Noise-based Wavelet Denoising Technique for Partial Discharge Measurement

ZHOU-SHENG ZHANG and DENG-MING XIAO
Dept. of Electrical Engineering
Shanghai Jiaotong University
Shanghai, 200240
CHINA
zzsheng417@163.com and dmxiao@sjtu.edu.cn

Abstract: - For enhancement the insulation quality of medium voltage and high voltage power cables, on-site partial discharge (PD) diagnosis tests such as detection, location and identification are used to find defects or faults and assess ageing degree of the cable insulation. Typical test methods such as oscilating voltage waves (OVW), very low frequency (VLF) for medium cables and frequency-tuned resonance (FTR) for high voltage cables are adopted by far, especially for XLPE cable system. However, on-site interferences and noises make this PD detection very difficult. It requires a better method to extract PD pulses from severe noise circumstance. Wavelet transform technique used to suppress noises from PD signal (PDs) requires reasonable mother wavelet, amount of scales and thresholds to produce its best effect. This paper proposed a new wavelet-based denoising technique for on-site PD measurement of power cables. It aimed at applying discrete wavelet transform (DWT) with better denoising effect to on-site PD measurement. Firstly, it described and analyzed the testing methods for on-site PD measurement. Secondly, resonable amount of scales selection algorithm and threshold determine algorithm have been studied with this denoising technique. Finally, simulation studies associated with this method are presented. Moreover, previous wavelet denoising techniques are also studied here to compare to the new technique. Results indicate that this technique can not only attain better denoising effect but also improve the sensitivity of PD detection.

Key-Words: - Partial discharge, discrete wavelet transform, power cables, oscilating voltage wave, very low frequency, frequency-tuned resonance.

1 Introduction

Medium voltage (MV) and high voltage (HV) power cables have been used in electrical power system more and more gradually. Faults and defects may be introduced to power cable and its accessories during transportation and installation. After installation, the insulation of cables and accessories may include small voids and cavaties, cantaminants and protrusions at different interfaces. Moreover, transportation and installation can bring mechanical cuts to the cable and its accessories. These faults or defects may be harmless at the beginning of the cable sevice but they will make the insulation breakdown and result in unexpected failures of whole cable system after long-term use [1, 2]. The influence of failures of cable system on reliability of the electrical power system is adding increasingly. Replacement or maintenamce for defective cables relies on scientific testing means, analysis on datas and assessment. Consequently, after laying tests and on-site tests during service of power cables are important and compulsory.

After laying tests of new cables and diagnosis tests of old cables generally include withstand voltage test and partial discharge (PD) detection. The former one is destructive and the latter is nondestructive. Insulation defects in the cable or in the accessories may not cause failure during a withstand voltage test of a few minitues but they are harmful for the long-term service. The PD detection can reveal these defects and assess their serious degree. So far there are three main testing methods for on-site PD detection.They are oscillating voltage waves(OVW) and very low frequency(VLF) for MV cables, and frequency-tuned resonance(FTR) for HV cables.

PD detection involves the capture and storage of PD datas, processing of PD signals, diagnosis and assessment of insulation. PD monitoring is approved the most effective technique for the cable insulation assessment. PD signals occur in the form of individual or serious of electrical pulses. They are small and are likely to submerge in noises. So, electromagnetic interference is a major problem in PD measurement. Rejection noise from PD signals is a precondition to analyze the characteristics of PD signals.

PD pulse is always nonperiodic and fast transient. It is nonbalanced. So, traditional signal processing methods such as Fourier transform technique are limited for PD signal extraction. Wavelet and its transform techniques can realize the local analysis simultaneously and has been used widely in signal processing areas [3, 4, 5, 6, 7].

The difficult parts of wavelet-based denoising for PD signal extraction are the wavelet function selection, determination of the number of scales and reasonable threshold value algorithm. Wavelet function must be maximum correlativity to the real PDs and should be smooth in interisting frequency ranges. The number of scales must be reasonable, or else it can result in inefficient noises rejection by insufficient scales, and reversely add processing time by superfluous scales. Mean value-based threshold algorithms can not reject noises at small number of scales. All of these need a new DWT denoising method to reject noises and to extract PDs from interferences.

This paper proposed a new wavelet transform method suitable for on-site PD measurements. This method can dynamically construct threshold values according to the current noising characteristics. Moreover, the most appropriate amount of scales is calculated and analyzed. It is mainly associated with sampling rate. The present denoising method can reject noises with little number of scales even at large sample rate. The most important is that present method uses maximum values of noise to construct thresholds, which can reject noises completely.

2 On-site PD Measurement and Noise and Wavelet Technique

2.1 On-site PD Measurement

On-site PD measurement generally uses the applied testing voltage to simulate the voltage stress, which occur during the service of the cables. Now, there are three main methods have been presented in engineering application. They are OVW, VLF and FTR testing system. OVW method and VLF method are suitable for MV cable test, and ISR method for HV cable test. The voltage waveforms of them are shown in figure 1a), 1b) and 1c) respectively. The waveform of VLF may be sine wave, triangle wave, semi-triangle wave, rectangle wave or cosine square wave. Among these waveforms, the triangle wave is easy to realize from charge and discharge of RC. The OVW voltage used for PD measurement has the oscillating frequency typically from several tens Hz to several hundreds Hz [8], and the typical frequency of VLF voltage is 0.1Hz. The FTR voltage used for PD measurement of HV cables has the frequency typically from 30Hz to 300Hz [9].

Typically, the rise time of the discharge pulse is only a few ns and it's during has the order of 10ns [10]. The shape of discharge pulse is determined by the shape and size of the defect and the applied detecting circuit. Normally, the detecting circuit is either a RC impedance circuit or a RLC impedance circuit. For three main testing methods, i.e. OVW, VLF and FTR, the real circuit construction adopted are possibly different, but the dectecting methods are the same.

