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Denoising of Experimental Corona Discharge Signals in Insulation Sample using Adaptive Signal Processing

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ABSTRACT- The pre-processing of the Partial Discharge (PD) signal is very important and crucial stage in analysing condition of the electrical insulation. The PD information is lost in the presence of various noises. The wavelet based adaptive Thresholding de-noising techniques are well suited for reducing the noise. This paper considers the various adaptive thresholding techniques such as Heursure, Minimaxi, VisuShrink, SureShrink, thresholding methods for denoising of the PD signals obtained in various insulation samples using the experimental setup. The PD pulses produced by the insulation samples were detected in the form of discharges through the impedance and is fed through a cable to the PD detector along with a amplitude modulating signal. The developed Wavelet Transform based adaptive thresholding algorithm suitably removes the interferences from the measured PD signals. The performance indices are evaluated which justifies the strength of the algorithm in denoising of experimental PD data.

KEYWORDS*:* Adaptive thresholding, signal processing, Denoising, Partial discharge.

I.INTRODUCTION

Insulation plays a very vital role in the normal and proper functioning and operation of High Voltage (HV) electrical equipment. It is, therefore, very important to maintain the insulation in a proper working condition for the purpose of proper operation and to increase the life span of the electrical equipment. If any problem occurs in the insulation, it causes failure of the electrical equipment in which the insulation is present, due to high electrical stresses leading to weakening of the dielectric strength. Due to the inclusion of voids, irregularities and impurities inside or along the surface of insulation material electrical discharges called Partial Discharge (PD) occurs, when it is subjected to high voltage. According to IEC standard 60270, PD is localized electrical discharges which do not completely link the insulation between the terminals. These discharges are called “partial” because they occur in the locations where surface irregularities, voids, impurities, surface moisture are present which occupy a smaller portion of the electrical path and that are limited in magnitude because the discharges that occur will be in series with good insulation.

An electrical discharge characterized by a corona and which occur when one of two conducting surfaces in a gas is sharp edge such that it concentrates the electric field at its tip and ionizes the surrounding medium. A corona will occur when the strength of the electric field around a conductor is high enough to form a conductive region, but not high enough to cause electrical breakdown.Once the PD starts, it degrades the insulation due to its cumulative effect. Therefore, detection of PD is one of the important necessities to keep the HV power equipment in healthy condition.

A **corona discharge** is an electrical discharge brought on by the ionization of a fluidsuch as air surrounding a conductor that is electrically charged. A corona will occur when the strength (potential gradient) of the electric field around a conductor is high enough to form a conductive region, but not high enough to cause electrical breakdown or arcing to nearby objects. While the energy of corona discharges is only several picocoulombs per cycle, deterioration can build up over several months. Corona discharge pulses are random pulses with a width of several ns and a peak current of several mA. Their frequency is spread over an extremely wide range, from several hundred kHz to several GHz.

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A very important task in PD signal pre-processing is the removal of noises which are of high magnitude compared to PD signal. The external noises encountered during on-site PD measurements are Periodic pulse shaped interferences, Discrete spectral interferences (DSI), Stochastic pulse shaped interferences and Random Noises.
This paper describes the pre-processing of the experimental Corona Discharge data obtained in the test object. A sharp needle was used as the point electrode. The Wavelet Transform (WT) based adaptive denoising algorithm is used to remove noises from the measured experimental PD signal. The PD measuring experimental set-up is used to collect the signals and performance evaluation is performed using four thresholding rules, which is indexed as '*r*' in the algorithm. The performance is evaluated by computing Signal to noise ratio (SNR) which is computed at each level for all thresholding rules and the comparison of the techniques has been shown.

