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Empirical mode decomposition based denoising of partial discharge signals

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Abstract: -Empirical Mode Decomposition (EMD) has recently been introduced as a local and fully data-driven technique aimed at analyzing nonstationary signals, by decomposing nonstationary signals into Intrinsic Mode Functions (IMFs). In this contribution, we employ it to process the signals of partial discharge, a typical type of nonstationary signal. Based on the IMFs extracted from the corrupted signal, together with the vector threshold, we propose a novel scheme for denoising. By processing of simulation signals and on-site data, it is demonstrated that the proposed method is effective. What is more, the preliminary comparison with wavelet- based denoising is performed.

Key-Words: - Empirical Mode Decomposition, Intrinsic Mode Function, Vector threshold, Partial discharge, White noise, Denoising

1 Introduction

Detection of partial discharge is of great importance for online monitoring the insulation of large power generators. However, due to the excessive noise existing on site, partial discharge signals are usually overwhelmed. For analyzing the partial discharge and assessing the insulation condition accurately, it is always in the first place to suppress noise[1].

The commonly used method for denoising partial discharge signals in the past decade was wavelet. However, in this contribution, we would not deal with wavelet any more, on the contrary, introduce another method, recently developed by NASA, namely, Empirical mode decomposition (EMD).

EMD, alias Huang transform, pioneered by Huang et al.[2], is designed mainly for analyzing nonstationary signals. The technique adaptively decomposes the signals in a sum of “well-behaved” AM-FM components[2], referred to as Intrinsic Mode Function (IMF). Originally, EMD was developed for analyzing nonlinear and nonstationary signals, but fortunately, it can also be applied to linear and stationary signals. Further, together with Hilbert transform, it shows great power in signal processing, and in NASA’s words, it offers a complete solution to all signal processing needs. Presently, EMD based Hilbert transform (Hilbert-Huang Transform, HHT) has been widely used in various fields (e.g., earthquake, ocean,

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finance analysis), and promising results have been reported[3-5].

In this contribution, we employ EMD to analyze the partial discharge, a typical nonstationary signal. Based on the obtained IMFs, together with vector threshold, we propose a novel denoising scheme. The objective of our study is to evaluate the scheme by processing simulation and on-site signals. Furthermore, preliminary comparison with wavelet-based denoising is conducted.

2 Empirical mode decomposition

The idea lying behind EMD is that:
"signal=fast oscillations + slow oscillations,"
Based on this, for a given signal $x(t)$, we can represent it as

$$x(t)=\sum_{k=1}^{K} a_k(t)\cos\varphi_k(t) \qquad (1)$$

where $a_k(t)$ and $\varphi_k(t)$ denote amplitude and frequency modulated, respectively. Further, it can be represented as

$$x(t)=\sum_{k=1}^{K} x_k(t) \qquad (2)$$

with $x_k(t)$ presenting variation of both amplitude and frequency. $x_k(t)$ satisfying the prerequisites is referred to as an IMF[6]: the count of zero-crossing and extremum differs no more than 1;②the mean of $x_k(t)$ approximates zero. And EMD is such a technique designed for obtaining these IMFs.

For a given signal $x(t)$, the procedure of decomposition by EMD can be summarized as follows:

1) Identify all extrema of $x(t)$
2) Interpolate between minima (resp. maxima) with cubic splines , end up with lower envelop $e_{\min}(t)$ (resp. upper envelop $e_{\max}(t)$)
3) Compute the mean $m(t)=(e_{\max}(t)+e_{\min}(t))/2$
4) Extract the detail $d(t)=x(t)-m(t)$
5) Iterate on the residual $m(t)$