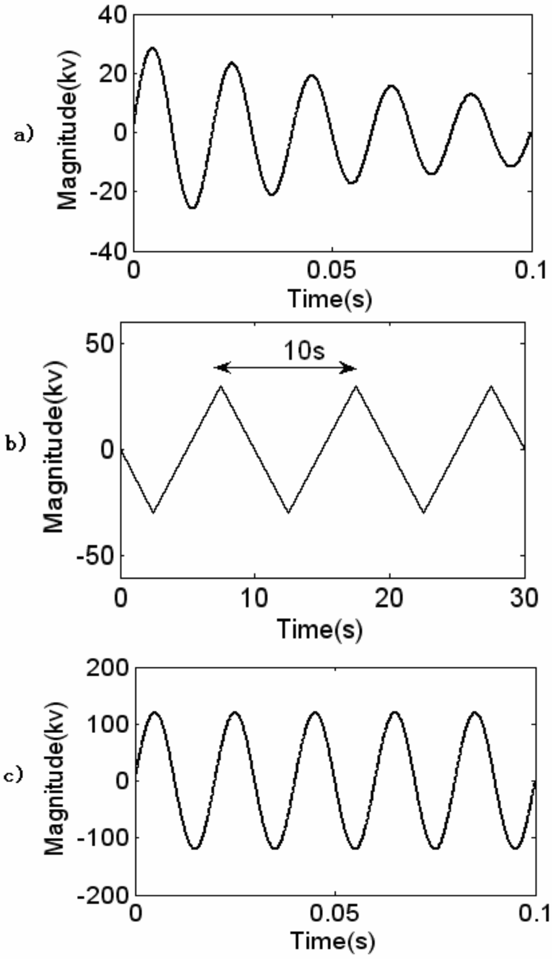


Fig.1 Voltage waveform of power supply. a) VW voltage waveform; b) VLF voltage waveform; c) FTR voltage waveform.

The output voltage pulse can be represented as a damped exponential pulse (DEP) in the RC impedance circuit and a damped oscillating pulse (DOP) in the RLC impedance circuit. Under the condition of numerical simulation, their mathematical models can be represented as the expressions of (1) and (2) respectively.

$$DEP(t) = A(e^{-\frac{t}{t_1}} - e^{-\frac{t}{t_2}}) \tag{1}$$

and

$$DOP(t) = A\sin(2\pi f_c t)(e^{-\frac{t}{t_1}} - e^{-\frac{t}{t_2}}) \quad (2)$$

Where A is the peak value of pulse, t_1, t_2 are the damping coefficients and f_c is the oscillating frequency of DOP.

2.2 On-site Noise Characteristic

One of the major bottlenecks for PD measurement and analysis is external interferences which directly affects the sensitivety and reliability of the acquired PD datas. In most cases, these external interferences may cause improper indication in the PD signal analysis, thereby reducing the credibility of PD measurement as a diagnostic method for the faults and defects of power cables. In practice, the major external interference sources under on-site conditions are [11]:

(i) Discrete spectral interferences (DSI) from radio transmissions and communication systems.

(ii) Repetitive and stochastic pulse shaped interferences from power electronics, switching operations, lighting and so on.

(iii) Stochastic noises associated with pulse current of thyrister and electrical noises and so on.

DSI is named continuous sinusoidal noise also. It is a narrow band interferene. Pulse (repetitive and stochastic pulse) interferences and stochastic interferences are wide band interferences. Interferences of the amplifiers in detecting circuit as a white noise can not be neglected [12].

2.3 DWT Denoising Technique

Removal interferences and noises from signal is one of the applications of DWT technique. DWT can decompose the original polluted signal in different frequency resolution according to multi-resolution analysis (MRA) method. The MRA of DWT is equivalent to filtering a time domain original signal by means of a pair of filters, i.e., the decomposition high pass filter(DHF) and the decomposition low pass filter(DLF). The DHF and DLF are called quadrature mirror filters (QMF). When decomposition, the original signal passes through the DHF and DLF with down-sampling algorithm by two to produce the high frequency components(also named high frequency coefficients) and the low frequency coefficients(also named low frequency coefficients), i.e., the details and approximations. The low frequency components are decomposed further at a degree that frequency resolution is satisfying. The structure of MRA is shown in figure 2. Where N is the final decomposition scale; Ca_i is the low frequency coefficient at scale i; and Cd_i is the high frequency coefficient at scale i. The down-sampling by two expresses that every sampling reduced the sampling rate by half. That is to say that signal length and frequency are halved at every time when the signal passes through the QMF.

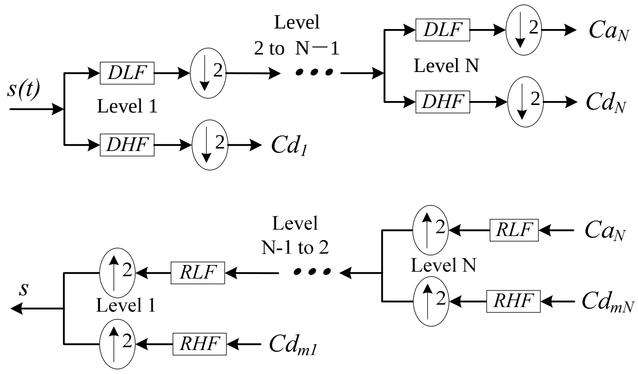


Fig.2 Signal decomposition and reconstruction

Generally, after decomposition, some of the coefficients have a main energy relating to the signal and others are relating to the interferences and noises. From this view of point, if we remove or reduce the energies relating to the interferences and noises in specific frequency resolution, the signal will be completely resconstructed and extracted. In practice, it is difficult to separate completely the signal energy and noises energy from the DWT coefficients. General researches for removal or suppression of noises are to set a threshold for the coefficient in a scale, i.e., most of the noise energies can not pass through the threshold but the signal can.

DWT denoising methods can be carried out either by hard threshold process or by soft threshold process.

The reconstruction of signal is the reverse process of the decomposition. It is realized by the reverse discrete wavelet transform (IDWT). The low frequency coefficient and modified high frequency coefficient at every scale pass through the reconstruction low pass filter (RLF) and the reconstruction high pass filter (RHF) respectively with up-sampling by two to assemble the low frequency coefficient of the up scale. Eventually, the signal is extracted.

From above discussion, the denoising process of signal by DWT technique includes three steps below.

Step1: signal decomposition. Select a suitable wavelet, and determine a decomposing scale N. And then, decompose the original noised signal $s(t)$ to the final scale N.

Step2: threshold selection and quantitative change. Choose a threshold for every high frequency coefficieng from the scale 1 to the scale N and make a soft threshold or a hard threshold quantitative change.

Step3: signal reconstruction. Use the decomposed low frequency coefficient of the scale N and the high frequency coefficients from scale 1 to scale N which has been quantitative changed to reconstruct the signal.

2.4 Application of DWT in PD Measurement

Wavelet denoising technique is recently a powerful tool for extracting the PDs from interferences and noises. Massanori et al. [13] analyzed the PD current pulse using Gaussian and Mexican wavelets. Ma et al. [14] applied continuous wavelet transform for PD pattern recognition. Hang et al. [15] applied wavelet transform to extract PD signal from the narrow band sinusoidal interferences. Shim et al. [16, 17] presented the possibility of applying wavelet transform for the PD denoising. Ming et al. [18] applied wavelet transform for PD characteristics studies. Satish et al. [11] proposed a semi-automatic wavelet-based method to extract PD signal from the pulsive type of interences. Satish et al. [11] utilized the discrete wavelet transformation to analyze the PD datas.