II. LITERATURE SURVEY

The detection and diagnosis of PD activity is adopted for condition monitoring purposes to analyze the insulation integrity and remaining life of HV equipment. PD analysis involves the capturing, processing and characterization of PD signals to determine the severity, type of developing PD and the location of it. The emphasis is on the processing of PD data for denoising.Extensive research works have been pursued in the area of application of digital signal processing.Feser et al. [1] suggested an FFT-based approach to eliminate DSI. This method is computationally intensive and there exists a difficulty in deciding the threshold.SherZaman et al.[2]suggested the application of adaptive signal processing based on principle of decorrelating the PD pulses from the noise, by sampling at a high frequency and inserting a delay in. the adaptive system.Shim et al. [3, 4] have reported on the possibility of using a wavelet method for denoising PD signals. They examined use of both soft and hard thresholding of wavelet coefficients and highlight its difficulties and necessity for exploring more powerful methods.Satish et al [5] proposed a wavelet based de-noising method for extracting PD signals from severe noises. They implemented the de-noising scheme on simulated signals corrupted by severe noise and interferences and evaluated the de-noising method using de-noising performance indices.Ma et al. [6] proposed a wavelet selection method and an automatic thresholding rule for the wavelet based de-noising of PD signals. The mother wavelet selection method uses cross correlation coefficient. Zhang et al. [7] proposed a new thresholding method for wavelet based de-noising of PD signal. The thresholding method decomposes the noise first using DWT and the threshold values for the PD signal de-noising are chosen according to the maximum values of noise coefficients at each level.D. Gnanadurai et al.[8] proposed an efficient and adaptive threshold estimation method for image denoising based on Generalized Gaussian Distribution by analyzing the statistical parameters of the wavelet subband coefficients. Zahra Sadeghipour et al. [9] proposed an adaptive thresholding of the noisy image for image denoising where different threshold based on statistical properties of noise for each representation coefficient of the noisy image. Sumithra M.G et al. [10] has presented a time adaptive wavelet with trimmed Thresholding process for denoising speech from different noisy conditions. The proposed technique has been compared with other well-known thresholding methods.HemanthTulsani et al. [11] proposed the impact of DWT, selection of the mother wavelet, choice of the different decomposition levels for denoising of the one dimensional PD data obtained immersed in white noise and DSI.

III.PRE-PROCESSING OF PD SIGNALS USING ADAPTIVE THRESHOLDING TECHNIQUES

The WT based denoising technique is divided into 3 stages:

- **I.** Application of WT for decomposition of signal
- **II.** Calculation and application of Threshold value
- **III.** Application of Inverse WT for reconstruction.

I. Applying wavelet transform

The prime stage of applying Wavelet transform is to decompose the PD signal into approximate and detailed coefficients, on which the thresholding is done.

II. Calculation and Application of Threshold value

The second stage is the calculation and application of threshold. The threshold value can be calculated by using adaptive thresholding techniques.The coefficients related to the noise can be either removed or modified by a certain

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value called threshold value. The suitable value of threshold needs a careful balance of estimated coefficients. The suitable threshold values are computed by the various adaptive thresholding rules.

i. VisuShrink (sqtwolog)-Fixed Form Threshold

The threshold calculation in this method is a type of global thresholding method which was proposed by Donoho and Johnstone [12],[13]. The threshold value is given in (1) as:

$$\lambda_{Visu} = \hat{\sigma}\sqrt{2\log N} \qquad (1)$$

where$N$ indicates the number of sample points, and $\hat{\sigma}$ indicates evaluation of the noise level.
This is an universal thresholding method which removes the noise components effectively. The possibility of all noise components being minimized to zero is very high for even large samples of information [15].

ii. Minimax Thresholding Rule

This method computes a stable threshold value to produce minimax performance for mean square error against an ideal procedure. This minimax estimator realizes the minimum of the maximum mean square error achieved for the worst function for a given set of samples [15].
The minimax thresholding is more conservative and is suitable when small details of function lie in the noise range.

iii. ***'SureShrink' (Rigrsure)-Stein's unbiased risk estimator –***

Stein's unbiased risk estimator is a method of thresholding which depends on the level. It computes a separate threshold for each detail level based upon SURE (Stein's unbiased risk estimator). By use of *SURE (t: x)* as the estimator of risk, the *SURE* threshold is given by, [15].

$$\lambda_{Sure} = \arg\min_{t\geq 0} SURE(t:x) \qquad (2)$$

iv. 'Heursure' method (Combination VisuShrink and SureShrink method)

This method is a combined form of Sure Shrink and VisuShrink thresholding methods. If the numbers of coefficients are less, then the VisuShrink method is used; else, SureShrink method is applied. This is also called as Hybrid method, Heursure [15].
After computing a threshold value, it is applied to modify the signal coefficients in the WT domain.
There are two categories in applying threshold function. They are Soft thresholding and Hard thresholding functions.
In the present work, both Hard and soft thresholding are applied.

