Partial Discharge Signal Denoising Using the Empirical Mode Decomposition

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***Abstract*—This paper presents the findings of an investigation into Partial Discharge signal denoising using techniques based on Empirical Mode Decomposition. The denoising techniques are based on thresholding the Intrinsic Mode Functions which result from the Empirical Mode Decomposition of a signal. The results of the tests carried out show clearly that these techniques can produce excellent results when applied to simulated Partial Discharge data. Furthermore, in the case of the data used in these simulations the techniques are able to outperform a Discrete Wavelet Transform based denoising technique.**

***Index Terms*—empirical mode decomposition (EMD), signal denoising, partial discharge**

I. Introduction

Within electrical power systems partial discharges (PD) monitoring provides an effective tool to evaluate degradations in insulating systems in high voltage equipment. However, field measurements of PD signals are very weak and are often seriously distorted by interfering noise sources within the environment. This presents great difficulties in PD detection and classification. In this respect, noise reduction of the sampled PD signal is crucial. In recent years a number of noise reduction techniques have been applied to PD. One of the most successful techniques utilises the wavelet transform,thresholding the resultant wavelet coefficients as proposed in [1]. Some very good results have been achieved based on this technique [2], [3], [4], [5]. Within this work we employ the wavelet inspired EMD denoising method[6] to PD signals.

The Empirical Mode Decomposition (EMD) is an algorithm used to break a signal down into a series of zero mean oscillatory modes, known as Intrinsic Mode Functions (IMF). The decomposition is achieved by a technique known as the sifting process.[7] Due to the nature of the sifting process the resulting IMFs tend to contain components which decrease in frequency as the order of the IMFs increase [8]. For this reason the technique lends itself well to a wide variety of applications [9]. One of the most significant being signal denoising.

Several techniques have been proposed to allow the EMD process to be used as a denoising tool. For example in [10], [11] techniques are based on using energy estimation of the IMFs as a tool to determine which IMFs should be retained. The most effective methods however are based on thresholding the IMFs to ensure the maximum amount of signal can be retained. Many techniques are based on direct thresholding of the IMFs as would be done in the case of wavelets denosing [6], [8]. Other novel approaches include denoising based on entropic interpretations of the IMFs [12]. In[13] three advanced, wavelet inspired techniques were proposed which produced excellent results. Although many of these techniques have been applied to real world signals[14],[15] relatively little work has been carried out to understand how they will perform when applied to partial discharge data. Although some errors have been highlighted relating to the envelope algorithm [14], the technique has proven to be a powerful denoising tool for signals with similar characteristics to PD [16], [17].

The simulations in this investigation are based on applying these techniques to noise corrupt partial discharge data. A comparison will then be drawn with a well-established and extremely effective denoising technique based on the discrete wavelet transform.

II. Empirical Mode Decomposition

A. *The Sifting Process* [7]

1) Locate the extrema of asignal, $x(t)$.
2) Perform a cubic spline interpolation to form an upper and lower envelope.
3) Calculate the mean of the two envelopes.
4) Subtract the mean from the original signal to produce the first potential IMF $x(t) - m_1 = h_1$
5) Test to identify if h_1 is a zero mean signal with the number of maxima and minima differing at most by one. If this is satisfied $h_1$is taken as being the first IMF (C_1)

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6) If this is not the case the process is repeated, replacing $x(t)$ with h_1.
7) A stopping criteria is applied by calculating the Standard Deviation (SD) of the signal

$$SD = \sum_{t=0}^{T} \left[\frac{|(h_{1(k-1)}(t) - h_{1k}(t))|^2}{h^2{}_{1(k-1)}(t)} \right] \quad (1)$$

The sifting process was halted when the SD reached 0.2.

