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Preliminary investigation of multi-wavelet denoising in partial discharge detection

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Abstract: - Partial discharge (PD) pulses detected on site usually take on various modes, and it is difficult for wavelet to select proper wavelet basis function in denoising. In particular, in the case of PD cluster with multi-mode, conventional wavelet denoising can hardly give satisfied result. Multi-wavelet is the new development of wavelet theory, extending the idea of wavelet by representing a signal with more than one scaling function, and outperforms wavelet in signal processing. In this contribution, we employ multi-wavelet to detect the partial discharge, investigating its denoising performance. For PD pulse of single-mode or PD cluster of multi-mode, we run massive simulations, using both multi-wavelet denoising and wavelet denoising. The results obtained demonstrate that, in comparison with wavelet, multi-wavelet denoising can preserve more signal features while removing noise from the measured data. In addition, multi-wavelet denoising needs no (or less) prior knowledge of partial discharge.

Key-Words: - Multi-wavelet, Wavelet, Partial discharge, Vector threshold, Denoising

1 Introduction

Partial discharge detecting technology is important for insulation assessment of power apparatus, and a great deal of work has been done in this field over the past decades. Partial discharge is weak electric signal, apt to be interfered by various noises existing on site, and usually the noises are so strong that PD signals are buried completely. Therefore, for analyzing the partial discharge correctly, first of all, noises must be suppressed in a proper way[1].

At present, the most commonly used method for noise suppression is wavelet denoising. Wavelet analysis, famous for its multi-resolution analysis (MRA), can usually give good results in signal processing. However, in practical application, there still exist some problems, of which the well-known is the selection of wavelet basis function. The selection of wavelet basis function is application dependent, mainly based on waveform matching, and different wavelet basis function usually means different result. And it is the same case in denoising PD data. Difference in wavelet basis functions result in difference in denoised PD signals, and sometimes this difference is significant.

For selecting the optimal wavelet basis function, Ma et al in [2] proposed a method based on cross correlation coefficient, however, this method needs prior knowledge of PD pulse waveform. In addition, PD pulses, subject to different discharge mechanisms, defect positions, propagation routes and detection circuits, usually take on different waveforms[3]. How can we determine the optimal wavelet basis function when the detected PD pulses have more than one mode?

For solving the problems mentioned above, a concept of wavelet subset was proposed recently [3], expecting lessening the effect of wavelet basis function by using several wavelet basis functions simultaneously. However, with this algorithm, another problem about PD signal reconstruction was brought.

Multi-wavelet is a relative newcomer in the word of wavelet. It extends the idea of the wavelet by representing a signal with more than one scaling function. And these scaling functions can be designed to be simultaneously symmetric, orthogonal, have short supports and high vanishing moments, which cannot be achieved at the same time for wavelet using only one scaling function[4]. Thus, multi-wavelet offers the possibility of superior performance in signal processing applications, compared with wavelet.

In this contribution, we employ multi-wavelet to extract PD pulses overwhelmed by noise, and investigate its performance in comparison with wavelet.

The organization of this contribution is as follows. Section 2 gives a short introduction to multi-wavelet. Section 3 explains how multi-wavelet based denoising works. Section 4 discusses the performance of multi-wavelet based denoising for PD of various modes and shows some experiment results. And the final section draws the conclusion and points out the work in the future.

2 Basic theory of multi-wavelet

Multi-wavelet is introduced as an extension to scalar wavelets, and many similarities exist between them, here we are about to introduce it briefly.