Hard Thresholding Technique

HardThresholding is the simplest method. It is the usual process of setting to zero the elements whose absolute values are lower than the threshold.If the absolute value of a coefficient is less than a threshold, then it is assumed to be 0, Otherwise, it is unchanged. Mathematically it is,

$$\boldsymbol{T_{hard}} = \begin{cases} \boldsymbol{x\ if\ |x| \geq \lambda} \\ \boldsymbol{0\ \ Otherwise} \end{cases} \qquad (3)$$

Soft Thresholding Technique

If the magnitude of a coefficient is less than a threshold λ, then it is considered as zero, otherwise its value is minimized by λ .

$$\boldsymbol{T_{soft}} = \begin{Bmatrix} \boldsymbol{x(|x| - \lambda)} & \boldsymbol{if\ |x| \geq \lambda} \\ \boldsymbol{0} & \boldsymbol{Otherwise} \end{Bmatrix} (4)$$

III. Applying Inverse Wavelet Transform

In this stage, the Inverse Wavelet Transform (IWT) has to be applied after the coefficients are modified.

IV. ALGORITHM

A simple and a very effective algorithm for denoising the experimental PD signal is developed, which presents optimal denoising implementing the adaptive thresholding in the wavelet domain for any corrupted PD signal and it is case

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independent. Here, the mother wavelet is chosen based on the noise components.[15]. The algorithm is presented below:

1. Start
2. Collect PD signal generated in the insulation sample using PD measuring experimental set-up.
3. Add Discrete Spectral Interference to the PD signal using Digital Signal Oscilloscope (DSO).
4. Consider the available wavelets-Daubechies, Symlet, Haar, Coiflet, Biorthogonal, Meyer, Mexican Hat, Morlet with index *w*. Set the wavelet number as *w=1, 2, 3,….., n* and also set the Adaptive thresholding methods as rule *r=1,…,4*. Set *w=r=1*.
5. Transform the noisy signal into approximate and detail co-efficients using WT with the wavelet '*w*'.
6. Consider basic soft Thresholding function
7. Set initial level *L*=1
8. Modify the detail co-efficients using rule '*r*'
9. Reconstruct the signal using IWT. Plot denoisedsignal, compute the performance indices at each level.
10. If level '*L*' gives the best result, the performance indices are saved and plot the graphs, otherwise increase *r=r+1* If$r \leq 4$, go to step (8), otherwise go to step (11).
    If level '*L*' do not give the best result, increase *L=L+1* go to step 8.
11. Increment the value of *p=p+1*. If $w \leq n$ go to step (5), otherwise compare the results to select the best wavelet and the thresholding method for de-noising
12. End

V. EXPERIMENTAL SETUP OF PD DETECTOR

Figure.1 shows the schematic circuit diagram of the experimental setup considered to collect practical PD signals. A 100kV, 20kVA rating high voltage discharge free transformer is used to supply high voltage to the PD test set up [16]. An auto transformer of rating 240V/270V, 40A controls the input voltage to the HV transformer. A 1000 pF coupling capacitance is connected in series with the input impedance Z_{m}.This impedance forms the detection circuit across which discharges occur. The PD data is collected by using Discharge Detector Model 5 of Bonar Instruments Limited, Manchester, and recorded in a digital signal oscilloscope (DSO) in a shielded room. The PD pulses generated in the test sample are detected by the input impedance and fed to the PD detector module through the cable along with a amplitude modulating signal, which is a radio frequency noise generated by a signal generator with carrier frequency of 615kHz and modulating frequency of 1.25kHz. This radio frequency signal represents the DSI, which are superimposed with the PD signals in the actual measurements. This resultant signal, which is similar to the PD signals represent the PD signals acquired in online measurements. The experimental PD signals are fed to the amplifier. The magnitude of the resulting quasi-integrated PD signal can be observed on the DSO. The circuit is calibrated to 5pC and a constant bandwidth of 20 kHz-300 kHz. The sampling rate is chosen to represent 50 Hz power frequency signal, which represents 20ms of the signal. All data acquisition is carried out to make sure a maximum possible full-scale deflection on the DSO. The PD signals with different noise/interferences, representing the corona discharges and PD sources are gathered.

