research on Waveform Matching Recognition Algorithm in Partial Discharge Pulse Extraction, *Transaction of China Electrotechnical Society*., 20(2005), No. 5, 87-91
[3] Xu J., Huang C.J., Jin H., Algorithm for Extracting PD Signals Based on a Wavelet-set, *Automation of Electric Power Systems*., 28(2004), No. 16, 36-40
[4] Sun C.X., Li X., Yang Y.M., The Method of Drawing the PD Signals from White Noise by Wavelet Analysis., *Transaction of China Electrotechnical Society*., 14(1999), No. 3, 47-50
[5] Zhong Y.M., QIN S.R., Research on the Uniform Theoretical Basis for Hilbert-Huang Transform, *Journal of Vibration and Shock*., 25(2006), No.3, 40-43
[6] Zhu., Shen Z., Eckermann S.D., Gravity Wave Characteristics in the Middle Atmosphere Derived from the Empirical Mode Decomposition Method, *Geophysical Research*., 102(1997), No.14, 545-561
[7] Nunes J.C., Niang O., Bouaoune Y., Bidimensional Empirical Mode Decomposition Modified for Texture Analysis, *Scandinavian Conference on Image Analysis*., 2003, 171-177
[8] Song L.X., GAO F.J., XI Z.H., Compared and Improved Research of Bidimensional Empirical Mode Decomposition Method, *Journal of Electronics & Information Technology*., 30(2008), No. 12, 2890-2893
[9] Huang N.E., Wu M.C., Long S.R., A Confidence Limit for the Empirical Mode Decomposition and Hilbert Spectral Analysis, *Proceedings of the Royal Society A*., 459(2003), 2317-2345
[10] Song P.J., Zhang J., The Application of Two-Dimensional EMD to Separating Contents of Oceanic Remote Sensing Images, *High Technology Letters*., 9(2001), 62-67
[11] Huang N.E., Wu Z.H., A Study of the Characteristics of White Noise Using the Empirical Mode Decomposition Method, *Proceedings of the Royal Society*., 460(2004), 1597-1611
[12] Yu D.J., Cheng J.S., Yang Y., Application of EMD Method and Hilbert Spectrum to the Fault Diagnosis of Roller Bearings, *Mechanical Systems and Signal Processing*., 19(2005), No.2, 259-270
[13] Judd M.D., Cleary G.P., Bennoch C.J., Power Transformer Monitoring Using UHF Sensors: Site Trials, *Proceedings of the 2006 IEEE International Symposium on Electrical Insulation*., 2006, 145-149
[14] Raja K., Devaux F., Lelaidier S., Recognition of Discharge Sources Using UHF PD Signatures, *IEEE Electrical Insulation Magazine*., 18(2007), No.5, 8-14
[15] Downier T.R., Silverman B.W., The Discrete Multiple Wavelet Transform and Thresholding Methods, *IEEE Trans on Signal Processing*., 46(1998), No.9, 2558-2561
[16] Satishl., Nazneen B., Wavelet-Based Denoising of Partial Discharge Signals Buried in Excessive Noise and Interference, *IEEE Trans on Dielectrics and Electrical Insulation*., 10(2003), No.2, 354-367
[17] Qian Y., Huang C.J., Chen C., Denoising of Partial Discharge Based on Empirical Mode Decomposition, *Automation of Electric Power Systems*., 29(2005), No. 12, 53-60

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