Signal De-noising Based On Empirical Mode Decomposition and a Comparison between EMD and Wavelet Processing

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Abstract:- Digital signal processing has become an important field of computer science and engineering from recent few decades. As the surrounding is always noisy and it is quite impossible to avoid them, it is very essential to implement a good way to de-noise the signal. Empirical mode decomposition is a very popular method of signal de-noising. But there is no mathematical formula to establish the method, the overall success of the method depends on the practical knowledge of the user. On the other hand wavelet is another well-established method of signal de-noising but is comparatively less efficient in some condition than EMD. Here, a hybrid de-noising method is presented by Empirical Mode Decomposition (EMD). 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 de-noising method has achieved good effect in the processing of simulation and measured data, which proves the effectiveness and superiority of the method.

Keywords:- Partial Discharge (PD), Empirical Mode Decomposition (EMD), Intrinsic Mode Function (IMF), Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Wavelet Processing.

I. 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. The traditional de-noising method relies on the prior knowledge of source signal or the precise identification of transmission system, which often encounters difficulties in real applications. Wavelet transformation has the features of low entropy, multi resolution, DE relevance 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 was first proposed in 1998 by Huang E of NASA. It is a time-frequency analysis method of processing a nonlinear non-stationary signal. Nuns et al applied the idea of one-dimension EMD to the field of image processing and proposed 2-dimensional empirical mode decomposition methods.

II. EMPIRICAL MODE DECOMPOSITION METHOD DECOMPOSES

EMD method is a brand-new processing method for non-stationary signal [2][3]. Its starting point is to analyze the IMF from complex signals. Any complex signal is consisted offal-AM. For non-stationary signal *x(t)*, if *xk(t)*represents the change of amplitude and frequency at the same time, it can be expressed in the following form :

$$x(t) = \sum_{k=1}^{K} X_k(t) \quad \ldots\ldots\ldots \text{(i)}$$

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 *m1*, then:

$$x(t)\ m_1 = h_1 \ldots\ldots\ldots\ldots\ldots \text{(ii)}$$

If *h1* cannot meet the condition of IMF, take *h1* as original signal and repeat the first step to get the average of up and down envelop curve, *m11*: Then, judge whether *h11 = h1-m11*meets the condition of IMF, if it does not, repeat the step for *K* times to get *h1*(k-1)-*m1k=h1k* and make *h1k* meet the conditions of IMF. Take *c1=h1k*, then *c1* is the first components that meets the condition of IMF of signal *x(t)*. Separate *x(t)* from *c1* to get:

$$r_1 = x(t) - c_1 \ldots\ldots\ldots\ldots \text{(iii)}$$

Take *r1* as original date to repeat the second and third step to get the second component *c2* 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:

$$r_1 - c_2 = r_2 \ \ldots\ldots\ldots\ldots\ldots \text{(iv)}$$

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$$r_{n-1} - c_n = r_n$$

When *rn* 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):

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

Where: *rn*– 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 multi resolution. 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):

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

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

III. WAVELET THRESHOLD

Coefficients of noise mainly concentrate in small scale while the wavelet coefficients of original signal 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 [1]. Suppose the signal *fi* with the length of N is polluted by *ei* then the measured signal with noise is:

$$X_i = f_i + e_i; \quad \text{Where } i=1,2\ldots,N. \quad \ldots\ldots\ldots \text{(vii)}$$

Where: *ei* – the Gaussian white noise that follows N (0, *σ*2). After the signal *Xi* 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 concentrate in large scale. Wavelet denoising is to estimate the wavelet change coefficient of original signals and then reconstruct.

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

The mean square error (MSE) :

$$e_{MSE} = \frac{1}{N} \sum_{i=1}^{N} (x(i) - \overline{x}(i))\text{^}2 \ldots\ldots\ldots\ldots\ldots \text{(viii)}$$

where: *N*– the total length of signal, *x(i)*– the original signal without noise, *x*ˆ(*i*) – the estimated value of reference signal that is, signals denoised.

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IV. SIMULATION SIGNAL PROCESSING

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 [5].

Single exponential decay oscillation form:

$$s_1(t) = Ae^{-\frac{t}{\tau}} \sin(2\pi f_c\, t) \ldots\ldots\ldots\ldots\ldots\ldots \text{(x)}$$

Double exponential decay oscillation form:

$$s_2(t) = A\left(e^{-\frac{1.3t}{\tau}} - e^{-\frac{2.2t}{\tau}}\right) sin(2\pi f_c t) \ldots\ldots\ldots\ldots \text{(xi)}$$

Where: *A*– pulse strength parameters, τ– attenuation Constant, *fc*– oscillation frequency which is 1MHz.

Residual noise is simulated with white noise during simulation. Figure 1 gives simulation signal with sampling frequency of 10MHz. Figure 2 is the ideal partial discharge signals with the amplitude *A* of 0.2mV.

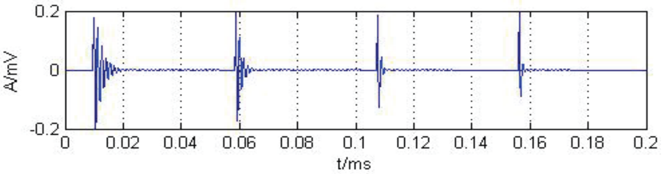

Figure 1. Ideal discharge signals

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 2.

