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Self-Adaptive Morphological Filter for Noise Reduction of Partial Discharge Signals

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Abstract

Partial Discharge assessment in the insulation of high voltage equipment is one of the most popular approaches for prevention of the insulation breakdown. In the procedure of this assessment, noise reduction of partial discharge signals to get the original PD signal for accurate evaluation is inevitable. This denoising process shall be carried out such a way that the main features of the partial discharge signal like “amplitude”, “rise time”, “energy” and etc. are kept as much as possible. Wavelet Transform and Mathematical Morphology are the useful signal processing algorithms which are exploited and proposed in literatures for noise reduction of partial discharge signals. In this paper two Wavelet based filters which have promising results are explored and finally compared with the proposed Morphological based filter. Unlike the traditional morphological based filters the advantage of the proposed method is the ability of structure element length selection in a completely self-adaptive procedure. Also the results of noise reduction in different noise level are presented that the proposed method shows superiority in all circumstance.

Keywords: Partial discharge, Noise reduction, Wavelet transforms, Mathematical morphology

Article history: Received 29-Mar-2018; Revised 25-Apr-2018; Accepted 20-May-2018.

1. Introduction

One of the useful and effective approaches for on-line monitoring of the insulation of high voltage equipment is partial discharge (PD) measurement [1]. The monitoring of this phenomenon before deterioration of insulators could prevent of unwanted outage in power systems [2, 3]. Nevertheless, the effect of environmental interference and noise lead to complexity in the analysis of measured data [4].

There are three main categories of the noises that are mixed with the original PD signal: (i) narrow-band noise, (ii) white noise, and (iii) pulse-shaped noise. There have been established and applied many signal processing methods for denoising of PD signal polluted with these kinds of noises [5]. The most popular method, wavelet transform (WT) and methods like neural network, support vector machine and correlation based algorithms are introduced for removing the white noise from PD signals. For removing narrow-band interference, methods like wavelet packet transform and ensemble empirical mode decomposition (EEMD) are employed [2, 6, 7 and 8]. Also, Pulse-shaped signal that are often mixed with PD signal, usually are generated by lightning, corona, and switching. In [9] a wavelet-entropy based method for denoising of this kind of noise is proposed. An optimum wavelet selection for noise omission of PD signal is proposed in [10] that is called energy based wavelet selection (EBWS). In [10] a new approach for optimum wavelet selection is proposed, but the effect of noise on the way of wavelet selection is ignored. Also, the optimum decomposition level is not clear for this kind of wavelet-based method.

In [11] a wavelet packed based method with energy conversation-based threshold for denoising of PD signal is proposed. The results of this method in comparing with conventional wavelet-based techniques are more promising. In this method a wavelet selection algorithm, named correlation based wavelet selection (CBWS) is employed as the best way for wavelet selection. Then, wavelet packet for decomposition of noisy PD signal and a new thresholding method are proposed that is named Energy Conservation Based Tresholding (ECBT). Even though, the results of the introduced method by [11] are superior to the others WT methods, but the main restrictions of wavelet based method i.e., selection the optimum wavelet (it is affected by noise) and decomposition level are still unsolved. A new Mathematical Morphology Based Filter (MMBF) was proposed for noise reduction of PD signal by [14] and compered with WT filters. Even though, the simulated results show the superiority of MMBF, but the main problem of these kinds of filters, the selection of the optimum length of structure element (SE), is not investigated. Authors in [13] studied and explored this restriction of MMBF and proposed a lookup table based method for optimum SE selection which is still needs a prior knowledge of PD signal characteristic.

In this paper a new self-adaptive morphological filter (SAMF) method is proposed for noise reduction of PD signal. The performance of this method is compared with ECBT and CBWS with employing introduced indexes in the appendix. The results show supremacy of the proposed method in all noise level and various PD signal amplitudes. Furthermore the whole procedure of the proposed method is carried out without any necessity to having prior knowledge of the PD signal or the noise characteristic.