Almost all applications above discussed three main subjects on wavelet transformation: noises characteristic analysis; selection of mother wavelet and determination of threshold. Moreover, most applications described above are associated with using average statistic characteristics of wavelet coefficienties on different scales for thresholding. These applications, which decrease the estimation of noise energy, are easy to incur over denoising or under denoising with unreasonable selection of the number of scales. If the statistic estimation of noise energy has maximum value, the disadvantage of over denoising or under denoising will be avoided successfully. This directly brings on the development of a new wavelet-based denoising technique suitable for on-site PD measurements in this paper.

3 A Novel DWT Denoising Technique for PD Extraction

A new wavelet-based denoising technique has been proposed in this paper. This method firstly described the selection algorithm of mother wavelet. On the basis of this, it indicated that number of decomposition scales is mainly associated with sampling rate and sampling time by analyzing the energy of PDs with the selected mother wavelet. After these, a new threshold algorithm is proposed. The present threshold algorithm considers the maximum noise energy estimation.

Under the equal applied voltage, a substitutional testing object is used for PD free measurement. The measured datas include noises and low frequency ac voltage signal (OVW, VLF or FTR). The ac voltage signal is removed by routine filtering technique or DWT technique. And then noise signal is extracted. Because of the equal applied voltage and PD free measurement, extracted noises signal is the actual noise, which is used in later PD measurement. We can decompose this noise signal with selected mother wavelet and amount of scales. Comparing the detail coefficients in every scale, the coefficient which holds maximum absolute value is saved as the threshold in later PD denoising. Because these maximum coefficients are completely produced by noises, increased components of coefficients in later PD denoising are totally produced by PD signal. Selecting the maximum absolute value of noise coefficient as the threshold, now, PD measurement can be done in the same applied voltage. PD signal corrupted by noises is denoised by DWT with same mother wavelet and amount of scales. Eventually, PD signal is extracted from noises.

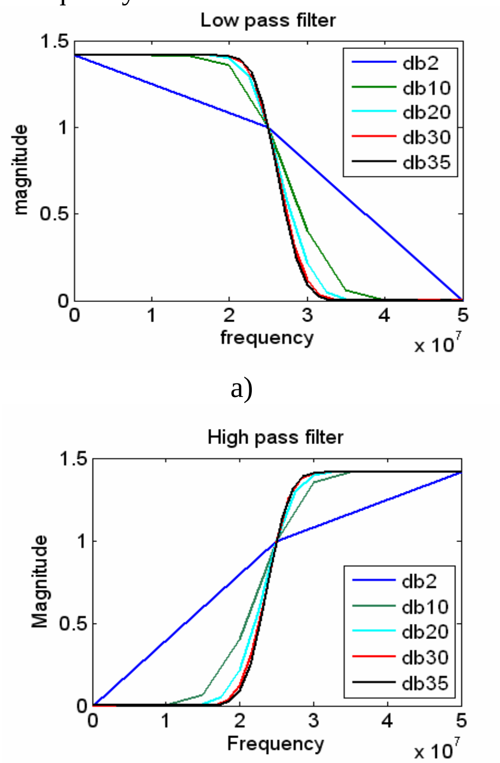
Simulating studies and experiment tests for this new DWT denoising technique are presented in this paper. Moreover, in order to compare with the new denoising method, previous old “mean threshold” method [14] is also studied in this paper. Results indicate that the new denoising method can extract PD signal well.

3.1 Mother Wavelet Selection

According to DWT denoising method for PD measurement discussed above, firstly, we must select a mother wavelet. Selection a basis wavelet function is one of the crucial steps to this DWT technique. The more the PD signal is similar to the wavelet function, the higher the coefficients associated with the PD signal will be [19, 20]. Some of the studies suggested the Daubichies wavelet family for PD measurement, such as Daubichies-2(db2) [10] and Daubichies-30(db30) [21]. These selections for wavelet function are based on plenty of experiments by comparing the correlation coefficient γ between PD signal and multifarious wavelet functions. Finally, the wavelet function with maximum correlation coefficient is adopted.

However, in practical application, there are usually small differences among the desired correlation coefficients. In this case, we can use the filter characteristic to find the optimal wavelet.

Signal decomposition is completed by filters of the specific wavelet function to produce low frequency coefficients and high frequency coefficients. We consider that the size of coefficient is associated with filter characteristic, through which the signal passed. Especially, if we interpret coefficient using the conception of signal energy (energy can be described as the square of coefficient [22]), it should be smooth in desired frequency band. This can avoid errors in threshold calculation. As a example of this consideration, the responses in frequency domain of the low pass filters and high pass filters of the Daubichies wavelet db2, db10, db20, db30 and db35 are shown in figure 3. If a sampling rate 100MHz is adopted in a measurement, the highest frequency of the figure 3 is 50MHz which corresponds to the angle frequency π. The cut-off frequency is 25MHz.



a)

b)

Fig.3 Frequency responses of filters of db2, db10, db20, db30 and db35. a) low pass filters; b) high pass filters.

We can see the differences from their filter characteristics. On the left side and right side of the cut-off frequency, the filter magnitude of db2 changes with frequency according to approximate direct proportion or inverse ratio. However, the filter magnitude of db30 and db35 is sharp at the cut-off frequency but almost smooth at other frequencies. The higher the order of Daubichies wavelet, the bigger the frequency band of filter. Thus, high order wavelet is preferable.

So, we can choose the mother wavelet according to three principles below:

(i) The mother wavelet is orthogonal [20].

(ii) Compare the correlative coefficient between signal and wavelet function. The bigger the correlative coefficient is, the higher the coefficients produced by DWT of corresponding wavelet function are.

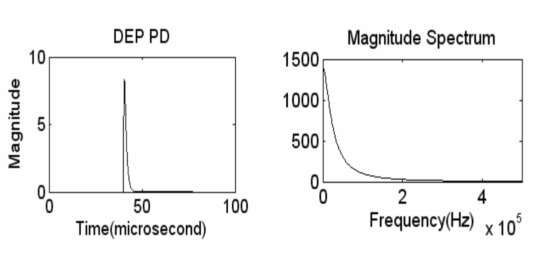
(iii) Consider the responses in frequency domain of filters of wavelet function. The smoother the response curve both sides of cut-off frequency is, the smaller the differences (i.e., signal components vary with filters in different frequency) are.

