A New Threshold Function for De-noising Partial Discharge Signal Based on Wavelet Transform

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Abstract—The Partial Discharge (PD) signals, which are characterized by high frequency current pulses, are strongly coupled with external noise. In on-site PD measurement de-noising this PD signal from noisy environment is one of the major challenges. This paper proposes a new nonlinear threshold function for de-noising PD signal using wavelet transform (WT) technique. This new threshold function is continuous as the soft threshold function and also uses the unused coefficients (i.e. which are less than threshold value) which are set to zero in different threshold function. This method first applied on two different type PD signals with White Gaussian Noise (WGN) and simulation results shows that new threshold function can give better performance by changing the variable parameter. Improved signal to noise ratio (SNR) and correlation coefficient indicate that the performance of this method is better than other de-noising technique. Finally, a field detected signal is tested and the de-noised signal indicates that method is effective and efficient for this application.

Keywords—wavelet transform; partial discharge; signal de-noising; thresholding; MATLAB

I. INTRODUCTION

Electrical insulation plays a very critical role in the performance of high voltage (HV) power equipment. When HV are applied across damaged insulating material, it may either totally breakdown or PDs may occur. Most of the failure in power equipment is due to insulation breakdown which is occur consequence of gradual and cumulative damage by PD signal on the insulation over the year. In view of this, continuous monitoring and diagnostic measurement of insulation system is essential. Amongst others, PD measurements have emerged as an indispensable, non-destructive, sensitive and powerful diagnostic tool. Using this diagnostic data, an overall assessment of the insulation system is possible.

PD are normally low level current pulses with fast rise time and short duration, typically not more than a few hundred nanoseconds. Its waveform shape varies depending on type of fault, PD detecting sensor, insulation characteristics etc [1]. However, on-site PD measurement has a major problem because it is strongly coupled with external noise (usually of very high amplitude compared to PD signal) like discrete spectral interferences (DSI) noise from radio transmission and power line carrier communication system, commutator noise from rotating machines, colored noise (mostly pink noise) i.e. √/f noise, power electronics switching circuit noise, noise from corona discharge etc. Recent advances in fast analogue to digital converter (ADC), digital PD measurement using Digital Signal Processing (DSP) are become easier for noise suppression.

There are several algorithms for de-noising PD signal using filter, such as, moving average, FFT thresholding [2], digital filtering (infinite impulse response, IIR and finite impulse response, FIR [3-4]), adaptive filtering [5-7] etc. The conventional filtering techniques have linearity of operation and can able to remove DSI and colored noise and applicable for stationary signal, but cannot de-noise WGN [11]. Moreover, when the spectrum of this non-stationary PD signal contain some transient impulses with sharp edge and of very short duration, it is difficult to suppress the noise signal using linear filters. The linear filter tends to eliminate or keep both noise and this type of important signal component because both of them may have similar appearance in spectrum. Also, the FIR filter based noise reduction techniques in the transform domain have been investigated [8-9]. However, since the transformation used is usually linear, the overall filtering is equivalent to a linear filter. The convergence speed of the adaptive linear filter may be improved in the transform domain; however, the optimal noise reduction performance is the same as the conventional time domain linear filtering.

To overcome these difficulties, nonlinear methods have been proposed and especially those based on Wavelets thresholding [10-18]. In these method wavelets coefficients can be set to zero if their magnitudes are less than a pre-determined threshold value. Among the wavelet-based de-noising methods, shrinkage methods proposed based on soft and hard thresholding functions by Donoho [10] are simple and effective. He also presented a threshold estimation formula based on Stein unbiased risk estimation (SURE) [11]. However, drawback of wavelet shrinkage is that de-noised signals are distorted due to its threshold function. Distortion of a de-noised signal is closely related to both base wavelet selection and threshold estimation. In [12] an optimal base

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wavelet function is selected for de-noising signal if the correlation between the base wavelet and the objective signal is greater than that between any other wavelet for selection and the objective signal. This approach is called the correlation-based wavelet selection (CBWS) scheme below. An energy-based wavelet selection (EBWS) was also proposed in [13] to obtain small distortion of de-noised PD signals and give better result than CBWS.