The rest of this article is categorized as: in section 2 the simulated PD signals are introduced. In section 3 the wavelet transforms based filters are studied and two most well-known methods are reviewed. Section 4 is assigned to considering the conventional morphological based filters and introducing the proposed method. The simulation results and discussion about the denoisng methods are presented in section 5. And finally in section 6 conclusion of the paper is explained.

2. PD Signal Simulation

PD signals have very wide diversity in their characteristic like amplitude, pulse width, rise time and fall time [4]. In this paper three different PD signals with the equation and represented characters in **Error! Reference source not found.** are simulated which the results are shown (for amplitude 10 mA) in **Error! Reference source not found.**. In the rest of this paper these PD signals are used for study and analysis on the noise reduction algorithms.

$$y(t) = A(e^{-\alpha_1 t} - e^{-\alpha_2 t}) \quad (1)$$

Table.1.
The simulated PD signals data

Signal Type	*Amplitude (mA)*	α_1	α_2	*Pulse width*	*Rise time*
PD Signal 1	10, 30, 50	5×10^{7}	12×10^{6}	5×10^{-6}	3.7×10^{-7}
PD Signal 2	10, 30, 50	9×10^{7}	22×10^{6}	3×10^{-6}	2.1×10^{-7}
PD Signal 3	10, 30, 50	14×10^{7}	35×10^{6}	2×10^{-6}	1.3×10^{-7}

A) *Wavelet Transform Based Filters*

Basic Principle of the Wavelet Transform based filters for noise reduction of PD Signals

All denoising methods try to conserve the energy of PD signal and extract the main features like “amplitude”, “rise time”, “pulse width” and . . . of the PD signal. Although, there have been progress in the presented methods in the literatures, but PD signal distortion in denoising process still has happened and the above mentioned features are affected. WT is one the most effective and popular algorithm in noise reduction of PD signals. The general procedure for WT methods includes three steps: (i) By using Discrete Wavelet Transform (DWT) the input noisy signal is decomposed through a set of high and low pass filters and the results are two time series sub-bands which are named approximation and detail. (ii) Thresholding function applies to the detail sub-bands to remove noises coefficient and preserve the coefficients of original PD signal. (iii) Finally the thresholded detail sub-bands and the approximation sub-bands are applied to inverse discrete wavelet transform (IDWT) to reconstruct denoised PD signal [4, 11, and 14].

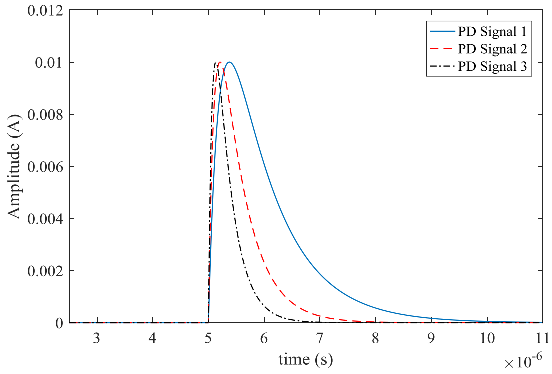


Fig. 1. The simulated PD signals

B) *Energy Based Wavelet Selection (EBWS)*

Determination of the optimum mother wavelet, the level of decomposition and the thresholding way are the main obstacles for WT filters [4]. Because of the nature of PD phenomenon, the generated PD signals have a very wide spectrum and characteristics. Hence, for each PD signal with special characteristic there is a special optimum mother wavelet [15]. To overcome this restriction, in [10] Energy Based Wavelet Selection (EBWS) is proposed. An index, named Energy Percentage, is introduced for selecting the optimum mother wavelet from a library of useful mother wavelets in each decomposition level. Then using a thresholding method, coefficient of details in each level are truncated and finally denoised PD signal is reconstructed.

C) *Energy Conservation Based Thresholding (ECBT)*

In [11] a wavelet based method, ECBT, has been proposed. A correlation based method, correlation based wavelet selection (CBWS), for optimum mother wavelet selection [15] is used and a new thresholding algorithm is proposed by authors in [11]. Moreover, Wavelet Packet Transform (WPT) is exploited to construct a full wavelet tree. The full procedure of this method is:

Optimum mother wavelet selection, CBWS, is carried out by calculation of a correlation index between noisy PD signal and each wavelet data set of the wavelet library. The optimum mother wavelet is corresponded with the wavelet that has the maximum calculated correlation index.