3.2 Decomposition Scale Selection

It is difficult to determine how many decomposition scales should be adopted during DWT. However, it is generally accepted that more decomposition scales could cause the better effect of denoising, especially for signals with low signal-noise-ratio (SNR) . The reasonable scales in number are different with different signals. Zhou et al. [22] suggested the maximum decomposition scale, i.e., 7 scales for PD signals calculated by energy distribution methods. Zhang et al. [20] adopted 10 scales to extract PD signal from noises. And so on.

As a matter of fact, we consider that the selection of decomposition scales is associated with the threshold determination methods. If the coefficients are not modified or have a little modification (mainly the high frequency coefficients) during the process of reconstruction signal, more or less scales are not important for DWT. However, if high frequency coefficients have much modification during reconstruction, the more scales reversely can cause serious distortion of PD signal. This is because of that the modification of coefficients is likely to modify the components of PD signal in corresponding frequency band. So, a maximum decomposition scale N should be selected carefully.

The maximum decomposition scale is mainly associated with the sampling rate for original signals. The higher the sampling rate is, the more the scales are. Under the fixed sampling rate, we can determine the maximum number of scales by calculating the energies of coefficients in every scale. As a example, the DEP type PD pulse signal is shown in figure 4 with its frequency spectrum.



a) b)

Fig.4 DEP type PD pulse and its spectrum. a) DEP pulse; b) frequency spectrum.

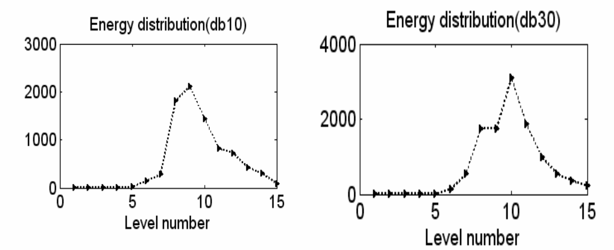
The sampling rate is 100MHz here. Energy of coefficients can be calculated by the equation in (3) and (4).

$$EA_k = \sum_{i=1}^{l_k} (Ca_i)^2 \tag{3}$$

$$ED_k = \sum_{i=1}^{l_k} (Cd_i)^2 \tag{4}$$

Where EA_k is the energy sum of approximation coefficients at the scale k, ED_k the energy sum of detail coefficients at the scale k and l_k the signal length at the scale k.

Energy distributions of detail coefficients of the DEP pulse signal vs scales ,which are decomposed by wavelet function db10 and db30, are shown in figure 5a) and 5b) respectively. Case of db10 is presented to compare the effect for different wavelet function.



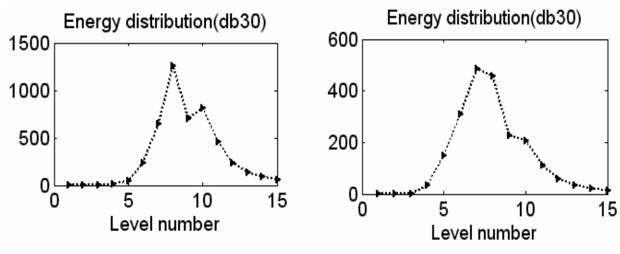
a) b)

Fig.5 Detail coefficient energy distribution. a) decomposed by db10; b) decomposed by db30.

When sampling rate is 100MHz, energies are concentrated at scale 6 to scale 15. Detail coefficients at scale 1 to scale 5 almost don't hold energies for this DEP signal. Moreover, energies are almost zero at more than 15 scales. So, the maximum scale N can be selected as 15 for this 100MHz sampling rate.

The scale holding maximum energy is different with different wavelet function, e.g., db10 at scale 9 but db30 at scale 10. Moreover, energy magnitude is different with different wavelet function, e.g., the maximum magnitude is 2100(for db10) but is 3000(for db30). But these do not affect the selection of maximum scale number. That is to say, mother wavelet function is inessential for maximum scale selection.

We also analyzed the influence of pulse duration. Energy distributions of DEP pulse, which has $\frac{1}{2}$ and $\frac{1}{4}$ times of original signal duration, are shown in figure 6a) and 6b) respectively.



a) b)

Fig.6 Detail coefficient energy distribution. a) 0.5 times of signal width; b) 0.25 times of signal width.

We can see from figure 6, parts of energy move toward small scales, e.g., energies are concentrated at scale 5 to scale 15 for $\frac{1}{2}$ times of signal duration and scale 4 to scale 15 for $\frac{1}{4}$ times of signal duration. Moreover, the scale holding maximum energy moves toward small scale number,e.g., scale 8 for $\frac{1}{2}$ times of signal duration and scale 7, 8 for $\frac{1}{4}$ times of signal duration. At the same time, energy magnitudes reduce when signal duration becomes narrow. Even if these, the maximum decomposition scale $N = 15$ is still satisfied.

From above discussion, a result can be obtained: the maximum decomposition scale is mainly decided by sampling rate when given wavelet function is used. However, it is not a feasible application for more scales due to the decrease of running speed. Thus a new method, with which the DWT denoising can perform well even at small number of scales, is preferable. The DWT denoising technique proposed in this paper is such a method, which uses the noise characteristics to achieve the threshold algorithm and gets better denoising results at small number of scales (usually 5).

3.3 Threshold Selection

It is a difficult thing for DWT denoising to selecting a reasonable threshold. Thresholding aims at removing the coefficients associated with noises, and preserving the coefficients associated with PD signals. Finally, coefficients preserved are reconstructed through IDWT to recover PD signals. If threshold values are selected more high, coefficients associated with PD signals are possibly discarded. Reversely, if threshold values are selected more low, noises can not be removed fully. On the other hand, threshold selection algorithms should be automatically completed in practical PD measurements. Especially for operators with no more experiences, automatical thresholding algorithms can bring more conveniences for on-site measurement.

Ma et al. [10, 23] proposed a scale-dependent automatic threshold selection algorithm, as shown in (5).

$$\lambda_j = \frac{m_j}{0.6745}\sqrt{2\log n_j} \tag{5}$$

Where λ_j is threshold value of approximation coefficients or detail coefficients at scale j, m_j is the median value of corresponding coefficients at scale j and n_j is the signal length at scale j. Rescaling factor 0.6745 is used to limit the coefficients fluctuation during denoising. It is well suitable for zero mean white noises suppression. Subsequently, some literatures [19, 24] adopted this thresholding method to realize wavelet denoising. However, this algorithm is not efficient at small number of decomposition scales for big sampling rate.