In practice, there exists a sifting process in the above procedure, an inner loop that iterates steps (1) to (4) upon the detail signal $d(t)$, until the latter can be considered as zero-mean according to some stopping criterion [2]. Once this is achieved, the detail $d(t)$ is considered as an effective IMF, the corresponding residual is calculated and only by then, step (5) applies. Eventually, the original signal $x(t)$ is first decomposed through steps (1) to (5) as

$$x(t)=d_1(t)+m_1(t) \qquad (3)$$

and the first residual $m_1(t)$ is itself decomposed as

$$m_1(t)=d_2(t)+m_2(t) \qquad (4)$$

so that

$$\begin{aligned} x(t) &= d_1(t)+m_1(t) \\ &= d_1(t)+d_2(t)+m_2(t) \\ &= \cdots \\ &= \sum_{k=1}^{K} d_k(t)+m_K(t) \end{aligned} \qquad (5)$$

The flow chart of EMD is illustrated in Fig.1.

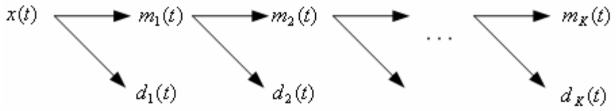

Fig.1 Flow chart of EMD

From the decomposition procedure above, it can be seen that EMD is not based on Fourier Transformation (FT), different from that of wavelet-based decomposition, and therefore not subject to the constraint of Heisenberg principle.

3 EMD based denoising scheme

The main application area of EMD is in the time-frequency analysis of signal, and little work on denoising has been reported to our knowledge. Vector-based denoising algorithm was pioneered by Downie in literature [7], originally developed for processing the multi-stream coefficients of multi-wavelet transform. In this contribution, we incorporate it in EMD, for suppressing the noise in detecting partial discharge.

For a given discrete signal $x(i)$, i=0,1,2,…N, after decomposing by EMD, we can get K IMFs d_k, k=1,2…, K and the Kth residual m_K. As to wavelet transform, if noise exists in signals, so does it in wavelet coefficients. As to EMD, if signal $x(i)$ has the distribution of Gaussian, its IMF d_k will have the same distribution[8]. Write the ith component of the Kth IMF and the residual m_K as $d_{k,i}$ and $m_{K,i}$. And therefore, original signal $x(i)$ is decomposed into a time vector series with dimension equal to K+1, $x(i)=m_{K,i}+\sum_k d_{k,i}$. As for the vector obtained by EMD, we can first decompose them and then do the regroupment, following the scheme displayed in Fig.2. After this, a series of new vectors will be obtained.

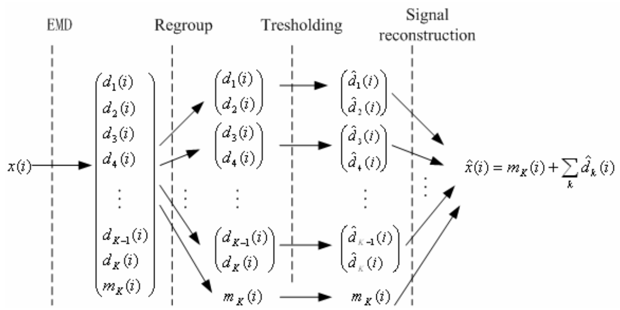

Fig.2 EMD based denoising scheme

For the newly obtained vectors, we can denote it as $D_i = \begin{pmatrix} d_k(i) \\ d_{k+1}(i) \end{pmatrix}$, and then D_i can be represented as $D_i = D_i^* + E$, where D^* is the signal coefficient and E has a multi-variable normal distribution $N(0,V)$. V is the covariance matrix of error term (can be obtained by robust covariance estimation suggested in [7]), depending on the dimension M of the new vector. Define a new quantity $\theta_i = D_i^T V^{-1} D_i$, when only white noise exists, θ_i will have χ^2 distribution [7]. The thresholding of vector D_i is based on θ_i and the threshold is $\lambda = 2\ln n$, provided in literature[7].