Then, using the selected mother wavelet and WPT, the noisy PD signal is decomposed up to level *J*. There will be 2^{J-1} approximation sub-bands and 2^{J-1} detail sub-bands in this level.

Afterwards, all coefficients of approximation sub-bands in level *J* are retained and coefficients of detail sub-bands are thresholded. The main idea of authors in [11] is in the way of thresholding.

Finally, invers WPT is used to reconstruct PD signal by the coefficients of approximation and the thresholded detail sub-bands at level *J*.

Determination of the depth of decomposition is not investigated in ECBT and EBWS methods and because of influence of noise on the wavelet selection algorithms; they are not secure enough, too. Moreover, in the procedure of thresholding, the ECBT needs a lookup table to calculate threshold value in each detail sub-bands that means a prior knowledge is necessary in this method. For considering the effect of noise on the way of optimum wavelet selection, CBWS and EBWS, in **Error! Reference source not found.** the results for different noise level are shown (PD Signal 1 and decomposition level is 1). As it can be seen, for noise free circumstance "sym4" and "db2" are selected as the best mother wavelets by CBWS and EBWS methods, respectively. It is expected that the mother wavelet selection by CBWS and EBWS be independent of the noise level whereas according to **Error! Reference source not found.** these methods are affected for different noise levels.

Table.2.
The result of mother wavelet selection for different noise level

Method	***SNR***					
	-10	***-5***	***0***	***5***	***10***	***Noise free***
CBWS	db4	sym4	db3	db2	sym4	sym4
EBWS	db6	db5	db2	db4	db6	db2

As it is discussed in the above paragraph, determination of the optimum decomposition level is not clear in ECBT and EBWS methods. The simulated results in **Error! Reference source not found.** show that the types of PD signal and the noise level effect on the optimum decomposition level. As it can be seen for the high level of noise (SNR=-5 dB) and the wide PD signal (PD Signal 1), the optimum decomposition level is 6 levels. While for the low level of noise (SNR=5 dB) and narrow PD Signal (PD Signal 3), the best decomposition level is 2 levels.

Table.3.
The optimum decomposition level

Signal Type	***SNR***	
	-5	***5***
PD Signal 1	6	4
PD Signal 2	5	3
PD Signal 3	4	2

3. Mathematical Morphology

Mathematical Morphology (MM) is a useful algorithm in the signal and image processing area which was proposed by Matheron and Serra in 1964. In this algorithm a probe that is named Structure Element (SE) is used to make verification on signal or image. The main and basic functions of MM are including Erosion and Dilation. All other functions (operators) are generated based on these two functions. The following formulas are shown the ways for Erosion and Dilation calculation on one dimensional signal [16]:

$$(f \Theta g)(n) = \min[f(n+m) - g(m)] \quad for \ \ m \in 0,1,2,...M-1 \tag{2}$$

$$(f \oplus g)(n) = \min[f(n-m) + g(m)] \quad for \ \ m \in 0,1,2,...M-1 \tag{3}$$

where f and g are one-dimensional signal and structure element function, respectively. Also, Θ and $\oplus$ are represented erosion and dilation, respectively. Two new operators that are obtained from the above mentioned functions are Opening and Closing which are defined by:

$$(f \circ g)(n) = (f \ominus g \oplus g)(n) \tag{4}$$

$$(f \bullet g)(n) = (f \oplus g \ominus g)(n) \tag{5}$$

For removing negative and positive impulse of the signal simultaneously, the Opening and Closing operators shall be employed as follows:

$$OC[f(n)] = (f \circ g \bullet g)(n) \tag{6}$$

$$CO[f(n)] = (f \bullet g \circ g)(n) \tag{7}$$

where OC and CO are Opening-Closing and Closing-Opening filters, respectively. And finally Morphological Filter (MF) is obtained using following equation:

$$y(n) = \frac{1}{2}\{CO[f(n)] + OC[f(n)]\} \tag{8}$$

In this filter positive and negative impulses are suppressed together.