According to above discussion, a new noise-based threshold selection method, which not only has automatic characteristic but also suppresses interferences at present energized voltage, is presented.

For on-site PD measurement of power cables, different energized voltages are applied for different measurement methods described previously, i.e., OVW, VLF and FTR. We can firstly use a PD-free load, which has equivalent capacitance compared with the under test cable, to perform the measurement at the same voltage required by OVW, VLF or FTR. Because of no PD signals, recorded signals compose of noises and energized voltage. Energized voltage is a low frequency signal in frequency domain, which is easy to extract from noise signals by generic filter methods. Thus the desired noise signals are obtained, and then are decomposed by DWT with selected mother wavelet and scales described previously. Choose the maximum of detail coefficients at every scale as the threshold of current scale which will be used for the next step about the PD signal reconstruction. The block diagram of threshold determination and PD signal extraction are briefly shown in figure 7. This method assured that the maximum noise coefficients (thresholds) are acquired in equivalent testing conditions with PD signals extraction.

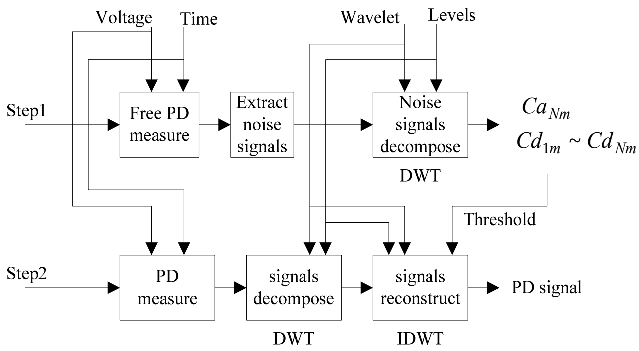


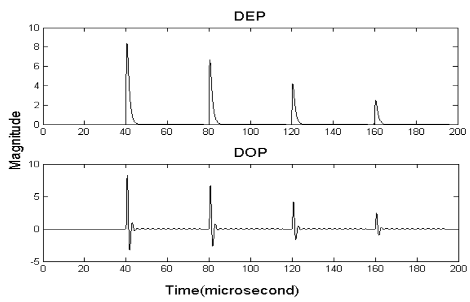
Fig.7 Threshold determination and PD signal extraction.

3.4 Simulation Studies of Denoising System

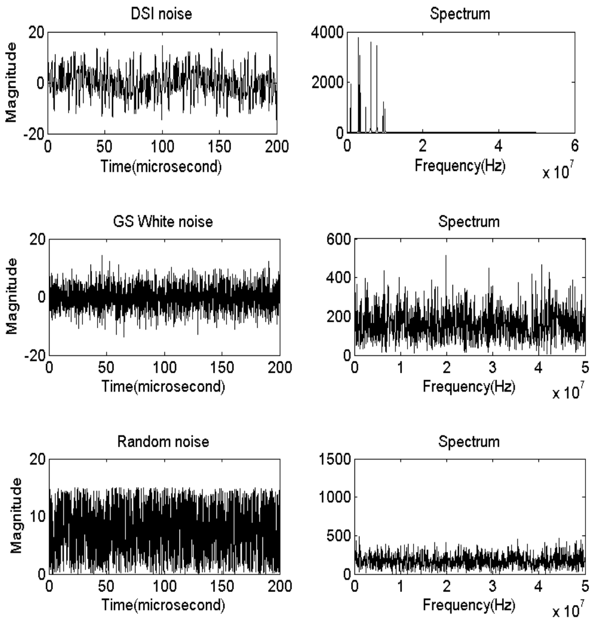
According to determination methods discussed above, simulation studies have been done, where mother wavelet db30 and number of scales 5 are selected. Threshold determination algorithm is shown in figure 7. Three types of noises (i.e., DSI, white noises and random noises) are simulated. Sampling rate is 100MHz. Sampling time is 200 μs. Sine wave for energized voltage is simulated. Four PD pulses (DEP or DOP) are arranged with different magnitude and 40 μs interval.

3.4.1 PD Signal and Noise Simulation

Simulated PD signals and noises based on mathematic model are shown in figure 8a) and 8b) respectively. DEP and DOP have four pulses respectively, according to degressive magnitudes. The magnitudes of DEP pulses are 8.4, 6.7, 4.2 and 2.5 units in turn. And the DOP pulses are 8.3, 6.6, 4.1 and 2.5 units. DSI noise is simulated by 10 different frequencies from 100kHz to 10MHz. White noise is the standard zero mean Gaussian white noise. Random noise is simulated by random production. The maximun magnitude of each type of noise is adjusted to 15 units.



a)



b)

Fig.8 Simulated PD signal and noises. a) .DEP and DOP partial discharge signal; b) DSI noise, GS white noise and random noise.

3.4.2 Denoising from Original Noise

In this section, we directly extract PD signals from noise which is assumed known. That is to say, DWT denoising is performed from original noise. The mixed noises of the DSI noise and GS white noise and random noise have the maximum value of about 40 units. The magnitudes of DEP pulses and DOP pulses are multiplied with 5. SNR is defined in (6) [10]. And then SNR of DEP pulses are 0.16db, -0.84db, -2.9db and -5.1db respectively. SNR of DOP pulses have the same values.

$$SNR = 10 * \log \frac{\max(signal)}{\max(noise)} \qquad (6)$$

Figure 9 and Figure 10 show the simulation results using the new denoising method proposed in ths paper and the conventional “mean threshold” method in (5). The “mean threshold” method presented here acts as a role of comparing with the new method.

From figure 9 and Figure10, we can see that the fourth pulse is almost immersed in noises. After DWT denoising process using the present wavelet denoising method proposed in this paper, the smallest fourth pulse is extracted from polluted signals. And we can see also that it is not efficient for conventional “mean threshold” method. This conventional method can possibly remove noise at many scales for large sampling rate, but is inefficient at small number of scales. The magnitudes of DEP pulses after denoise by new method has a average 7.62% descent and DOP pulses has a average 11.2% ascent.