The multi-wavelet basis uses translations and dilations of r （$r \geqslant 2$） scaling functions $\varphi_1(x)$, $\varphi_2(x)$,…, $\varphi_M(x)$ and r mother wavelet functions $\psi_1(x)$, $\psi_2(x)$,…, $\psi_M(x)$ .If we write $\mathbf{\Phi}(x)=(\varphi_1(x),\varphi_2(x),...,\varphi_M(x))^T$ and $\boldsymbol{\Psi}(x)=(\psi_1(x),\psi_1(x),\psi_2(x),...,\psi_M(x))^T$, then we have

$$\mathbf{\Phi}(x)=2\sum_{k=0}^{L-1}\mathbf{H}_k\mathbf{\Phi}(2x-k) \qquad (1)$$

$$\mathbf{\Psi}(x)=2\sum_{k=0}^{L-1}\mathbf{G}_k\mathbf{\Phi}(2x-k) \qquad (2)$$

where $\mathbf{H}_k$ and $\mathbf{G}_k$ denote $r\times r$ filter matrices, whereas L and r are the number of scaling coefficients and the multiplicity of multi-wavelet, respectively.

For the sake of clarity, we use $\boldsymbol{S}_{j,k}=(S_{2,j,k}, S_{2,j,k},...,S_{r,j,k})^T$ and $\mathbf{D}_{j,k}=\left(D_{1,j,k},D_{2,j,k},...,D_{r,j,k}\right)^T$ to represent the low-pass and high-pass coefficients. The forward and inverse multi-wavelet transform can be recursively calculated by[5,6]

$$\mathbf{S}_{j+1,k}=\sqrt{2}\sum_{n=0}^{L-1}\mathbf{H}_n\mathbf{S}_{j,n+2k} \qquad (3)$$

$$\mathbf{D}_{j+1,k}=\sqrt{2}\sum_{n=0}^{L-1}\mathbf{G}_n\mathbf{S}_{j,n+2k} \qquad (4)$$

$$\mathbf{S}_{j,k}=\sqrt{2}\sum_{n=0}^{L-1}\left(\mathbf{H}_n^T\mathbf{S}_{j+1,k+2n}+\mathbf{G}_n^T\mathbf{D}_{j+1,k+2n}\right) \qquad (5)$$

where j denotes the resolution level.

With the development of multi-wavelet theory over the past decade, multi-wavelet GHM, CL and SA4 etc., were constructed in succession by Geronimo, Chui et al[7-9]. In this contribution, as preliminary research, only the commonly used CL multi-wavelet ($r=2$) is considered, corresponding filter matrices of CL can be found in literature[8].

3 Multi-wavelet denoising scheme

3.1 Preprocessing of multi-wavelet

The filters of multi-wavelet transform are in the form of matrix, and this demands the input signals must be in the form of vector, and therefore, scalar signals must be mapped into vector signals by preprocessing. Correspondingly, the denoised results must be mapped back into scalar signals by post-processing. The flowchart of multi-wavelet denoising is depicted in Fig.1[5].

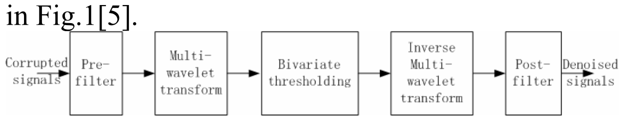

Fig.1 Flow chart of multi-wavelet denoising

Preprocessing can be done in two ways: one is using the prefilter[6, 10], and the other is balanced multi-wavelet basis[11]. Because prefilter can enable the resulting filterbank to possess desired approximation power and property such as orthoglnality, in practice it is preferred. For multi-wavelet transform, prefilter is not unique, proper selection of prefilter is important for the success in denoising. According to literature[4, 12, 13], together with our massive simulations, best denoising performance can be obtained with repeated row prefilter and approximation prefilter.

1) Repeated row prefilter

In this case, the given scalar input of length N is mapped to a sequence of N length-2vector.

$$\mathbf{y}_{0,k} = \begin{bmatrix} y_{0,k}^{(0)} \\ y_{0,k}^{(1)} \end{bmatrix} = \begin{bmatrix} f_k \\ \delta f_k \end{bmatrix}$$

where 0 denotes the initial decomposition level and δ is a constant. The constant δ is chosen so that the output from the highpass multi-filter is zero.

2) Approximation prefilter

The scalar input of length N, by preprocessing with this filter, can be mapped to a sequence of N/2 length-2 vector.

$$\mathbf{y}_{0,k} = \sum_{m=0}^{\mathrm{M}} \mathbf{P}_m \begin{bmatrix} f_{2(m+k)} \\ f_{2(m+k)+1} \end{bmatrix}$$

where $\boldsymbol{P}_m$ are 2×2 matrices.

