Proc. of the 5th WSEAS/IASME Int. Conf. on Electric Power Systems, High Voltages, Electric Machines, Tenerife, Spain, December 16-18, 2005 (pp182-186)

Application of Empirical Mode Decomposition based adaptive filtering algorithm to suppress DSI in partial discharge detection

HUANG CHENG-JUN
Department of Electrical Engineering
Shanghai Jiaotong University
800#, Dongchuan Road, Minhang district, Shanghai City
CHINA

QIAN YONG
Department of Electrical Engineering
Shanghai Jiaotong University
800#, Dongchuan Road, Minhang district, Shanghai City
CHINA

JIANG XIU-CHEN
Department of Electrical Engineering
Shanghai Jiaotong University
800#, Dongchuan Road, Minhang district, Shanghai City

Abstract: -Discrete spectrum interference (DSI) is one of the main interferences in online partial discharge monitoring system, usually comes from communication system, high frequency relay protection system, broadcast, etc. The energy of DSI is so high that, in most cases, partial discharge signals are overwhelmed. Without eliminating the DSI properly, we can hardly analyzing the partial discharge accurately. Among the existing tools, adaptive filter receives much more attention than others, due to its ability of suppressing DSI without needing the prior knowledge of the interference frequency. In this contribution, we employ it to eliminate the DSI in partial discharge detection. For DSI with single main frequency, adaptive filter does work. However, when the number of main frequency increases from one to more, the performance of the filter degrades. In some case, it even diverges, without output. For solving this problem, we incorporate Empirical Mode Decomposition (EMD) with the common adaptive filter, and propose a new scheme for suppressing DSI. By EMD, the DSI with multi-frequency are adaptively decomposed into different Intrinsic Mode Functions (IMF), with different frequency component into different IMF. In this way, the problem of suppressing multi-frequency DSI is reduced to the problem of suppressing single-frequency DSI, and accordingly, the problem can be solved with ease.

Key-Words: - Empirical Mode Decomposition, Intrinsic Mode Function, Adaptive filter, Partial discharge, Discrete spectrum interference, Main frequency

1 Introduction

Detection of partial discharge plays an important role in the insulation monitoring of large power plant. In the past decades, much work has been done in this field. When power apparatus is operating, there exist excessive interferences, and in most cases, partial discharges are overwhelmed by them. For analyzing the partial discharge properly, interferences must be eliminated[1]. Among various interference sources, discrete spectrum inference (DSI), resulting from communication system, high frequency relay protection system,etc, affects PD greatly, and ought to be suppressed in the first place.

For suppressing DSI, many methods have been developed, such as FFT based filter, adaptive filter, wavelet transform, etc. Among them, FFT filter and wavelet transform both suppress the DSI by eliminating the corresponding frequency component in frequency domain. Unfortunately, such methods need prior knowledge of interference main frequency, while in practice the main frequency is unknown. Compared with other methods, adaptive filter does not need information of main frequency, and receives much more attention[2]. However, it is well known that, there exist some problems in the algorithm of adaptive filter. As far as the most common used Least Mean Square (LMS) algorithm is concerned, there exists compromise between convergence speed, step and convergence accuracy. Improper parameters may lead to great error; even the filter becomes unstable. For single main frequency interference, it is easy to set the optimal parameters, but for DSI with multi-frequency, the situation becomes much complex. For solving this problem, we propose a new scheme, by incorporating a new signal processing tool, Empirical Mode Decomposition, namely, EMD.

EMD is a method, developed recently by NASA, mainly for analyzing nonstationary signals[3]. EMD can adaptively decompose the signal into a number of Intrinsic Mode Functions (IMFs) with different frequency bands. Utilizing this splitting characteristic, in this contribution, we incorporate EMD with common adaptive filter. By using EMD, we reduce the problem of multi-frequency DSI to the one of single-frequency DSI, and together with adaptive filter, single-frequency DSI can be further eliminated with ease. This is the idea of our work, and the objective of our work is to validate the scheme.

2 Empirical mode decomposition

2.1 Basic theory of EMD

EMD, alias Huang transform, assumes that any complex signal is composed of local AM-FM components. In this sense, a number of basic functions can be extracted from the complex signal, and these basic functions are referred to as intrinsic mode functions (IMF). An IMF must meet two prerequisites[3]:①the number of zero-crossings and extrema differs no more than 1②the mean of it approximates 0 according to some criterion.