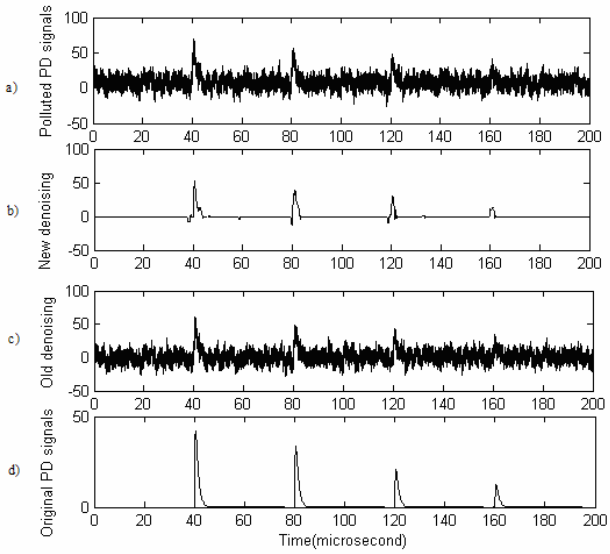


Fig.9 Simulation of extracting DEP pulses from noises. a) polluted PD signals; b) denoising result with present method; c) denoising result with conventional method; d) original PD signals.

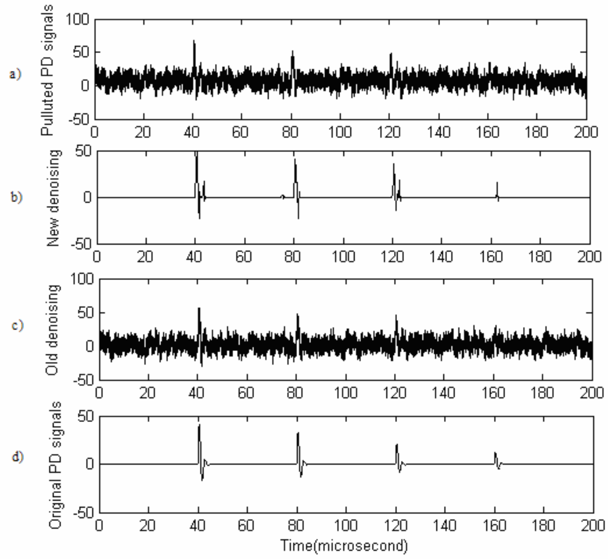


Fig.10 Simulation of extracting DOP pulses from noises. a) polluted PD signals; b) denoising result with present method; c) denoising result with conventional method; d) original PD signals.

3.4.3 Denoising from Extracted Noise

In this section, extracting noises is done firstly from recorded PD-free signals. This is to say, noise signals are not directly gived, but are obtained from removing the low frequency energized voltage signal after PD-free measurement. After obtaining the noises, we can calculate the thresholds by wavelet decomposing the noises as shown in "step1" of figure 7. Methods of removing energized voltage signal can be filter method, but we use wavelet decomposition method here.

Simulated original noise signals, polluted energized voltage signal and extracted noise signals are shown in figure 11a), 11b) and 11c) respectively. Extraction noise signals are realized by decomposing polluted energized voltage signal to 5 scales. Reconstructed noise signals, which will be the thresholds for later PD signal extraction, are shown in figure 11c).

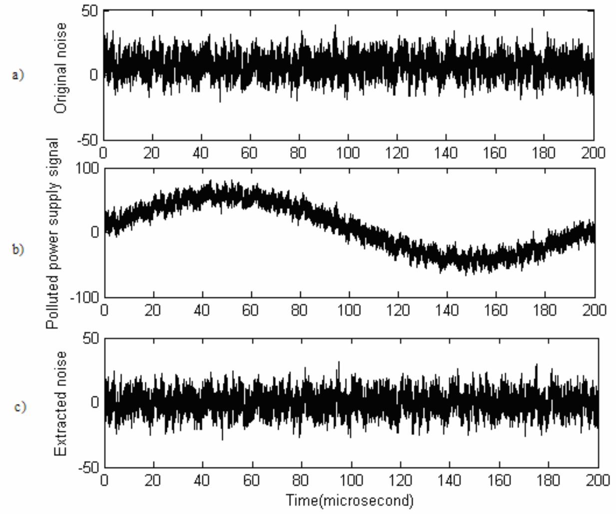


Fig.11 Extracting noise signals from polluted power supply signal. a) simulated original noise signals; b) polluted power supply signal; c) extracted noise signals.

After obtaining the noise signals, PD signals from noises circumstance can be extracted. The simulated results of extraction DEP PD pulses and DOP PD pulses are shown in figure 12 and figure 13 respectively. For comparison, we also gived the denoising results by conventional "mean threshold" denoising method.

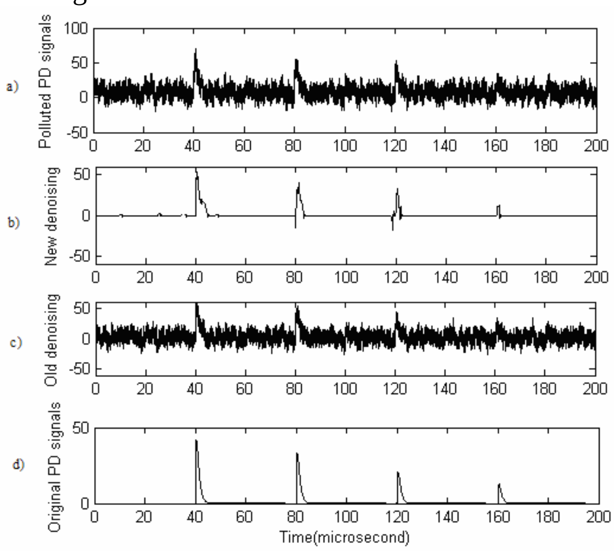


Fig.12 Simulation of extracting DEP pulses from noises. a) polluted PD signals; b) denoising result with present method; c) denoising result with conventional method; d) original PD signals.

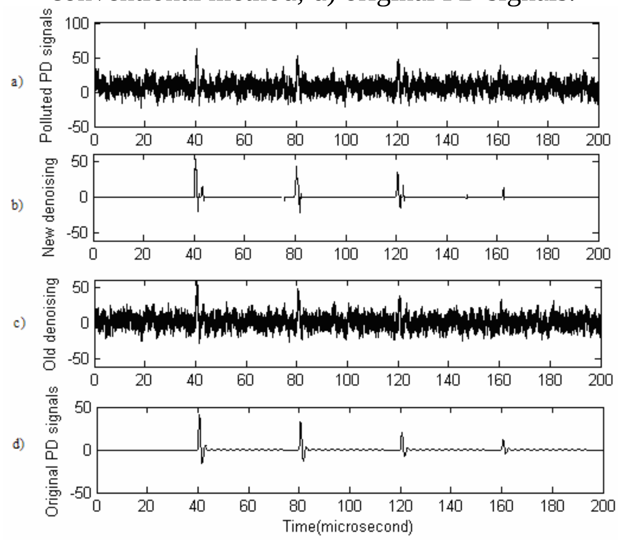


Fig.13 Simulation of extracting DOP pulses from noises. a) polluted PD signals; b) denoising result with present method; c) denoising result with conventional method; d) original PD signals.