The hard threshold function is discontinuous and soft threshold function is continuous with discontinuous derivative. For optimization problem continuous or higher order derivatives are required. The wavelet shrinkage methods, SureShink is an optimized scale depending de-noising technique based on Stein’s unbiased risk estimate (SURE) risk, which combines universal threshold selecting scheme and adaptive threshold selecting scheme. As, conventional soft-thresholding function is weakly differentiable (only in first order i.e. discontinuous), a new adaptive threshold estimation (ATE) is proposed to search for optimal thresholds using gradient-based adaptive algorithm [14] and verified for de-noising PD signal [15]. In [16-17] a similar type of thresholding function is described. However these approach ware time consuming and might become a non-convergent computation for de-noising PD signal, especially when added with strong WGN noise. In [18], new genetic adaptive threshold estimation (GATE) was proposed and gives better result than [15] and [16].

In this paper, a new threshold function is proposed for de-noising PD signal. The de-noising results also compare with Soft threshold function and the threshold function proposed in [15]. The analysis results show that the proposed method give better de-noising effect. Lastly the proposed method is also verified with field detected PD signal.

II. WAVELET TRESHOLD DE-NOISING TECHNIQUE

Assume a signal with WGN as follows

\[ y_i = x_i + n_i \quad i = 0, 1, 2, \cdots, N - 1 \]  

Where \( y_i \) is noised signal, \( x_i \) is the original signal and \( n_i \) is Gaussian white noise with independent identical distribution \( N(0, \sigma) \).

Step 1: Select a wavelet library \( \psi_j, \quad j = 1, 2, \cdots, n \).
Step 2: Determine the maximum number of level with which a signal can be decomposed [19].
Step 3: Apply discrete wavelet transform (DWT) to noised signal according to (2) and get wavelet coefficient \( d_{j,k} \) and scale coefficient \( a_{j,k} \) of each level \( j \).

\[ a_{j,k} = \sum_{i=0}^{N-1} c_{j-1,n} h_{n-2k} \]  

\[ d_{j,k} = \sum_{i=0}^{N-1} d_{j-1,n} g_{n-2k} \]  

Where \( h \) and \( g \) are independent orthogonal filter banks.

Step 4: Calculating energy sum of wavelet coefficient [19] at each level and determine optimal level for decomposition.

Step 5: Apply thresholding function [15] to wavelet coefficient at each level with a thresholding scheme and obtain the estimated wavelet coefficient.

Step 6: Reconstruct the signal according to the scaling coefficients of level \( j \) and estimated wavelet coefficients from level 1 to \( j \) by inverse discrete wavelet transform (IDWT) as equation (3) to obtain de-noised signal.

\[ c_{j-1,n} = \sum_{i=0}^{L-1} c_{j,n} h_{k-2n} + \sum_{i=0}^{L-1} d_{j,n} g_{k-2n} \]  

Thresholding is one of the important steps to remove noise. Thresholding function is the wavelet shrinkage function which determines how the threshold is applied to wavelet coefficients.

A. Hard Thresholding

Hard thresholding function used by Donoho [11] is called keep or kills, keep the element whose absolute value is greater than the threshold and set the elements lower than the threshold to zero.

B. Soft Thresholding

Soft thresholding function (SFT) used by Donoho [11] is called shrink or kill which is an extension of hard thresholding, first by setting the elements whose absolute value lower than the threshold to zero and then shrinking the other coefficients.

C. Adaptive Threshold Estimation (ATE)

Both soft and hard thresholding function have advantage and disadvantage. Soft thresholding function is continuous with discontinuous derivative. Due to discontinuities of hard thresholding function, it will be sensitive to small changes in the signal. To overcome the drawback of hard and soft thresholding, a new thresholding function [15] to obtain optimum threshold of wavelet shrinkage was proposed in [14-15]. The optimum threshold value was determined by an iterative process based on gradient-based algorithm.