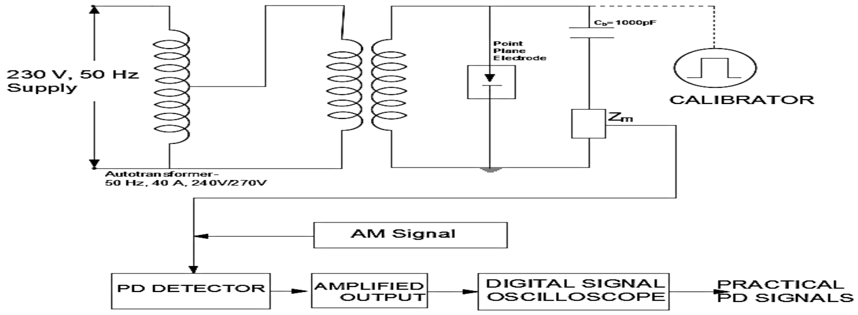

Figure. 1.Schematic Diagram of PD measuring setup

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The experimental setup in the shielded room and sharp needle as the test sample is shown in Figure 2.

Figure. 2.Experimental setup in the Shielded Room and sharp needle as test object

In this setup, the test object, a sharp needle was used as the point electrode.The applied voltage was 7.1 kV. The corona discharges along with the noise generated in the experimental set up (with no DSI) were fed to the PD detector circuit. The PD signals generated in the samples are considered with DSI generated by signal generator.

VI. RESULTS AND DISCUSSIONS

The denoising of the Corona discharge signal which is corrupted with Low magnitude and High magnitude are considered. The algorithm considers all the available wavelets and the best one is selected. For the PD signals considered in this work, db2 has been selected as the mother wavelet. The four thresholding rules are used for denoising and the performances of the four rules are compared using the SNR values.

Figure 3 shows the acquired corona discharge, corrupted signal and denoised signals using Heursure rule with both soft and Hard thresholding.

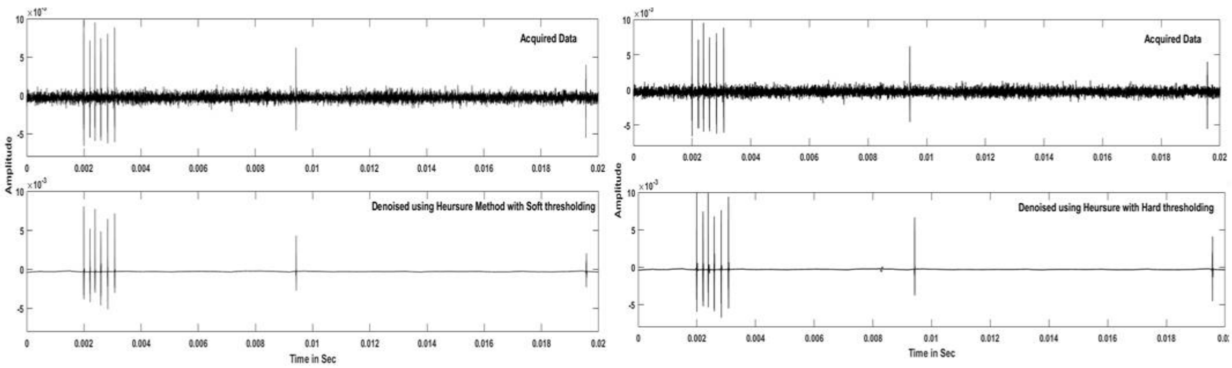

Figure3 .Denoised Corona discharge signal using Heursure Method with Soft and Hard Thresholding

Figure 4 shows the acquired corona discharge, corrupted signal and denoised signals using Minimaxi rule with both soft and Hard thresholding.