Both repeated row prefilter and approximation prefilter do well in practice. However, in comparison with the former, the latter computes less complexity, and hence in the successive sections only the latter is considered. Prefiltering process is invertible, and a post-filter can do the opposite process, i.e., mapping the data from multiple streams into one stream. The prefilter and post-filter used in our work can be found in literature [14].

3.2 Vector thresholding

Proper selection of threshold is critical to the success of multi-wavelet denoising. In the past years, numerous work have been reported in this field[4, 13-17], in which the results of Downie is significant. Based on Downie's work, thresholding can be classified into two categories: scalar thresholding and vector thresholding. Results reported in literature [5, 12, 14-17] and simulations we run indicate that vector thresholding is superior, and therefore in the following sections only vector thresholding is considered.

A vector based thresholding scheme can be summarized as follows[12, 14]:

1) Compute multi-wavelet coefficients $\mathbf{D}_{j,k}$

2) Compute the covariance matrix $\mathbf{V}_j$ used for decorrelating multi-wavelet coefficients. $\mathbf{V}_j$ is the distribution parameter of noise coefficients at resolution level j. It can be obtained by robust covariance estimation[12], or by deflator defined in [14], in the successive sections the latter is preferred.

3) Define a new quantity $\theta_{j,k} = \sqrt{\mathbf{D}_{j,k}^T \mathbf{V}_j^{-1} \mathbf{D}_{j,k}}$, in the presence of only white noise, $\theta_{j,k}$ will have a χ^2 distribution with freedom equal to r [12].

4) Estimate threshold λ_j. Threshold estimator models, such as universal threshold estimator[14], vector threshold estimator[12], SURE estimator[13], LGCV estimator[15] and optimal threshold estimator[16], etc., are well suited to eliminate white noise. For suppressing indeterminate noise, a "robust" threshold estimator should be adopted: $\lambda_j = m_j * \sqrt{2\ln n_j} / 0.6745$ [2], where λ_j, n_j and m_j are threshold value, number of coefficients, median value of coefficients at level j, respectively.

5) Thresholding. For a given threshold λ_j, the thresholding rule is $\hat{\boldsymbol{D}}_{j,k} = \boldsymbol{D}_{j,k} \cdot f(\theta_{j,k}, \lambda_j)$, where $f(\bullet)$ denotes the conventional hard thresholding or soft thresholding. Hard thresholding produces an improved PD signal to noise ratio in comparison with soft thresholding[2]. And therefore, in the successive sections, only hard thresholding is considered.

4 Multi-wavelet based denoising

In order to evaluate the performance of multi-wavelet denoising in PD detection, the results of wavelet denoising are provided as well.

4.1 Various modes of PD pulses

Due to different discharge mechanisms, defect positions, propagation routes and detection circuits, a complex power apparatus usually generate PD pulses of various modes[3, 18]. In theory research, 4 analytical expression are usually adopted to simulate these different PD pulses: damped single-exponent pulse (DSEP), damped resonant single-exponent pulse(DRSEP), damped double-exponent pulse (DDEP), and damped resonant double-exponent pulse(DRDEP)[18].

mode1 $$f_1(t) = A_1 e^{-t/\tau} \tag{8}$$

mode2 $$f_2(t) = A_2 e^{-t/\tau} \sin(f_c \times 2\pi t) \tag{9}$$

mode3 $$f_3(t) = A_3 (e^{-1.3t/\tau} - e^{-2.2t/\tau}) \tag{10}$$

mode4 $$f_4(t) = A_4 \left(e^{-1.3t/\tau} - e^{-2.2t/\tau}\right) \times \sin\left(f_c \times 2\pi t\right) \tag{11}$$

where A denotes the amplitude, whereas τ and f_c are time constant and resonant frequency, respectively. The waveform corresponded with the 4 typical PD pulses are shown in Fig.2.