8) When the stopping criterion is satisfied the remaining component is known as the residue. The signal can then be expressed as

$$x(t) = \sum_{k=1}^{n} C_k + r_n \quad (2)$$

B. Interval Thresholding

Interval thresholding (IT) is based on estimating whether or not, at any given interval (z_j), an IMF is above or below the threshold value, based upon the extremum which correspond to that interval. This maximum or minimum point is denoted as $C^{(i)} r_j^{(i)}$. The signal is then thresholded basedon the values of the extrema as shown below.[13]

$$C^{(i)}(z_j^{(i)} = \begin{cases} C^{(i)}(z_j^{(i)}), & \left| C^{(i)}(r_j^{(i)}) > T_i \right. \\ 0, & \left| C^{(i)}(r_j^{(i)}) \leq T_i \right. \end{cases} \quad (3)$$

C. Iterative Interval Thresholding

Iterative Interval thresholding is designed for instances where the first IMF contains mostly noise. The process begins by altering the sample points of the first IMF to produce an altered version of the first IMF.

$$C_a^1(t) = ALTER\ (C^1(t)) \quad (4)$$

This can then be summed with a partial reconstruction of the remaining IMFs ($x_p(t)$) to produce an altered version of the original signal as shown below.

$$x_a(t) = x_p(t) + C_a^1(t) \quad (5)$$

where

$$x_p(t) = \sum\nolimits_{i=2}^{L} C^i(t) \quad (6)$$

A signal to noise ratio tending towards zero for this first IMF will result in a noise variance of the two versions of the noisy signals tending towards the same value. When a predefined number of different versions of the noisy signal have been obtained the EMD process is performed. This is followed by the interval thresholdingmethod to produce de-noised IMFs for each version of the signal. A mean is then taken of the de-noised signals to produce a final output signal[13]

D. Clear Iterative Interval Thresholding

Clear Iterative Interval Thresholding (CIIT) method is similar to the IIT method; however, it is designed for signals which contain a significant amount of signal as well as noise in the first IMF. In this instance the process begins by thresholding the first IMF to create a noise free version $\check{C}^1(t)$. A partial reconstruction is then formed.

$$x_p(t) = \sum\nolimits_{i=2}^{L} C^i(t) + \check{C}^1(t) \quad (7)$$

The noise component of the first IMF $C_n^1(t)$ is then taken as shown.

$$C_n^1(t) = C^1(t) - \check{C}^1(t) \quad (8)$$

The process then follows that of the IIT replacing $(C^1(t))$ with $C_n^1(t)$ in Equation (4)[13].

III. Methodology

A. Simulation of Partial Discharge Data

The simulated partial discharge pulse used in this investigation can be expressed as shown is Equation (9). Where A is the amplitude (set to 5mV) of the pulse and t_o is the point in time where the pulse occurs. The damping factor (set to 0.8) and damping frequency (set to 500Hz) are then represented by τ and f_c respectively[2]. Figure 1 shows the simulated partial discharge data used in this investigation.

$$f(t) = A\left[e^{-\frac{1.3(t-t_o)}{\tau}} - e^{-\frac{t-t_o}{\tau}}\right] sin[2\pi f_c(-t_o)] \quad (9)$$

B. Addition of Gaussian Distributed Noise

Additive Gaussian White Noise (AWGN) was added to the signal at varying levels to simulate the noise typically encountered when measuring partial discharge activity. The quantity of noise added to the simulated partial discharge data corresponded to a SNR of -2, 0, 2, 5, 10 and 15 dB within our experiments. Fig. 2 shows the partial discharge data combined with AWGN with a SNR of 15dB.

C. Denoising Process and Performance Metrics

Each of the noise corrupt signals wasdenoised using each of the combinations outlined inTable I, below.

TABLE I. Denosing Techniques Adopted

Decomposition Method	Denoising Technique	Reference
EMD	CIIT	EMD-CIIT
EMD	IIT	EMD-IIT
EMD	IT	EMD-IT
DWT	Hard Thresholding	DWT-Hard

The performance of each technique was assessed by calculating the Signal to Noise Ratio (SNR). The Root Mean Square Error (RMSE) and the Correlation (R).

SNR was used to show the ratio of desired signal to unwanted noise. It is calculated as follows:

$$SNR = \frac{x_i(t)^2}{(x_i(t) - y_i(t))^2} \tag{10}$$

where $x_i(t)$ is the desired noise free signal, this was the original signal before noise was added, and $y_i(t)$ represents the output of the denoising process.