EMD does not admit analytical representation. And given a signal $x(t)$, its IMFs can be extracted by the following iterative process:

1) Identify all the extrema of $x(t)$
2) Get upper envelop $u(t)$ and lower envelop $v(t)$ of $x(t)$, by interpolating between maximum and minimum with cubic splines function;
3) Compute the mean of the upper and low envelop

$$m(t) = (u(t) + v(t))/2 \qquad (1)$$

4) Extract detail $d(t)$ from

$$d(t) = x(t) - m(t) \qquad (2)$$

If it meets the two prerequisites of IMF, then $d(t)$ is an IMF of $x(t)$; otherwise, regard $d(t)$ as the original signal, return to step 1). Repeat the above procedure, until $d(t)$ meets the prerequisites of IMF.

From above procedure, the final $d(t)$ is the first IMF, written as $c_1(t)$, and then, compute $r_1(t) = x(t) - c_1(t)$, $r_1(t)$ is the residual with regard to the first IMF $c_1(t)$.

Regarding $r_1(t)$ as a new signal to decompose, iterate the above step 1～4, and we can get the second IMF $c_2(t)$ and corresponding residual $r_2(t)$ of $x(t)$,

$$r_2(t) = r_1(t) - c_2(t) \qquad (3)$$

Following the above procedure, iterate on the residual, and we can get all the IMF $c_j(t)$ ($j = 1,2,...$) of $x(t)$. Eventually, a signal $x(t)$ comprising J IMFs, by EMD, can be represented as

$$x(t) = \sum_{j=1}^{J} c_j(t) + r_J(t) \qquad (4)$$

where, $r_J(t)$ is the last residual, a flat function.

2.2 Frequency-splitting characteristics of EMD

From the previous introduction, it can be seen that, the frequency-splitting principle of EMD is the same as wavelet transform. Both decompose the signal into two components, high frequency part and low frequency part, then, iterate on the latter, until all the information of different frequency band are extracted. Although the principle is similar, the frequency-splitting characteristics differ.

Wavelet transform is pre-determined frequency band decomposition, in other words, each frequency band is pre-determined, every resolution level is a band-pass filtering; EMD is different, EMD decomposes the data adaptively, the first IMF is high-pass filtering, residual is low-pass filtering, and others are all band-pass filtering[4]. Furthermore, the entire frequency band is unknown, depending on the physical construction of the signal.

3 EMD based adaptive filter

Among various algorithms available for adaptive filter, Least Mean Square (LMS) algorithm is in common use.The structure of a LMS based traverse adaptive filter is illustrated in Fig.1. In the diagram, input signal x is DSI superimposed to PD, and r is the reference DSI. In practical processing, r is obtained by delaying x for some interval. The output e is the expected PD signal.

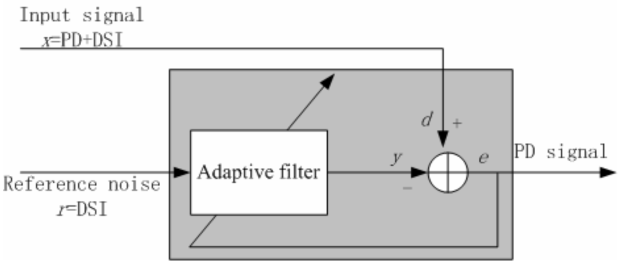

Fig.1 The diagram of adaptive filter

In the adaptive filter with LMS algorithm, the weight coefficient matrix is

$$W(n+1) = W(n) + \mu e(n) V(n) \quad (5)$$

where $W(n)$ denotes the weight coefficient, $V(n)$ the input signal, $e(n)$ the output, and μ the convergence factor. The value of μ is crucial to adaptive filter; it affects the convergence speed, stability and the accuracy of the final output. Usually, $0 < \mu < \frac{1}{N \cdot P}$, where N and P indicate the length and mean power density of the signal, respectively[5].

When eliminating DSI with single main frequency, it is simple for adaptive filter to set optimal parameters. However, it is not the case when faced with multi-frequency DSI, which has multiple main frequencies, usually scattering widely in spectrum, from tens of kHz to thousands of kHz (e.g., the frequency of carrier wave in communication system is 40 kHz ~ 500kHz, that of broadcast is tens of kHz～ thousands of kHz). It is difficult to select proper parameters in this case. What is more, the stability of the filter degrades, and in the worst case, the output of the filter diverges. For solving this problem, we employ EMD to preprocess the data, decomposing the signal into a number of IMFs, at the same time, DSI of multi-frequency is decomposed and several new single-frequency DSIs are obtained. Fortunately, DSI with different frequency are decomposed into different IMF. Therefore, by filtering all the IMFs, the DSI in the original data are filtered. The idea of EMD based filter is illustrated in Fig.2.