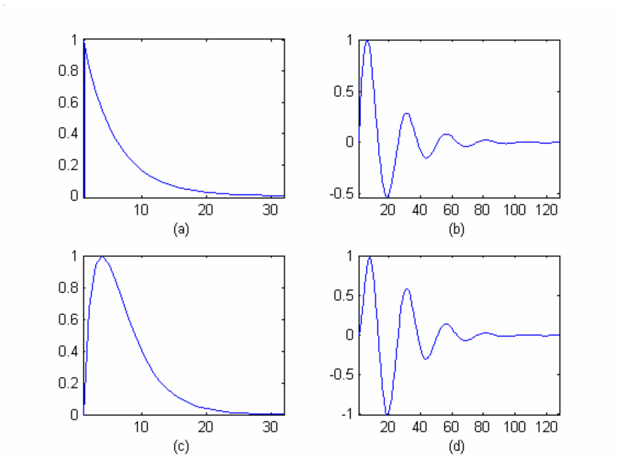

Fig.2 Typical PD pulse shapes: (a) DSEP, (b) DRSEP, (c) DDEP, and (d) DRDEP

For PD pulse of any mode shown in Fig.2, we can select corresponding optimal wavelet basis function by using the method suggested in[2]. However, in the case of multi-wavelet, as it possesses several basis functions and its filterbank is in the form of matrix, we cannot calculate the cross relation coefficient between PD pulse and the basis functions. At present, no method is available for us to compare the denoising performance of multi-wavelet and wavelet directly, to our knowledge.The objective of denoising is to remove noise from the measured data as effectively as possible while preserving the signal features essential to the application[2]. In this sense, we adopt Mean square Error (MSE) as the criterion to measure denoising performance, together with massive simulations. As to wavelet based denoising, we choose db2 and db8 as the wavelet basis function, which are optimal in most cases[2], and wavelet coefficients are to be hard thresholded with the threshold $\lambda_j = m_j * \sqrt{2\ln n_j} / 0.6745$ proposed in[2].

4.2 Denoising PD pulses of single-mode

Electrical interference on site can be classified into three categories: white noise, discrete spectrum interference(DSI), and periodic pulsive noise, in which white noise is the most common interference, and as preliminary study, in this contribution, the main interference to be suppressed is white noise. In this section, the main objective is to investigate the denoising performance of multi-wavelet for PD pulse of single mode.

PD is in the form of pulse with very wide frequency band. In accordance with this high frequency attenuation characteristic, in simulation, we set the time constant τ in the range of 100ns～2.5us, with simulation step equal to 50ns; the peak value of each PD pulse is 1mV, and resonant frequency f_c is 1MHz, unless otherwise specified, sampling frequency is 10MHz. The white noise superimposed has the normal distribution $N(0, 0.3^2)$, and the length of the simulation data is 1024.

For either mode displayed in Fig.2, with the parameters above, we run the simulation 100 times independently, and final result is the mean of 100 observations, see Fig.3-6.