D. Proposed Thresholding

As the ATE involve an iteration process for searching optimum threshold value, this method is time consuming and also might become a non-convergent when signal is embedded in strong noise. Moreover to determine the value of learning rate is also difficult task for automatic PD de-noising. To overcome this, a new thresholding function is proposed in this paper as follows

\[ \hat{d}_{j,k} = \begin{cases} 
\text{sgn}(d_{j,k}) \times (|d_{j,k}| - THR_j \times \kappa \sqrt{d_{j,k}^2 - THR_j^2}) & |d_{j,k}| \geq THR_j \\
0 & |d_{j,k}| > THR_j
\end{cases} \]  

(4)
The $\hat{d}_{j,k}$ is new estimated co-efficient, $d_{j,k}$ is detail wavelet co-efficient and $THR_j$ is threshold value at level $j$. The varying parameter $\kappa$ is key of this thresholding function. When it is one, thresholding function tends to soft threshold and when zero threshold function is tends to hard threshold. Therefore by changing the value of $\kappa$, thresholding function can give optimal threshold value between soft and hard function. Unlike soft thresholding function this function is tuned the wavelet coefficients whose absolute value is less than threshold value. In order to make this function more flexible this function can be modified as follows

$$\hat{d}_{j,k} = \begin{cases} 
\text{sgn}(d_{j,k}) \times \left( d_{j,k} \times 2 \times \left| d_{j,k} \right| / (2 \times THR_j) \right)^{1/\kappa} & \left| d_{j,k} \right| \geq THR_j \\
\text{sgn}(d_{j,k}) \times \kappa & \left| d_{j,k} \right| \leq THR_j 
\end{cases} \quad (5)$$

Figure 1 shows estimated threshold function by equation (5). This tuning increases the capability of function since it attenuates the coefficients that are below the threshold value and close to it to a value less than the far coefficients.

III. DE-NOISING OF PD SIGNALS

The two mathematical models of PD signal described in [13] i.e. Damped Exponential Pulse (DEP) (S1) and Damped Oscillatory Pulse (DEP) (S2) added with WGN are simulated in MATLAB. The White Gaussian Noise (WGN) is generated in MATLAB by using signal + wgn command.

To evaluate the de-noising effect, four parameter, mean square error (MSE) [13], magnitude error (ME) [13], SNR of de-noised signal in dB (SNR) [20] and cross-correlation (CC) [13] are used. The lower the MSE and ME and higher the SNR and CC is better the de-noising effect. In this paper de-noising effect is analysis for different signal-to-noise ratio [13] starting from 0.05 to 4 also.

IV. RESULT AND ANALYSIS

Three de-noising approaches were used for de-noising PD signal are as follows

- Method 2: By ATE proposed in [15].
- Method 3: Proposed in this paper.

The PD signals are generated at a sampling rate of 60 MHz. Here two wavelet family sym6 and db20 were used for de-noising PD signal. The PD signals were embedded in WGN with SNR equal to 0.05 to 4. The de-noising results of two type PD signals with SNR = 0.05 are shown in Fig. 2-3. The de-noising performances of PD signals are tabulated in Table I.

A field detected PD signal is also measure and collected by an online PD monitoring system of 11 kV cast resin current transformer in NTPL, Kolkata. The sampling rate of online monitoring system is 10 MHz. Figure 4 shows the field detected PD signal and de-noised PD signal using new threshold function and also compare with SFT and ATE. It is show that by using new threshold function not only the pulses with greater magnitude than the noise are extracted but also pulses with lesser magnitude than the noise level are also extracted (indicated by red circle).
V. Conclusion

In this paper, a study of de-noising PD signal with a new threshold function was proposed and also compare with SFT and ATE. For this purpose two simulated PD signals are added with WGN. The de-noising effect is also analysis by two different wavelet families in WT.

The following conclusion can be made from above simulation results:

1. The value of MSE and ME has gradually decrease from method 1 to 3 i.e. these value is lower by proposed method than ATE and SFT.
2. The value SNR and CC has gradually increase from method 1 to 3 i.e. these value is higher by proposed method than ATE and SFT.
3. The proposed method is able to improve SNR of de-noised signal even if signal was embedded in high noise level i.e. with SNR = 0.05.
4. As the number of ME’s negative values were more by using db20 than sym6, it can be conclude that compare with db20, sym6 is better wavelet family for this application i.e. by choosing proper wavelet mother function WT can able to suppress the noise sufficiently.

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