For a given threshold λ, either hard thresholding or soft thresholding can be implemented. Hard thresholding rule can be written as:

$$\hat{D}_i = \begin{cases} D_i, \theta_i \geq \lambda \\ 0, \theta_i < \lambda \end{cases} \qquad (6)$$

and corresponding soft thresholding can be formulated as:

$$\hat{D}_i = \begin{cases} D_i(1-\lambda/\theta_i), \theta_i \geq \lambda \\ 0, \theta_i < \lambda \end{cases} \qquad (7)$$

As far as the form of vector regroupment is concerned, the aforementioned one is under the condition of M=2. In theory, there exist various combination forms, such as M=3, M=4, etc, with threshold equal to $\lambda = 2\ln n + (M-2)\ln\ln n$ correspondingly[7]. The research conducted shows that the processing results coincide well with each other without distinctive difference when M varies. And in the successive sections, M=2 is preferred (only if the number of IMFs is odd, M=3 is considered for the last 3 IMFs).

4 EMD based denoising

For evaluating the performance of EMD based denoising scheme, the results obtained by wavelet-based denoising are provided as well.

4.1 Criterion for evaluation

To compare the performance of EMD and wavelet in denoising, two criteria are adopted:

1) Mean Square Error(MSE)[7]

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

where $x(i)$ is the original reference signal (noise free signal), with length equal to N, and $\hat{x}(i)$ is the estimate of the reference signal, namely, the denoised signal.

2) Cross correlation coefficient[9]

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

$R(m)$ indicates the similarity between original reference signal and the denoised signal in waveform. In the successive section, let m=0 directly, and all the results are normalized.

4.2 Denoising simulation signals

The partial discharge detected on site usually turns to be oscillatory and damped. In theory research, it can usually be simulated with either of the following modes: damped single-exponential pulse and damped double exponential pulse[10].

$$f_1(t) = Ae^{-t/\tau}\sin(f_c \times 2\pi t) \qquad (10)$$

$$f_2(t) = A\left(e^{-1.3t/\tau} - e^{-2.2t/\tau}\right)\sin(f_c \times 2\pi t) \qquad (11)$$

where A denotes the signal amplitude coefficient, whereas, τ and f_c are time constant and resonant frequency, respectively.

In simulation, let A=0.25mV for (10) and A=1mV for (11), with time constant τ equal to 1 μs, 2μs, 3μs, respectively; resonant frequency f_c is 1MHz and sampling frequency is 10MHz. With these parameters, we can get the simulation signal as shown in Fig.3 (a). The white noise superimposed has the distribution of $N(0, 0.05^2)$, and the corrupted signal is illustrated in Fig.3 (b).

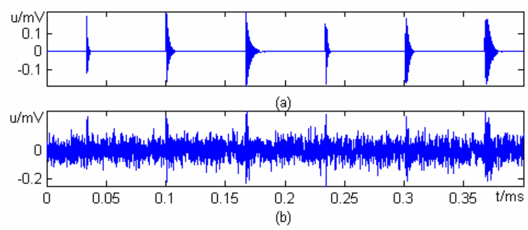

Fig.3 Simulation signal of partial discharge: (a) original reference signal; (b) corrupted signal

Next, we decompose the corrupted signal with EMD. Similar to wavelet-based decomposition, EMD decomposes the original into a series of IMFs with different frequency band, varying from high frequency to low frequency, see Fig.4. The corrupted signal is decomposed into 10 IMFs with one corresponding residual.