RMSE was used to give an indication of error between the desired noise-free signal and the approximation obtained by the denoising process. RMSE is calculated as follows:

$$RMSE = \sqrt{(x_i(t) - y_i(t))^2} \tag{11}$$

R is used to identify how closely the approximated signal correlates to the desired noise-free signal. It is possible that if a signal is shifted as part of a denoising process the SNR and RMSE metrics would produce poor results. However it may be the case that when the shift is reversed that the approximation is in fact a good representation of the signal. The correlation is therefore an essential addition to the SNR and RMSE techniques. The correlation is calculated as follows:

$$R_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}} \tag{12}$$

where x and y represent two data vectors, one from the original signal and the other from corresponding data point of the approximation of the desired signal.

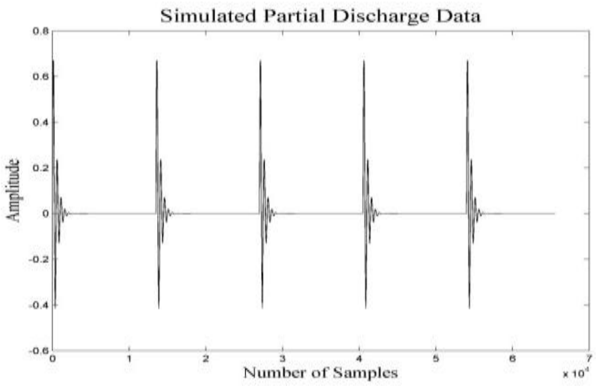

Figure 1. Raw partial discharge data

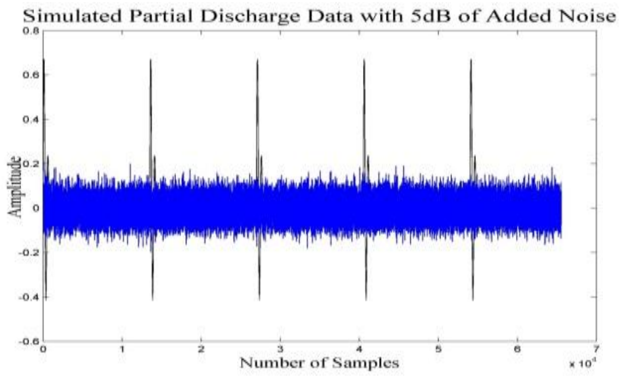

Figure 2. Noise corrupt partial discharge data

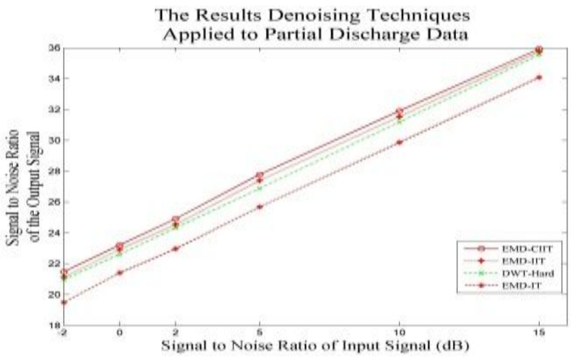

Figure 3. SNR of denoised output

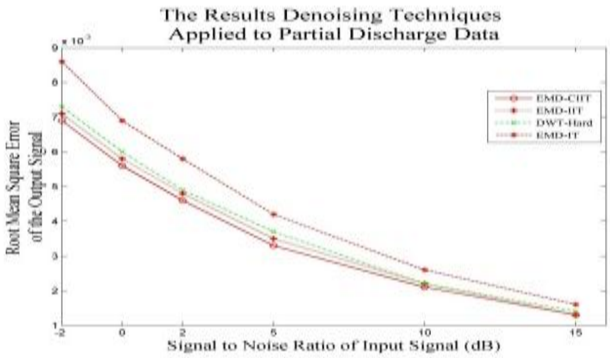

Figure 4. RMSE of denoised output

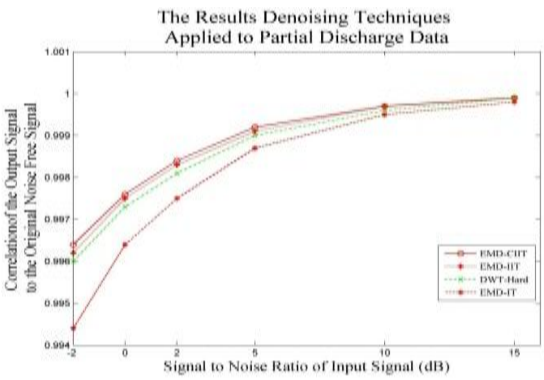

Figure 5. Correlation of denoised output

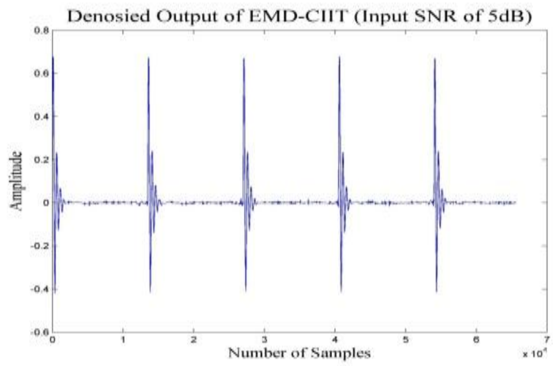

Figure 6. Denoisedoutput of EMD-CIIT

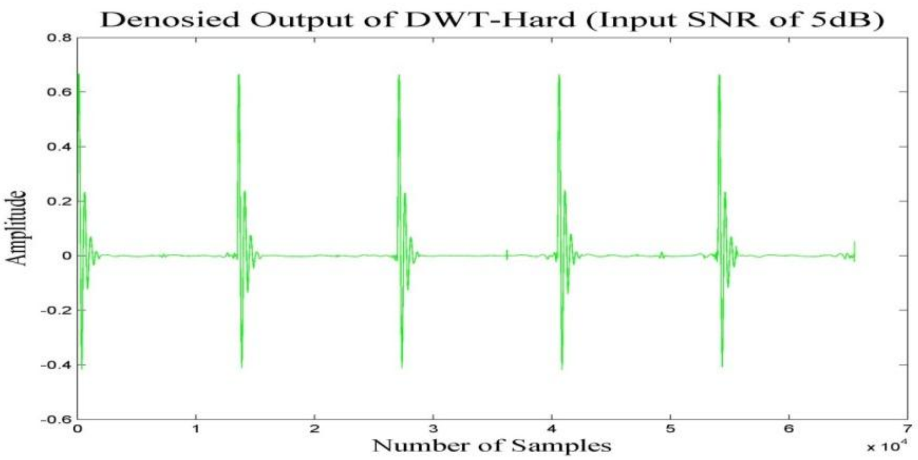

Figure 7. Denoisedoutput of DWT-Hard

IV. Results

The results of the simulations are presented in terms of the performance metrics outlined. Fig.3 to Fig. 5 show trends of the output Signal to Noise Ratio, Root Mean Square Error and Correlation respectively. Two of the outputs of the denoising process are shown in Fig. 6 to Fig. 7. Fig. 6 shows the EMD-CIIT and Fig. 7 shows the DWT-Hard. Both show the results taken from a simulation using a SNR of 5dB.