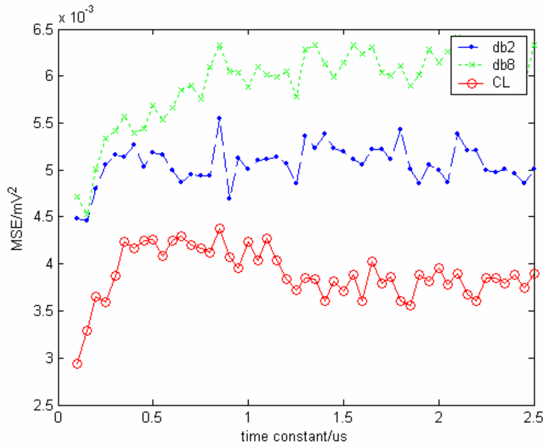

Fig.3 Multi-wavelet vs. wavelet in denoising PD of DSEP

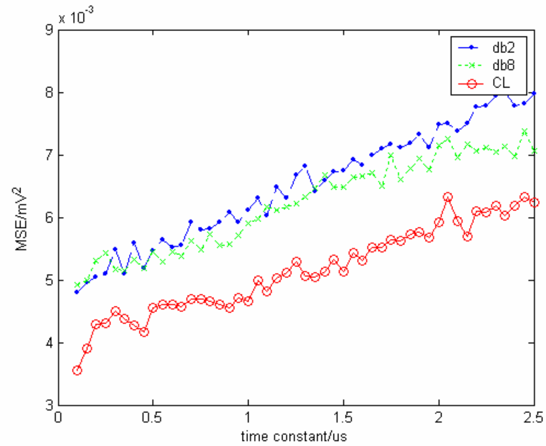

Fig.4Multi-wavelet vs. wavelet in denoising PD of DRSEP

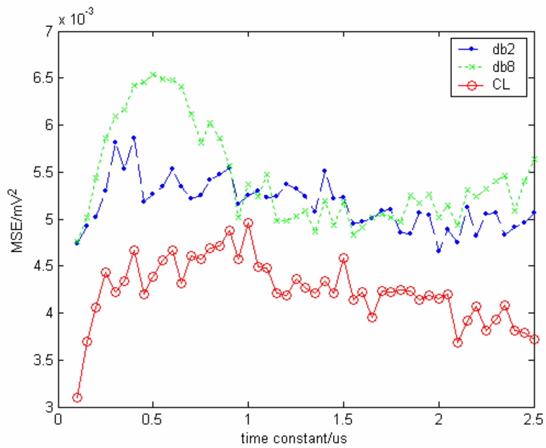

Fig.5 Multi-wavelet vs. wavelet in denoising PD of DDEP

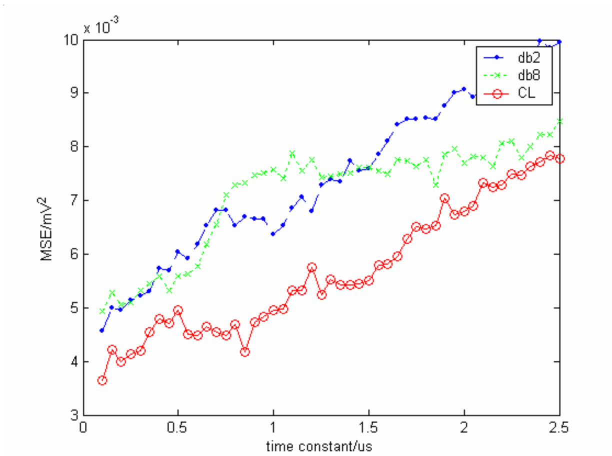

Fig.6 Multi-wavelet vs. wavelet in denoising PD of DRDEP

From Fig.3 and Fig.4, it can be seen clearly that, for PD of mode1, denoising performance with db2 is better than that with db8, but when dealing with PD of mode 2, db8 is superior to db2. This observation is consistent with the conclusion obtained in literature[2].

In Fig.5 and Fig.6, comparing the denoising performance of db2 and db8, however, it is difficult to determine which is better. Such as in Fig.6, when time constant lies between 800ns and 1.2us, db2 seems better, however, when time constant falls into the area above 1.5us, db8 turns to be superior. In fact, from this, we can find a problem that cross relation coefficient cannot determine an optimal wavelet basis function absolutely. It is because that cross relation coefficient is calculated only from a typical and calibrated waveform of PD pulse, with the variety of time constant and resonant frequency, such a typical PD pulse in fact can hardly exist, in other words, cross relation coefficient cannot justify the performance in all cases.

Now, we compare the denoising performance of multi-wavelet and wavelet. From Fig.3-6, it is obvious that for PD pulse of any mode, multi-wavelet CL is superior to wavelet db2 or db8 in the suppression of white noise.

In summary, from the results above we can conclude that: for PD pulse of any mode(shown in Fig.2), the denoising performance of multi-wavelet CL outperforms that of wavelet db2 and db8.

4.3 Denoising PD pulses of multi-mode

In the previous section, the denoising results for PD pulse of single mode are provided, and in this section, we will give the results for PD pulses of multi-mode. It aims to further confirm the denoising performance of multi-wavelet, what is more, investigate the performance under different noise level.