A) Typical Morphological Filter

In the typical morphological filters, the operator (OC-CO in equation 8) with a specific length of SE applies on the noisy PD signal in one stage. But in [14] a new approach, Forward and Backward Morphological Filter (FBMF) is proposed that has shown high performance in comparison with conventional MFs. The procedure is applying MF to the noisy PD signal in three steps: (i) MF with a flat SE whose length is 2 samples are used in the first level. Then MF with 3 samples of SE applies to the result of the previous level. This process will be continuing up to a predefined length of SE (maximum length). (ii) The step (i) is repeated on the noisy PD signal vice versa. It means the length of SE in the first level is the maximum and it is decreased in each new level up to 2 samples in the last level. (iii) Finally the average of the denoised PD signals in steps (i) and (ii) is calculated to get the final denoised PD signal.

The important parameters which need to be determined in MF are the shape and the length of SE. For denoising of PD signals, using a flat SE has been very useful and shown the acceptable result [13, 14]. But determination of the suitable length of SE is a challenge that needs be tackled. The problem is that, if the length of SE is small, MF has not satisfactory performance for high level of noise and if a SE with very large length selects, the PD signal might be distorted severely. Moreover, the suitable length of SE is different for the various PD signals. It means for PD signal with big pulse width and amplitude, the optimum SE length is large and vice versa. Authors in [13] attempt to come up of these restrictions by employing sets of look-up tables that present the optimum length for SE for three different simulated PD signals. Also, for various noise levels, pre-simulated lookup tables are considered, too. As a matter of fact a considerable number of simulations for different PD signal and SNR are necessary to make look-up tables and select the optimum length of SE for denoising by MF. Briefly, relaying on the prior knowledge in this method is the main limitation. In **Error! Reference source not found.** the result of optimum SE lengths (sample) for the three simulated PD signals are shown. As it can be seen the optimum SE lengths in the high level of noises and big PD pulses width and amplitude are larger than others circumstances. These results obtained from the presented way by [13] for feature of "PD signal Amplitude".

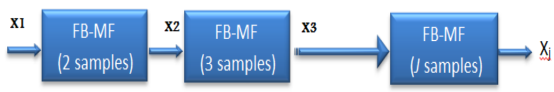
Table.4.
The result of optimum SE lengths (sample)

Signal Type	*Amplitude*	*SNR* -5	*SNR* 0	*SNR* 5
PD Signal 1	0.01	12±1	9±1	7±1
	0.03	13±1	10±1	8±1
	0.05	14±1	11±1	9±1
PD Signal 2	0.01	6±1	5±1	4±1
	0.03	7±1	6±1	4±1
	0.05	8±1	7±1	5±1
PD Signal 3	0.01	4±1	3±1	2±1
	0.03	5±1	3±1	3±1
	0.05	5±1	4±1	3±1

B) The Proposed Method

In this paper a new Self-Adaptive Morphological Filter (SAMF) is proposed to overcome the explained restrictions in subsection C. In fact, by employing SAMF, the length of SE is selected with respect to the noise level and type of the PD signal through a self-adaptive way. The whole procedure of the SAMF is:

By using FB-MF, the noisy PD signal is denoised by two samples of the SE length at level 1. Then the FB-MF with three samples of SE length, as level 2, is applied to the denoised PD signal in level 1. The SE length is increased 1 sample in each new level and FB-MF is applied to the previous level denoised PD signal. This process will be continued up to level J (j is selected 40 samples in this paper).



Then the following factor is calculated in each new level for the above explained process:

$$e_j = \sum_{1}^{n} \left| X_j - X_{j-1} \right| \tag{9}$$

where X and n are the denoised PD signal and its length at each level, respectively. It should be noted that X_0 is equal with the noisy PD signal before applying FB-MF. In **Error! Reference source not found.**, X_0 (Noisy PD signal, SNR= -5), X_1 and difference (D_1) of X_1 and X_0 and also X_1, X_2 and difference (D_2) of them are shown. As it can be seen, D_2 has smaller values in comparison with D_1 and finally e_2 (=2.32) is lower than e_1 (=7.52).