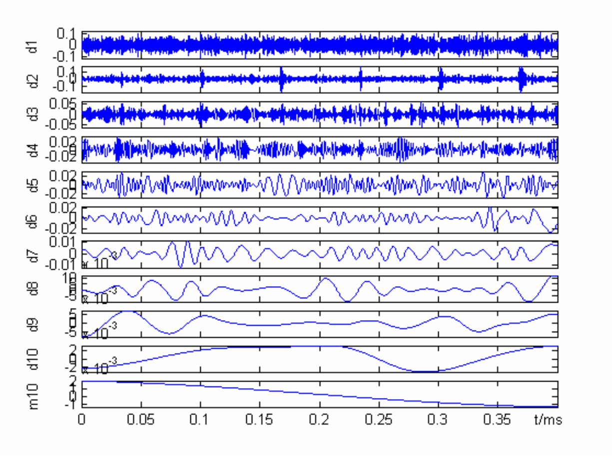

Fig.4 Decomposition of signals by EMD

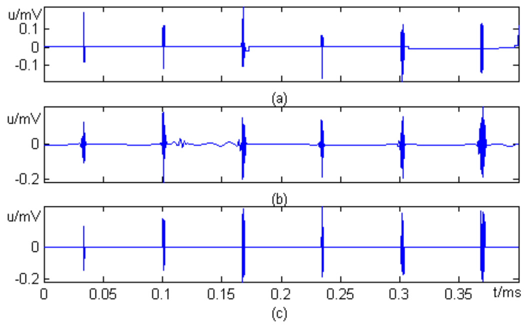

Fig.5 Processing results of simulation signal: (a) denoised signal with Haar wavelet; (b) denoised signals with db8 wavelet; (c) denoised signals with EMD based scheme

The denoised results by using wavelet and EMD, are shown in Fig.5(a), (b), (c), (d), respectively. The adopted wavelet base functions are Haar wavelet and db8 wavelet, the former is the most commonly used in signal processing and the latter is reported as the optimal wavelet base function for detecting partial discharge pulse in the sense of waveform matching [11]. For the sake of clarity, the number of decomposing levels of wavelet denoising is the same with EMD based scheme, all equal to 10. Furthermore, only hard thresholding is implemented, with the threshold $\lambda_j = m_j * \sqrt{2 \ln n_j} / 0.6745$ suggested in [12], where λ_j 、 n_j and m_j are threshold, coefficient length and median of the coefficients at resolution level *j*, repectively.

From the results in Fig.5, it can be seen that Haar wavelet, db8 wavelet and EMD based scheme can all suppress the noise and extract the partial discharge pulses effectively. However, as far as preserving the waveform of partial discharge pulses is concerned, db8 wavelet gives the best result, Haar wavelet is inferior to db8 wavelet. EMD based scheme is not based on the principle of waveform matching, and not affected by the waveform of partial discharge pulses. Different mode of partial discharge usually means different selection of wavelet base function. In this sense, EMD based scheme is relatively robust. From table 1, it can be also observed that the performance of EMD is better than that of Haar wavelet, and almost the same as db8 wavelet.

Table 2 Denoising performance of wavelet and EMD

	MSE（×10-4）	*R*
Haar	2.9063	0.6873
db8	1.8708	0.8121
EMD	2.3346	0.7577

4.3 Denoising on-site data

Practical data was derived from the partial discharge online monitoring system installed on some power generator. Sampling frequency is 6.67MHz, and the signal length is 30000 points (see Fig.6 (a)). Before denoising, the signal was filtered by a FIR highpass filter. From the results obtained by using two kinds of wavelet and EMD based scheme, it can be seen that they all can suppress the noise and extract the partial discharge pulses effectively (see Fig.6 (b), (c) and (d)).

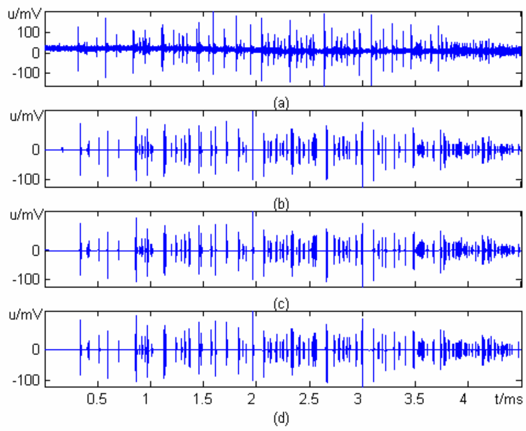

Fig.6 Processing results of on-site data: (a) on-site detected signals; (b) denoised signals by Haar wavelet based method; (c) denoised signals by db8 wavelet based method; (d) denoised signals by EMD based scheme.