In the simulation, 4 PD pulses of different modes, either in one form of Fig.2, are selected and arranged in sequence, corresponding time constants are 1μs, 1μs, 2.5μs, 2.5μs, respectively. Pulse peak value of either pulse is 1mV, with resonant frequency and sampling frequency is the same as previous section. The interval between two successive pulses is 512 points and the length of the simulation data is 2048. The interference superimposed is white noise with standard deviation ranging from 0.01 to 0.5mV (step equal to 0.01mV). It is the same as before, simulations are conducted repeatedly independently 100 times, and the eventual result is the mean of 100 observations, see Fig.7.

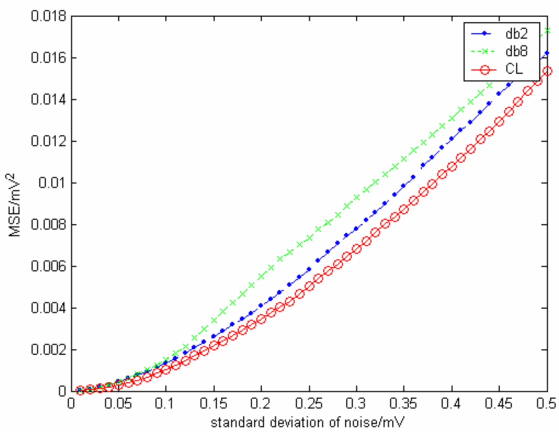

Fig.7 Multi-wavelet vs. wavelet in denoising PD cluster under different noise level

From Fig.7, it can be seen that, with the increase of noise level, the denoising performance degrades. However, the denoising performance of multi-wavelet CL outperforms wavelet db2 and db8 all the while.

4.4 A typical instance

For the sake of clarity, we give an instance (see Fig.8 (a)), typical for multi-mode PD signals. The original PD signal and corresponding simulation parameters can be found in literature[3], and in the interest of concision, the parameters are no more provided here.

Consistent with [3], besides white noise, we add DSI to the original PD signal. Furthermore, the interferences added are much stronger than those in [3].

(a) White noise has a $N\left(0,0.4^2\right)$ distribution,

(b) DSI can be formulated as:

$$f_{DSI}(t) = 0.3 \times (\sin(600k \times 2\pi \times t) + \sin(850k \times 2\pi \times t) + \sin(1.1M \times 2\pi \times t) + \sin(1.5M \times 2\pi \times t)$$

(11)

The PD pulses, superimposed by DSI and white noise, are shown in Fig.8 (b), with signal-to-noise ratio equal to -11.4dB.The length of the data is 2048.

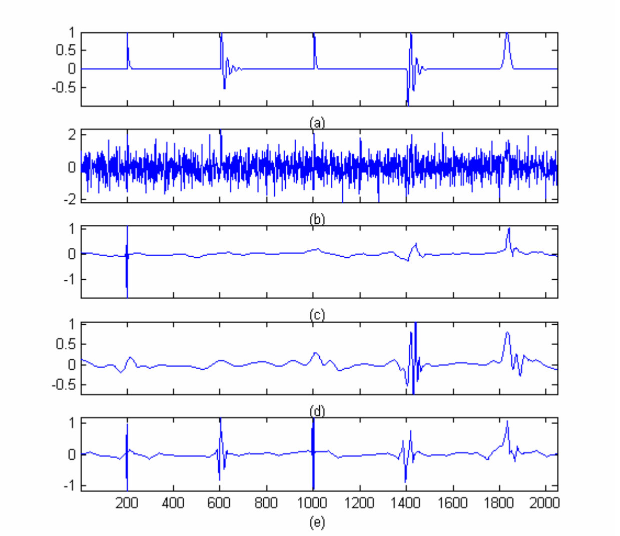

Fig.8 Multi-wavelet vs. wavelet in denoising typical multi-mode PD cluster: (a) simulation PD pulses; (b) corrupted signal; (c) denoised result with db2 wavelet; (d) denoised result with db8 wavelet; (e) denoised results with CL multi-wavelet.