The proposed factor in step 2, e_j, is computed for all levels:

$$e_j = \{e_1, e_2, \ldots, e_j\} \qquad j = \{1,2,3,\ldots J\} \tag{10}$$

Then using curve fitting in MATLAB, a function for the above calculated factors is approximated. In **Error! Reference source not found.** (a) data and estimated function (E-index) for a noisy PD signal (PD Signal 1, amplitude 50 mA and SNR= -5) are shown. As it can be seen the E-index is a decreasing exponential function of SE length that is completely monopolized for any PD signal and any noise level. In **Error! Reference source not found.** (b) the E-indexes for three different noise levels are displayed (PD signal 1, Amplitude 50 mA and SNR = -5, 0, 5). As shown the E-index for high level of noise (SNR= -5) has bigger values than the low level. Also, in **Error! Reference source not found.** (c) the results of E-indexes calculation for three different PD signals (PD signal 1, 2, 3, amplitude 50 mA and SNR= -5 dB) are shown.

With respect to the explanation and the results of E-index calculation in step 3, by using a thresholding function (Eq. 11) on the calculated E-index, the optimum SE can be selected. In **Error! Reference source not found.** (d) the threshold and the selected SE length are depicted.

$$Thr.Func. = 0.2 \times (\max(E - index))^{0.65} \tag{11}$$

In the final step the selected SE in the previous step are used as the optimum SE length for denoising of PD signal using FBMF.

4. Results and Discussion

In this section the proposed method (SAMF) with the investigated and discussed methods (EBWS and ECBT) are compared. The factors that are used for general assessment of the performance of the denoising methods include: “PD Signal Amplitude”, “PD Signal Rise Time”, and “Correlation of the denoised PD signal and the Original Noise free PD Signal” which are illustrated in the Appendix.

In **Error! Reference source not found.** the results of noise reduction of the denoising methods with the circumstances including “PD signal 1”, “Amplitude 10 mA” and “Noise level (SNR) -5 up to 5 dB” have been shown. Also, in **Error! Reference source not found.** these methods have been compared using the above mentioned factors.

In **Error! Reference source not found.** the results of comparing the noise reduction methods with the circumstances including “PD signal 3”, “Amplitude 50 mA” and “Noise level (SNR) -5 up to 5 dB” are shown. Also, in **Error! Reference source not found.** the denoised PD signal by the three mentioned methods is depicted. As it can be seen in all simulated circumstances, the SAMF has shown much better results than other two methods, ECBT and EBWS.

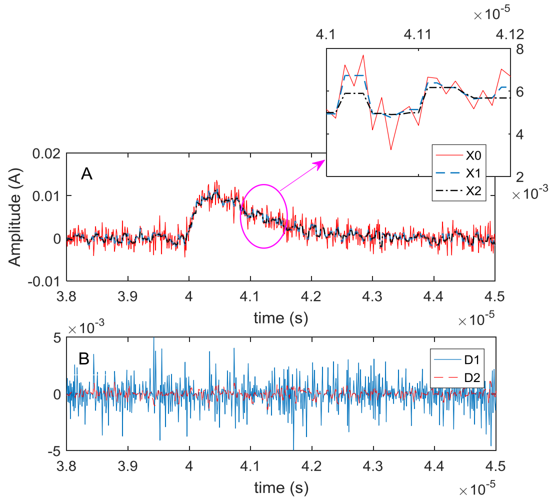
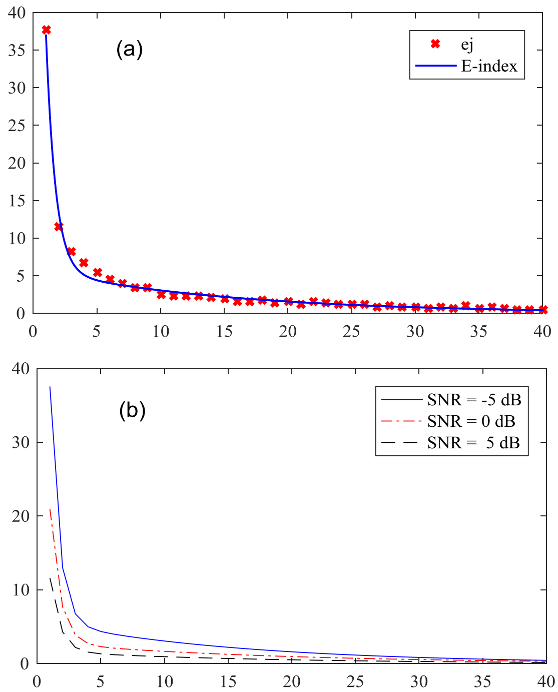