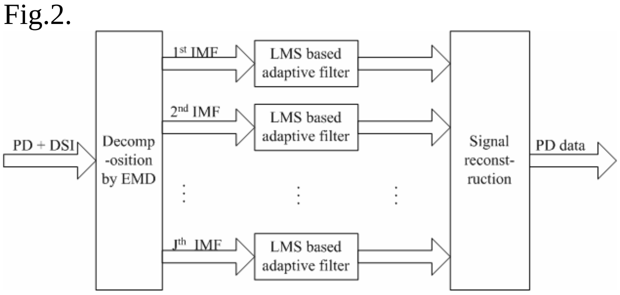

Fig.2 The scheme of EMD based adaptive filter

4 Processing of simulation signals and on-site data

For evaluating the performance of the EMD based filter, the results processed by common adaptive filter are provided as well.

4.1 processing simulation data

In practical engineering, the PD pulses detected on site usually show to be damped pulses or oscillatory damped pulses. In theory research, they can be simulated by either of the following modes[6]:

$$f_1(t) = A_1 e^{-t/\tau} \quad (6)$$

$$f_2(t) = A_3 (e^{-1.3t/\tau} - e^{-2.2t/\tau}) \quad (7)$$

$$f_3(t) = A_2 e^{-t/\tau} \sin(f_c \times 2\pi t) \quad (8)$$

$$f_4(t) = A_4 \left(e^{-1.3t/\tau} - e^{-2.2t/\tau}\right) \times \sin\left(f_c \times 2\pi t\right) \quad (9)$$

where A indicates the amplitude coefficient, whereas τ and f_c are time constant and resonant frequency, respectively. In simulation, the parameters are set as follows: peak value of each pulse is 1mV, τ =1us, f_c =1MHz, and sampling frequency is equal to 10MHz. With these values, we can obtain PD pulses as shown in Fig.3. The DSI superimposed can be formulated as

$$f = A(\sin(125k \times 2\pi \times t) + \sin(250k \times 2\pi \times t) + \sin(500k \times 2\pi \times t) + \sin(1M \times 2\pi \times t) + \sin(2M \times 2\pi \times t)) \quad (10)$$

where A denotes the amplitude of DSI. The DSI has five main frequencies: 125kHz, 250kHz, 500kHz, 1MHz and 2MHz. In simulation, set A =0.5mV. After adding the DSI, the PD pulses are almost overwhelmed completely (see Fig.4).

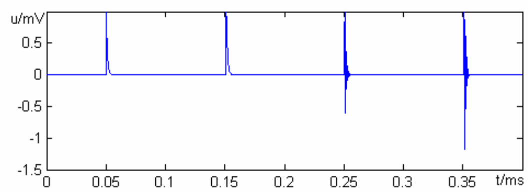

Fig.3 Simulation pulses of partial discharge

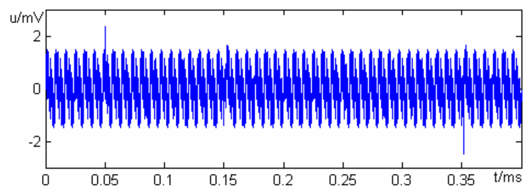

Fig.4 DSI superimposed to the simulation PD pulses

For the simulation pulses displayed in Fig.4, we firstly decompose it with EMD. The decomposition results are illustrated in Fig.5. Five DSIs with different main frequency are successively separated out, accordingly related to 1~5 IMF, respectively. Together with Hilbert-Huang spectrum (about HHT, the reader is referred to literature[3]), the result can be even clearer. From Fig.5, we can observe that, the results obtained by EMD are similar to those by using wavelet transform. In essence, EMD and wavelet transform are both used for splitting signals on some spectral basis. The difference between them is that EMD splits adaptively, the frequency band of each IMF is determined by the physical components constructing the signal, while wavelet transform does it based on a pre-determined frequency band, precluding the possibility of adapting to local variation of the oscillations.