From the denoised results above, it can be observed that, multi-wavelet CL can preserve complete information of PD pulses in comparison to wavelet db2 and db8.

4.5 Processing of on-site data

The on-site data is derived from the PD monitoring system installed on the generators of BaoGang power plant[1]. The work group led by Huang has developed two types of online PD monitoring systems, HSB-1 and HSB-2, successively from the late of last century until now. The sampling frequency of HSB-1 is 6.67MHz, and that of HSB-2 is 25MHz. In the following process, we select one data set from either system, the data length of HSB-1 is 8192, and that of HSB-2 is 32768. The original data and the processed results are illustrated in Fig.9 and Fig.10. In either plot, results obtained by using wavelet db2, wavelet db8 and multi-wavelet CL are provided together.

From Fig.9 and Fig.10, it can be observed that CL multi-wavelet can preserve more PD pulses when suppressing the interference in comparison to wavelet db2 or db8. Although not as much obvious, it is consistent with the result obtained in the previous section.

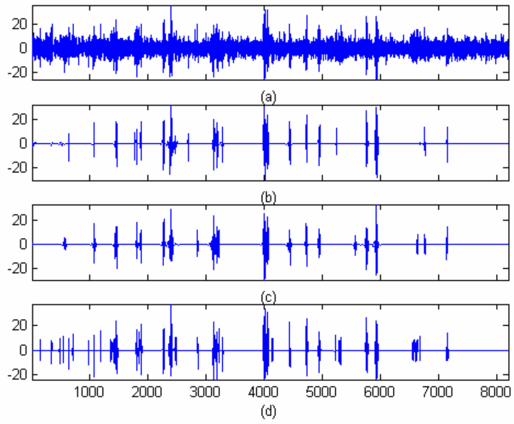

Fig.9 Multi-wavelet vs. wavelet in denoising data of HSB-1 monitoring system: (a) original on-site data; (b) denoised result with db2 wavelet; (c) denoised result with db8 wavelet; (d) denoised result with CL multi-wavelet.

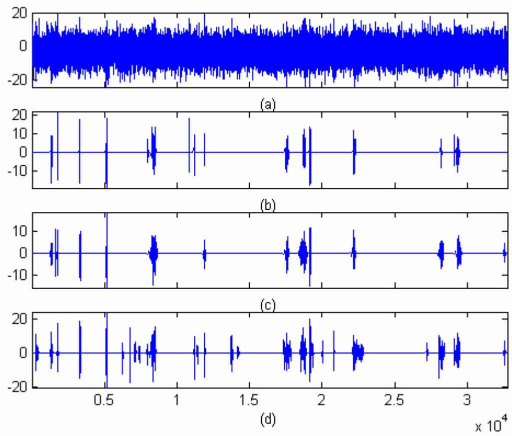

Fig.10 Multi-wavelet vs. wavelet in denoising data of HSB-2 monitoring system: (a) original on-site data; (b) denoised result with db2 wavelet ; (c) denoised result with db8 wavelet; (d) denoised result with CL multi- wavelet.

5 Conclusion and future work

Multi-wavelet is the new development of wavelet theory, and possesses more advantages than classical wavelet in signal processing. In this contribution, we employ it to detect the partial discharges overwhelmed by interferences, mainly by white noise. Through massive simulation, together with on-site data processing, it can be concluded that:

1) Compared with wavelet, multi-wavelet based method needs no (or less) prior knowledge of PD pulses,

2) Compared with wavelet (db2 or db8), multi-wavelet (CL), depending less on the waveform of the PD pulses, excels in extracting PD pulses of various modes,

3) From the results obtained, multi-wavelet (CL) outperforms wavelet at least in the suppression of white noise.

With the development of multi-wavelet, various new multi-wavelets have been reported, which is optimal and how to determine it demand further research. Besides, in this contribution, we deal mainly with the suppression of white noise; in practice, DSI is another important interference, how to eliminate it with multi-wavelet transform still need much more work.

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