Two of the EMD based denoising techniques simulated (CIIT and IIT) produced better approximations of the original PD data than the discrete wavelet transform combined with hard thresholding. The third technique was unable to match the performance of the DWT. The stronger performance of the CIIT and IIT methods, when compared with the IT method, suggests that the signal altering and averaging process played a significant role in optimising the denoising performance.

The EMD-CIIT produced slightly better results than the EMD-IIT method. When referring to the definition of these processes it is clear that the first IMF resulting from the EMD of this simulated data must have contained a significant amount of desired signal as well as noise. Had this not been the case it would not have been necessary to perform the initial thresholding of the first IMF as was done in the case of the EMD-CIIT method.

V. Conclusion

The results of this investigation show that, in the case of the simulated PD data used, it is possible to produce excellent denoising results using EMD based denoising techniques. Furthermore the performance of these wavelet inspired EMD based denoising techniques can also outperform the well-established Discrete Wavelet Transform based denoising method using a hard thresholding technique.

This presents a clear case for further investigatory work into denoising partial discharge data using these techniques. A possible limitation within this study is the constant number of samples between PD pulses. Further work would be required to determine the effect that the number of data samples would have on the denoising performance. This demonstrates that there is still significant work to be done in this area, but it holds very significant promise forapplication within future PD based diagnostic systems.

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