As the original partial discharge is unknown, we cannot compute the MSE and *R* directly. Since the denoised results differs slightly, we consider the mean of three denoised results as the estimate of original reference signal, and then compute the denoising quality, see table 2. From table 2, it can be seen that EMD based scheme can achieve almost the same result as wavelet denoising.

Table 2 Denoising performance of wavelet and EMD

	MSE	*R*
Haar	4.9384	0.9679
db8	4.3965	0.9722
EMD	4.6991	0.9710

5 Conclusion and future work

EMD is a newly developed tool for analyzing nonstationary signals. Together with vector threshold, it can be used to denoise, and from the results obtained in the simulation, we can conclude that:

1) EMD based denoising scheme can suppress the white noise effectively, while persevering enough partial discharge pulses;
2) EMD based denoising scheme can achieve almost the same results as wavelet-based denoising;

Although with it the white noise can be eliminated successfully, the scheme proposed in the paper does not work in the case of discrete spectrum interference (DSI), which is also very common in practical partial discharge detection. And therefore, in future work, it should be taken into consideration how to deal with the interference of DSI by using EMD.

References:

[1] Huang chengjun, *Study of partial discharge on-Line monitoring system for large tubrine generators based on wavelet analysis* ,Shanghai Jiaotong University, 2000.

[2] Huang, N.E., Zheng S., Steven R.L., et al, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, *Proceedings of the Royal Society A*, Vol.X,No.454,1998, pp.903-995.

[3] Zhang, R.R., VanDemark L., Liang J., et al., On estimating site damping with soil non-linearity from earthquake recordings, *International Journal of Non-Linear Mechanics*, Vol.39,No.9, 2004,pp.1501- 1517.

[4] Pan, J., Yan X.H., Zheng Q., et al., Interpretation of scatterometer ocean surface wind vector EOFs over the Northwestern Pacific,*Remote Sensing of Environment*,Vol.84,No.1, 2003, pp.53-68.

[5] Huang, N.E., Wu M.L., Qu W.D., et al., Applications of Hilbert-Huang transform to non-stationary financial time series analysis, *Applied Stochastic Models in Business and Industry*, Vol.19,No.3,2003,pp.245-268.

[6] Huang, N.E. Review of empirical mode decomposition, *Proceedings of SPIE—Wavelet Applications* VIII, 2001, Orlando.

[7] Downie, T.R. and B.W. Silverman. The Discrete Multiple Wavelet Transform and Thresholding Methods, *IEEE Transaction on signal processing*, Vol.46,No.9,1998,pp.2558- 2561.

[8] Wu, Z. and N.E. Huang, A study of the characteristics of white noise using the empirical mode decomposition method, *Proceedings of the Royal Society A*, Vol.X, No.460,pp.1597-1611.

[9] Satish, L. and B. Nazneen, Wavelet-based denoising of partial discharge signals buried in excessive noise and interference, *IEEE Transactions on Dielectrics and Electrical Insulation*, Vol.10,No.2,2003,pp. 354-367.

[10] Xu Jian,Huang Chengjun, Shao Zhenyu, etc, Research on a wavelet-based algorithm for extracting PD cluster of diversiform features, *Automation of Electric Power Systems*, Vol.28, No.16, 2004, pp.36- 40.

[11] Ma, X., C. Zhou, and I.J. Kemp, Interpretation of wavelet analysis and its application in partial discharge detection, *IEEE Transactions on Dielectrics and Electrical Insulation*, Vol.9, No.3, 2002,pp. 446-457.

[12] Ma, X., C. Zhou, and I.J. Kemp, Automated wavelet selection and thresholding for PD detection, *IEEE Electrical Insulation Magazine*, Vol.18, No.2, 2002,pp.37-47.