For DEP type or DOP type , magnitudes of pulses extracted from filtering noise (see Figure 12 and Figure 13) have almost no changes to magnitudes of pulses extracted from original noise (see Figure 9 and Figure 10). Simulation results indicate that the new DWT denoising technique proposed in this paper can remove interferences and noises well.

4 Experiment Tests

A practical signal composed of PDs and noise has been recorded from testing site. The noise pre-recorded is presented in Figure 14a). Denoising results, which are performed by present DWT denoising method proposed in this paper and by conventional method, are shown in Figure 14b) and Figure 14c) respectively. Moreover, half of the ordinate is left to give a comparing of magnitudes. The sampling time is 20ms. Wavelet function db30 and maximum scale 5 are selected during denoise.

Three clear PD pulses are extracted from serious noise environment when the present denoising technique is adopted, which is shown in Firgure 14c). However, noises can not be rejected completely by conventional method, where maximum scale 5 is adopted. So, noise-based DWT denoising method proposed in this paper is preferable to mean value-based denoising method.

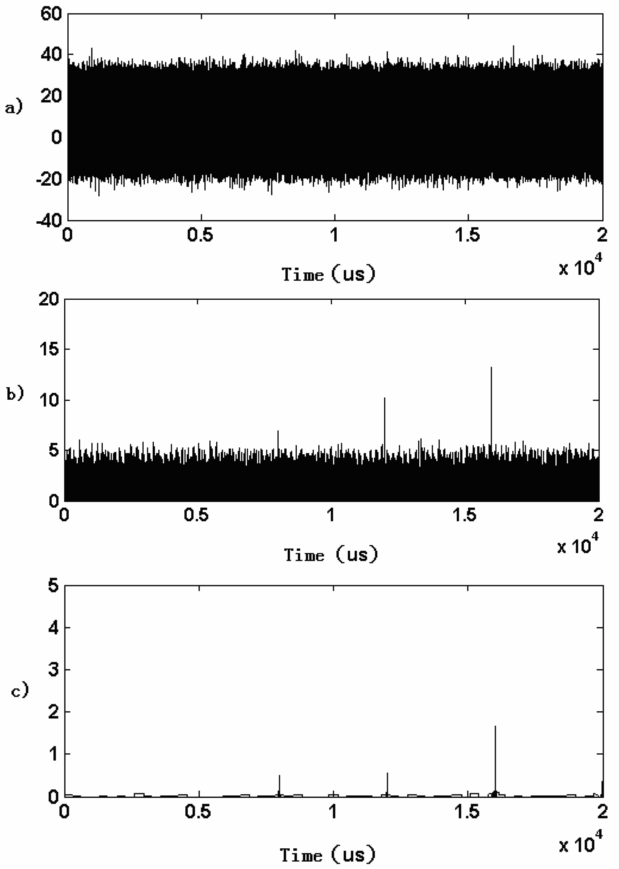


Fig.14 Experiment results. a) pre-recorded noise; b) denoising result by conventional method; c) denoising result by present method.

5 Discussion and Conclusion

Electromagnetic interference is a major problem in on-site PD measurement of power cables. Rejection noise from PD signals is a precondition to analyze the characteristics of PD signals. Wavelet-based denoising technique helps us detect the PD signal from on-site noise circumstances. Especially for low level PD signal which possibly submerged in noises, routine filtering technique becomes inefficient but wavelet-based denoising technique is feasible. A new wavelet-based denoising technique is proposed in this paper. It mainly aimed to resolve three major factors in wavelet denoise, i.e., mother wavelet selection, amount of scales selection and threshold selection for practical on-site PD measurement of cables.

There are by far three dominating methods for on-site PD measurement, i.e., OVW, VLF and FTR. Voltage waveform, signal capture principle and noise characteristic of them are analyzed in this paper. Characteristics of PD pulse and noises must be investigated before applying wavelet-based denoising technique. As on-site noises are complicated and unfixed, they can not be considered simply a GS model. Random noises must be considered also. Previous wavelet-based denoising techniques are aimed at removing noises at more scales for large sampling rate, and are limited for practical running speed. These limitations bring on a new wavelet denoising method.

Mother wavelet selection is associated with PD signal. Previous correlation coefficient comparison brings us a method to select mother wavelet. However, responses in frequency domain of filters of wavelet function are considered by authors in this paper. It is recommended to consider correlation coefficient and response in frequency domain synthetically. From the view of energy, authors calculated and analyzed the amount of scales. The number of scales is associated with sampling rate. Thus a noise-based threshold algorithm is presented by authors to reject noises at little number of scales, especially for large sampling rate.

A new threshold selection algorithm, which is determined by maximum noise characteristics, is proposed for on-site PD measurement. Simulation studies indicate that this new wavelet-based denoising technique can extract PD signal well from high level noise circumstance. Moreover, previous threshold algorithm is also studied in this paper so as to compare with the new algorithm. On-site experiment studies with this new wavelet denoising technique are performed by authors also. Results indicated that the present method is preferable to reject noises and extract PDs.

This novel technique is helpful for future research of pulse shape analysis accompanied by some optimization techniques such as Neural Networks or Genetic Algorithm.

References:

[1] J. J. Smit, E. Gulski and E. Pultrum, Partial Discharge Fault Analysis of SIR-based Cable Terminations, *10th ISH*, 1997, pp.513_516.

[2] E. Gulski, F. J. Wester, J. J. Smit, P. N. Seitz, and M. Turner, PD Detection in Power Cables using Oscillating Wave Test System, *IEEE Intern. Sympos. Electr. Insul.*, 2000, pp. 444_447.

[3] I. Daubechies, The Wavelet Transform, Time-Frequency Localization and Signal Analysis, *IEEE Trans. Information Theory*, Vol. 36, 1990, pp. 961-1005.

[4] X. Mal C. Zhou and 1. J. Kcmp, Investigation into the Use of Wavelet Theory for Partial Discharge Pulse Extraction in Electrically, Noisy Environments . *Proc. 8th International Confercnce on Materials, Measurements and*

Applications, Edinburgh.UK, 2000, pp. 123-126.