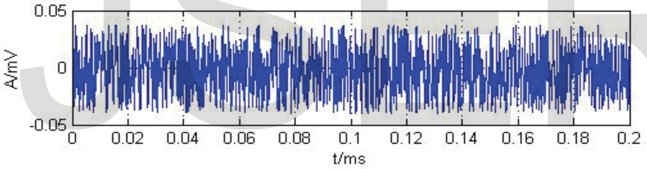

Figure.2. White noise signals

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

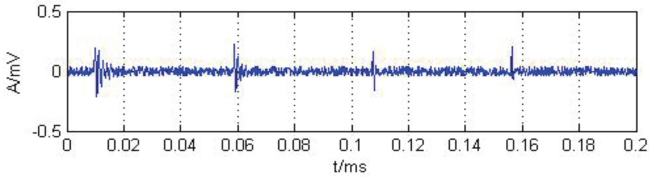

Figure.3. Partial discharge signals with noise

9 IMF and 1 Residual component are gained through the EMD of the above partial discharge signals with noise as is shown in Figure 4. 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.

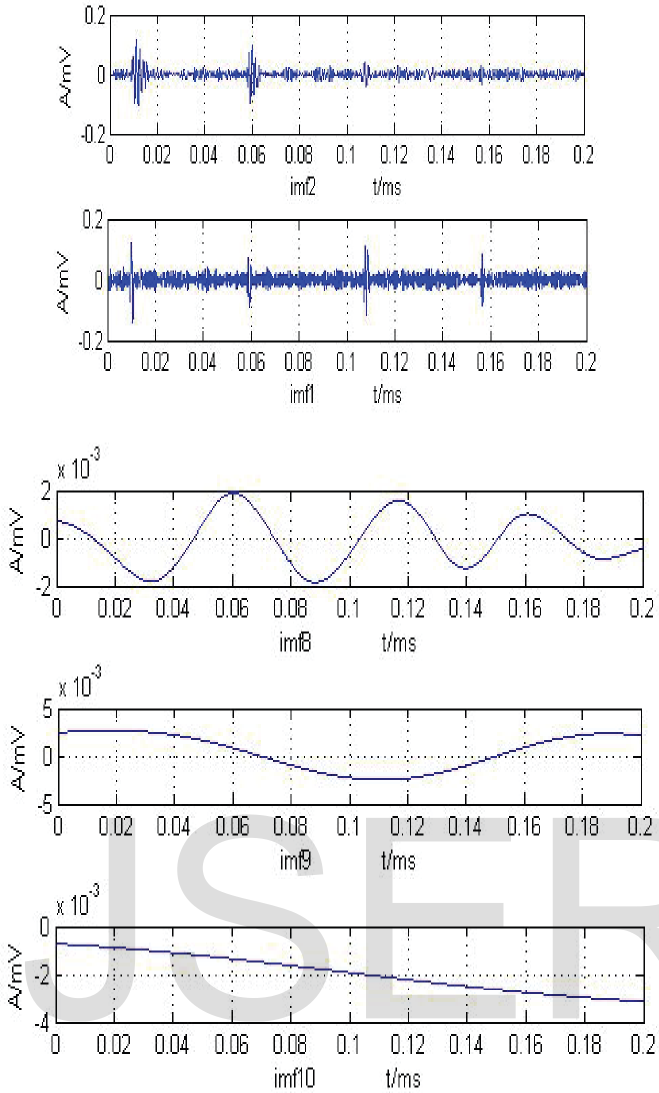

Figure 4. Decomposition of signal by EMD

V. DE-NOISING PERFORMANCE COMPARISON

The result Specific index can be seen in Table 1.lts show that the wavelet threshold de-noising based on empirical mode decomposition is better in effect than empirical mode decomposition [4]. It is close to wavelet threshold de-noising.

Algorithm	e_{MSE}
EMD Combine with Wavelet	0.000173
EMD	0.000236

Table 1. De-noising performance of wavelet and EMD

VI. CONCLUSION

Empirical mode decomposition is efficient but when it is combined with wavelet, it provides the most optimal and noise free signal. EMD is a powerful analysis method for nonlinear and non-stationary signals that divides frequency according to the physical forms of the signals. The thesis combines it with threshold value de-noising. EMD is used in the field of the decomposition of partial discharge signal. The result of the simulation and field data processing of partial discharge signals show that compared with traditional de-noising methods, empirical mode decomposition based on wavelet threshold de-noising algorithm can eliminate noise more effectively with less signal distortion. It is suitable for the application of engineering and processing. In the partial discharged noising, compared with wavelet transform, the EMD yields that the algorithm is simple and quick, IMF is gained through the direct separation from original signal. Its physical meaning is obvious; it is not based on Fourier transform, and is not affected by Fourier transform waveform matching principle. The decomposition effect is not affected by the wavelet function selection .and the limit of uncertainty principle; it is not based on the waveform matching principle. The decomposition effect is not affected by the wavelet function selection. Hence, this method is quite enrich.

REFERENCES

[1]. Paul S Addison, The illustrated wavelet transform handbook, (IOP Pub., 2002).

[2] Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q.,Yen, N.-C., Tung, C. C., and Lu, H. H.1998. "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis." Proc.: Mathematical, Physical, and Engineering Sci., 454 1971, 903–995

[3] Wu, Z., and Huang, N. E. 2004. "A study of the characteristic of white noise using the empirical mode decomposition method." Proc. R. Soc. London, Ser. A, 460 2046 , 1597–1611. 85

[4] Kijewski-Correa, T., and Kareem, A.2006. "Efficacy of Hilbert and wavelet transforms for time-frequency analysis." J. Eng. Mech., 13 210, 1037–1049.

[5] Iffat Ara, Md. Najmul Hossain, Md. Abdur Rahim," ECG Signal Analysis Using Wavelet Transform", International Journal of Scientific & Engineering Research, Volume 5, Issue 5, May-2014, ISSN 2229-5518.