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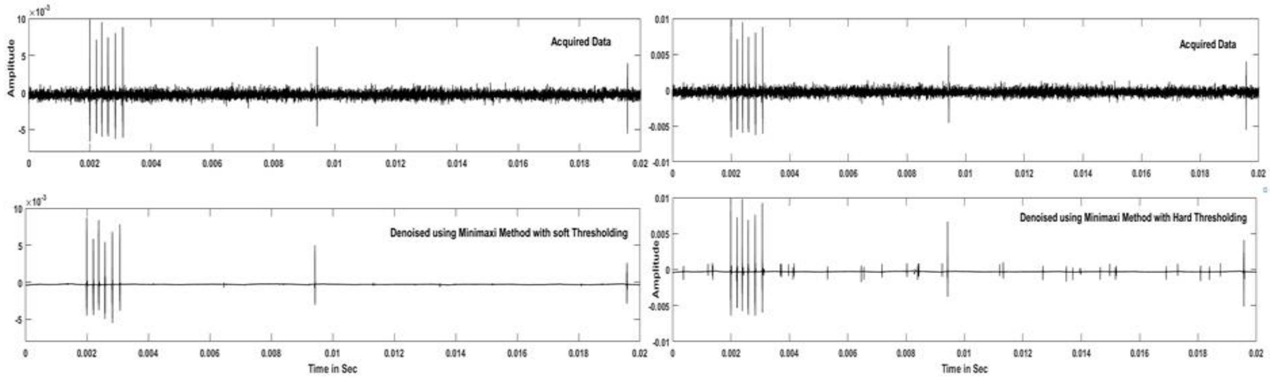

Figure 4.Denoised Corona discharge signal using Minimaxi Method with Soft and Hard Thresholding

Figure 5 shows the acquired corona discharge, corrupted signal and denoised signals using SureShrink rule with both soft and Hard thresholding.

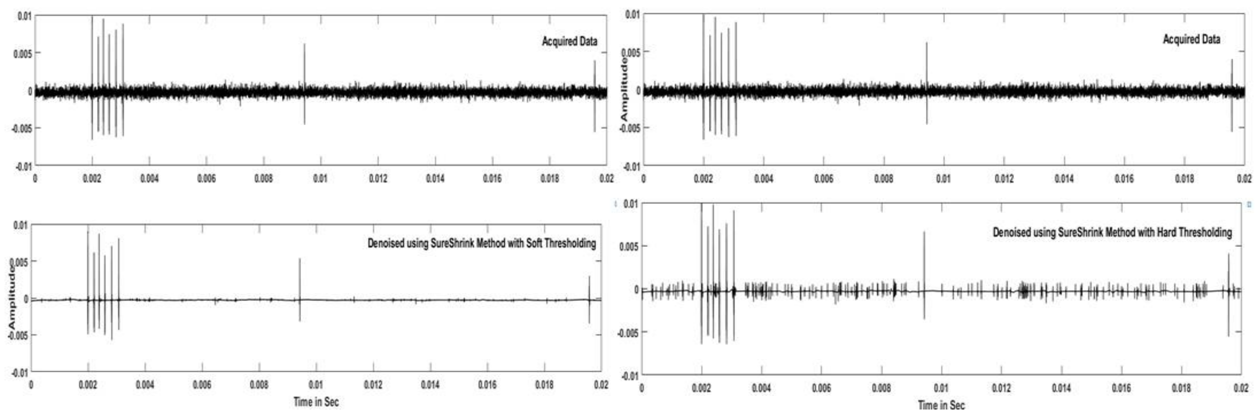

Figure5 .Denoised Corona discharge signal using SureShrink Method with Soft and Hard Thresholding

Figure 6 shows the acquired corona discharge, corrupted signal and denoised signals using VisuShrink rule with both soft and Hard thresholding.