[5] Xiao Yan, Yu Weiyong, Huang Chengjun and Jiang Chuanwen, Suppression of Partial Discharge's Discrete Spectral Interference Based on Spectrum Estimation and Wavelet Packet Transform, *WSEAS Transactions on Circuits and Systems*, Vol. 4, No.11, 2005, pp. 1508-1515.

[6] Mohammad S. Naderi, M. Vakilian, T.R. Blackburn, B.T. Phung and Mehdi S. Naderi, A New Technique for Extracting Partial Discharge Signals in Transformer Winding by Application of Wavelet Analysis, *WSEAS Transactions on Power Systems*, Vol. 1, No.1, 2006, pp. 77-83.

[7] Qian Yong, Huang Cheng-jun and Jiang Xiu-chen, Investigation of Multi-wavelet Denoising in Partial Discharge Detection, *WSEAS Transactions on Circuits and Systems*, Vol. 5, No.1, 2006, pp. 85-91.

[8] Bolarin Oyegoke, Petri Hyvonen, Martti Aro and Ning Gao, Selectivity of Damped ac(DAC) and VLF Voltages in After-laying Tests of Extruded MV Cable Systems, *IEEE transactions on dielectrics and electrical insulation*, Vol. 10, No. 5, 2003, pp. 874-882.

[9] Schufft W, Coors P, Hauschild W and Spiegelberg J, Frequency-tuned resonant test systems for on-site testing and diagnostics of extruded cables, *High Voltage Engineering, 1999, Eleventh International Symposium on* (Conf. Publ. No. 467), Vol5. 1999, pp. 335-339.

[10] X. Ma, C. Zhou and I.J. Kemp, Interpretation of wavelet analysis and its application in partial discharge detection, *IEEE Trans. Diel. Elect.Insul.*, Vol.9, 2002, pp.446-457.

[11] L. Satish and B. Nazneen, Wavelet-based Denoising of Partial Discharge Signals Buried in Excessive Noise and Interference, *IEEE Trans. Dielectr. Electr. Insul.*, Vol. 10, 2003, pp. 354_367.

[12] H. Zhang, T.R. Blackburn, B.T. Phung and D.Sen, A novel wavelet transform technique for on-line partial discharge measurements part 1: WT de-noising algorithm, *IEEE transactions on dielectrics and electrical insulation*, Vol. 14, No. 1, 2007, pp. 3-14.

[13] M. Massanori, T. Okana, S. Nishimoto, I. Kitani and K. Arli, Study on Application of Wavelet Analysis for Degradation Diagnosis of Partial Discharge in Void, *IEEE 5th Intern. Coni. On Conduction and Breakdown in Solid Dielectrics*, Leicester, UK, 1995, pp. 371-375.

[14] X.D. Ma, C. Zhou and I.J. Kemp, DSP based partial discharge characterization by wavelet analysis, *IEEE 19th Int. Symp. On Discharge and Electrical Insultaion in Vacuum*, Xi'an, China, 2000, pp. 780-783.

[15] H. Wang, K. Tan and D. Zhu, Extraction of Partial Discharge Signals Using Wavelet Transform, *IEEE 5th Intern. Conference on Properties and Applications of Dielectric Materials (ICPADM)*, Seoul, Korea, 1997, pp. 322-325.

[16] I. Shim, 1. J. Soraghan and W. H. Siew, Detection of PD Utilizing Digital Signal Processing Methods, Part 3: Open-Loop Noise eduction, *IEEE Electrical Insulation Magazine*, Vol. 17, No. 1, 1997, pp. 6-11.

[17] I. Shim, 1. 1. Soraghan and W. H. Siew, A Noise Reduction Technique for On-line Detection and Location of Partial Discharges in High Voltage Cable Networks, *Measurement Science Technology*, Vol. 11, 2000, pp. 1708-1713.

[18] Y. Ming and S. Birlasekaran, Characterization of Partial Discharge Signals Using wavelet transform and statistical techniques, *IEEE Intern. Sympos. Electr. Insul.*, Boston, MA, USA, 2002, pp. 9-13.

[19] H. Zhang, T.R. Blackburn, B.T. Phung and Z.Liu, Application of signal processing techniques to on-line partial discharge detection in cables, *Intern. Conf. Power System Technology*, Paper No. MB7.2D.L, 2004.

[20] H. Zhang, T.R. Blackburn, B.T. Phung and D.Sen, A novel wavelet transform technique for on-line partial discharge measurements part 2: on-site noise rejection application, *IEEE transactions on dielectrics and electrical insulation*, Vol. 14, No. 1, 2007, pp. 15-22.

[21] I. Shim, J. J. Soraghan and W. H. Siew, Detection of PD Utilizing Digital Signal Processing Methods Part 3: Open-Loop Noise Reduction, *IEEE Electr. Insul. Mag.*, Vol. 17. No. 1, 2001, pp.6-13.

[22] X.Zhou, C.Zhou and I.J.Kemp, An Improved Methodology for Application of Wavelet Transform to Partial Discharge Measurement Denoising, *IEEE transactions on dielectrics and electrical insulation*, Vol. 12, No. 3, 2005, pp. 586-594.

[23] X. Ma, C. Zhou, and I. J. Kemp, Automated wavelet selection and thresholding for PD detection, *IEEE Elect. Insul. Mag.*, vol. 18, no. 2, 2002, pp. 37–45.

[24] Li-Jung Chen, Whei-Min Lin, Member, IEEE, Ta-Peng Tsao, and Yu-Hsun Lin, Study of

Partial Discharge Measurement in Power Equipment Using Acoustic Technique and Wavelet Transform, *IEEE Transaction on Power Delivery*, vol. 22, no. 3, 2007, pp. 1575–1580.

Zhousheng Zhang received the B.Sc. degree in physics from Huazhong Normal University, China in 1992. He worked with Hubei Institute for Nationalities during 1992-1996 as a instructor. He received the M. Sc. Degrees in electrical engineering from Huazhong University of Science and Technology, China in 1999. He worked with Hitachi Japan during 1999-2000. Since then, he worked with Xuji Hitachi Electric Co. during 2000-2006, developing relay protection software platform and substation automation. He is currently pursuing his Ph.D degree at Shanghai Jiaotong University, China on the measurement, identification and wavelet analysis of partial discharge of power cables.

Dengming Xiao was born in Liuzhou, China on December.6, 1953 . He received his B.Sc, M..Sc. and Ph.D. degrees in1982,1987 and 1994 , respectively, all from Xi’an Jiaotong University, China. He is now a professor in electrical engineering and director in high voltage engineering at Shanghai Jiaotong University. His research interests are high voltage engineering, power apparatus online diagnosis and gas discharges.