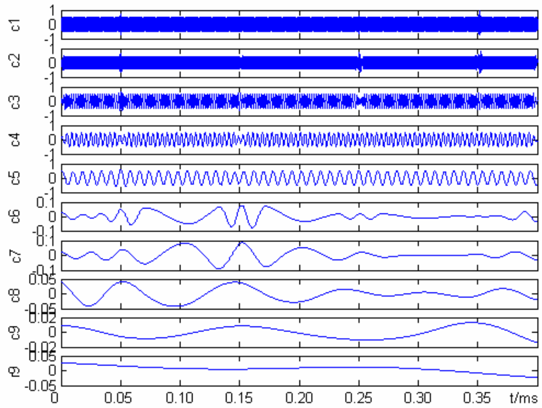

Fig.5 IMFs of the simulation signal

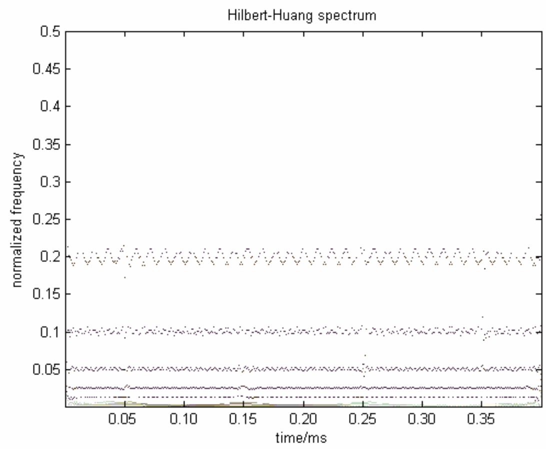

Fig.6 HH spectrum of the simulation signal

In accordance with the flowchart in Fig.2, the IMFs in Fig.5 are filtered respectively and adaptively. Now, the inputs of adaptive filter are no more DSI with multiple main frequencies, but multiple DSIs with single main frequency. By reconstructing the filtered IMFs, PD data free of DSI can be obtained, see Fig.7.

The result derived from common adaptive filter is shown in Fig.8. Comparing Fig.8 with Fig.7, we can readily observe that, EMD based filter is superior to common adaptive filter. When the result of common adaptive filter is not convergent, this advantage is in particular significant.

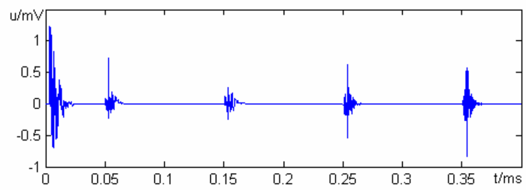

Fig.7 Result derived form EMD based filter

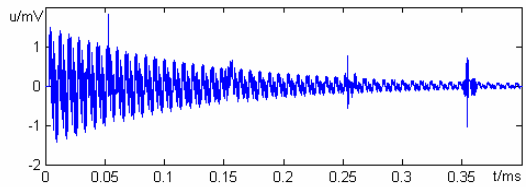

Fig.8 Result derived from common adaptive filter

4.2 processing on-site data

The practical data was derived from an online PD monitoring system installed on a power plant (see Fig.9). Sampling frequency of the system is 6.67MHz. The DSI in sampling data is not obvious, and for the sake of clarity, we add strong DSI in the form of (10), with A =20mV. From Fig.10, it can be readily observed that many PD pulses are overwhelmed by the strong DSI.

Comparing Fig.11 with Fig.12, we can conclude that EMD based filter outperforms common adaptive filter in extracting PD pulses from strong DSI interference.

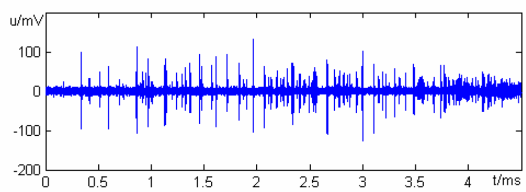

Fig.9 Partial discharge data detected on-site

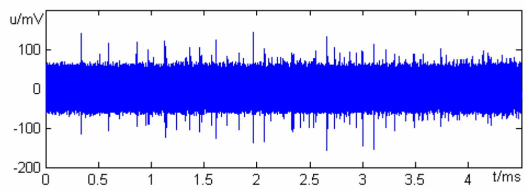

Fig.10 DSI superimposed to on-site PD data

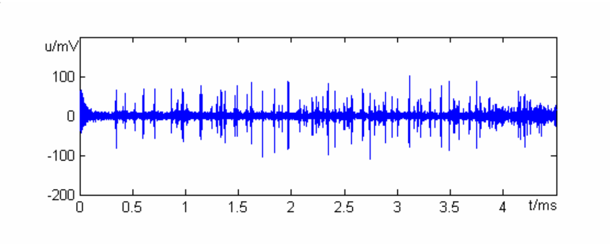

Fig.11 Result derived from EMD based filter

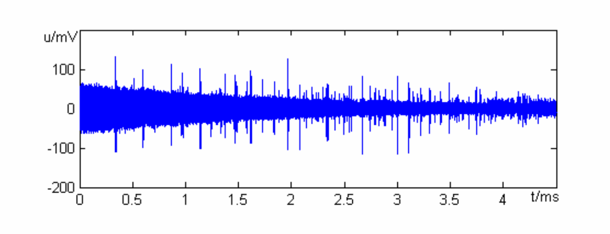

Fig.12 Result derived from common adaptive filter

5 Conclusion

EMD is a newly developed tool for analyzing nonstationary signals, and it can decompose the signal according to its components physically and adaptively. In this contribution, we incorporate it with adaptive filter, expecting to solve the problem of multi-frequency DSI suppression.

Processing of simulation and on-site data demonstrates that, EMD together with adaptive filter can reduce the multi-frequency DSI to multiple single-frequency DSIs, and better performance can be achieved compared with common adaptive filter.

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