Fig. 2. a) Results for X0, X1 and X2 and b) Results for D1 and D2



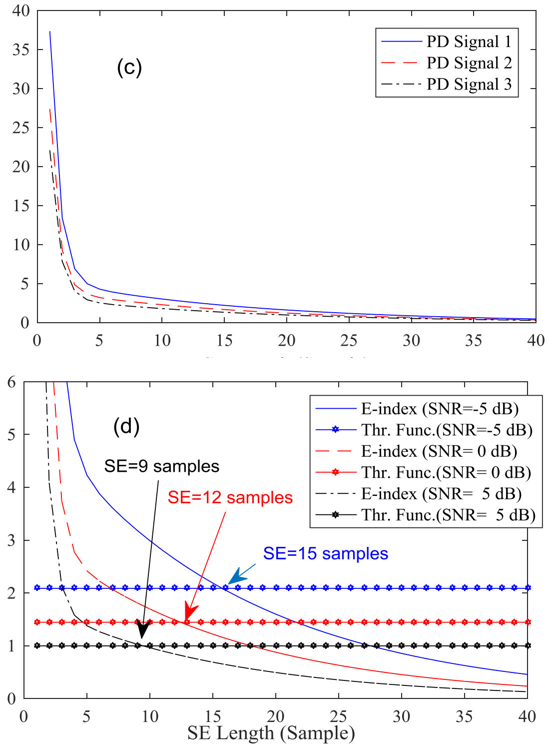


Fig. 3. a) The calculated ej for the noisy PD signal and fitted curve (E-index) b) The E-indexes for three different noise levels c) The E-indexes calculation for three different PD signals d) The calculated thresholds and the selected SE length for denoising

Fig. 4. Results of noise reduction for the noisy PD signal 1, Amplitude 10 mA and SNR= 0 dB

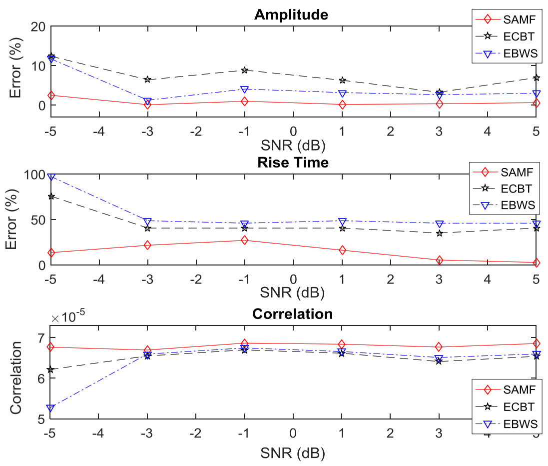


Fig. 5. Calculated factors for comparing denoising methods for the noisy PD signal 1 and Amplitude 10 mA

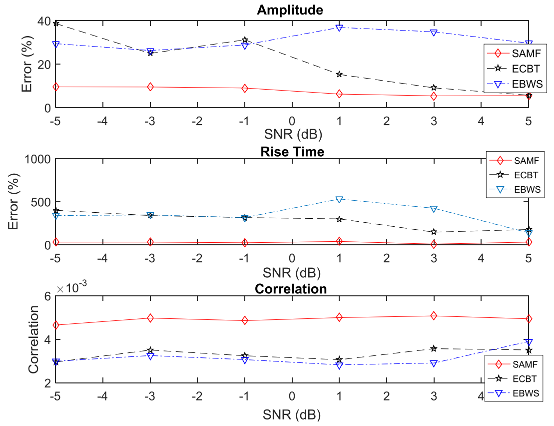


Fig. 6. Calculated factors for comparing denoising methods for the noisy PD signal 3 and Amplitude 50 mA

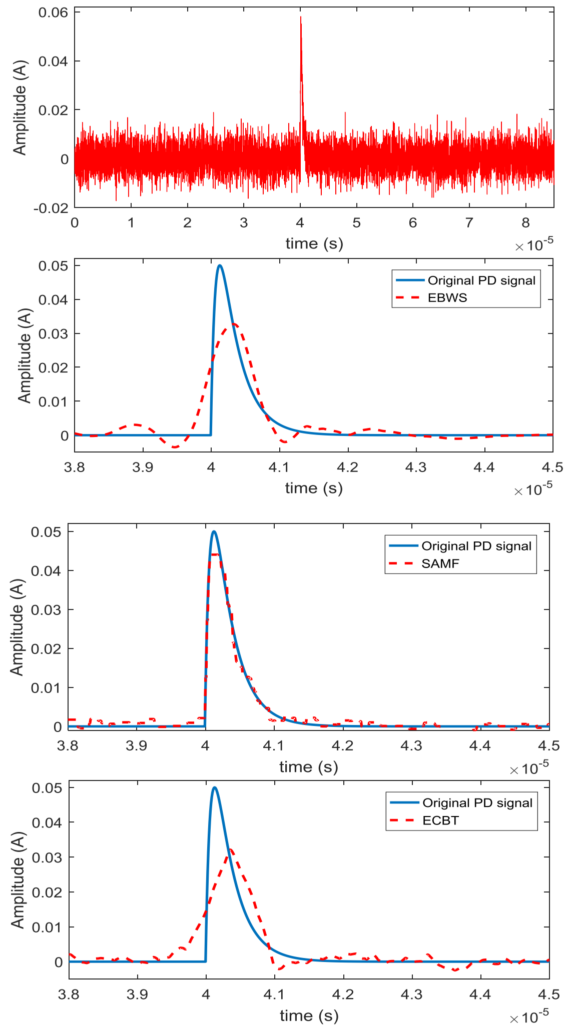


Fig. 7. Results of noise reduction for the noisy PD signal 3, Amplitude 50 mA and SNR= -5 dB

5. Conclusion

In this paper ECBT and EBWS two wavelet transform based filters, for noise reduction of PD signals have been analyzed and reviewed. The restrictions of these methods, depending on the noise level in wavelet selection and the determination of decomposition level, have been explored and finally compared with the proposed morphological based filter, SAMF. Dependency on the prior knowledge is an important restriction that shall be noted in the considering of the noise reduction methods. Unlike the studied WT based and the usual MF based methods, the proposed method, SAMF, is a completely self-adaptive method from this point of view. The factors including "Amplitude", "Rise-Time", and "Correlation with the original PD signal" are used for comparing the noise reduction methods in that the proposed method has shown the best result in all noise levels and PD signal types.

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Appendix

In this paper the following factors are used for the error calculation or performance assessment of the denoisng methods:

$$Amplitud-Error=\left|\frac{\max(X)-\max(Y)}{\max(X)}\right|\times 100$$

$$Rise\ Time-Error=\left|\frac{RT(X)-RT(Y)}{RT(X)}\right|\times 100$$

$$Correlation=\frac{\sum_{i=1}^{N}(X(i)-\bar{X})\times(Y(i)-\bar{Y})}{\sqrt{\sum_{i=1}^{N}(X(i)-\bar{X})^2\times\sum_{i=1}^{N}(Y(i)-\bar{Y})^2}}$$

where X, Y and N are the original PD Signal, the denoised PD signal and the length of PD signal, respectively.