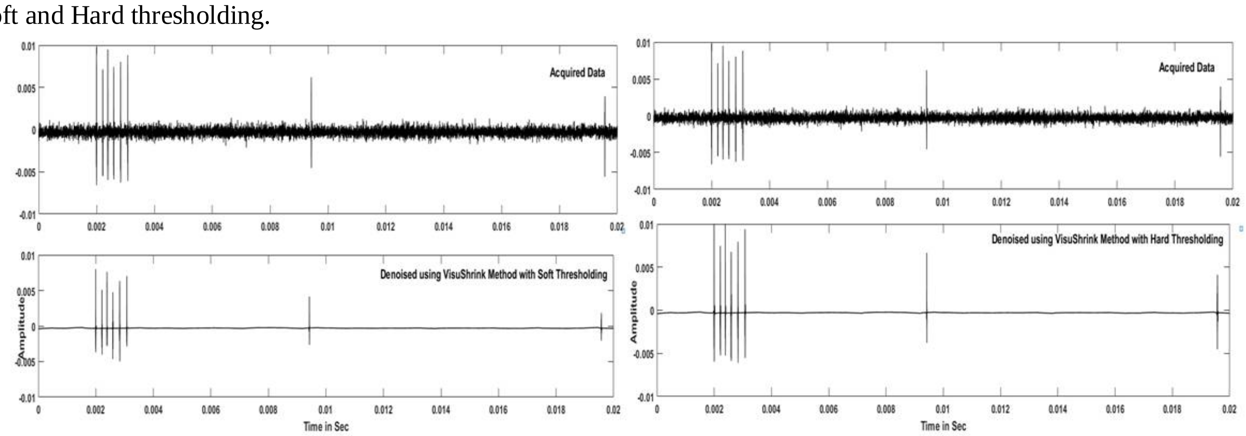

Figure 6.Denoised Corona discharge signal using VisuShrink Method with Soft and Hard Thresholding

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It is clear that the noisy corona discharges collected from the insulations can be denoised well with the adaptive thresholding methods. It also indicates that the VisuShrink method of thresholding using WT denoises the corona discharge signals corrupted by low magnitude DSI. Figure7 shows the plot of SNR versus different levels of decomposition using all the four rules, which indicates that the VisuShrink method eliminates the noises from the corrupted signals.

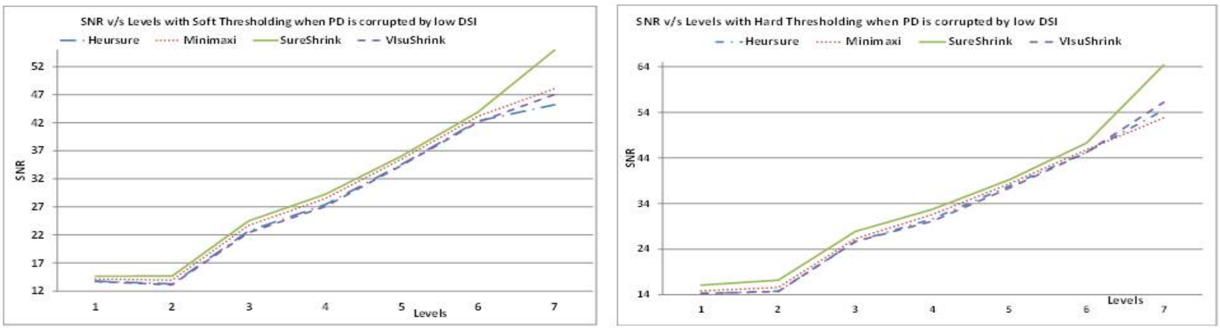

Figure 7.SNR v/s Number of Levels When PD is corrupted by Low magnitude DSI with Soft and Hard thresholding

Figure 8 shows the acquired corona discharge, corrupted signal by High magnitude DSI and denoised signals using Heursure rule with both soft and Hard thresholding.

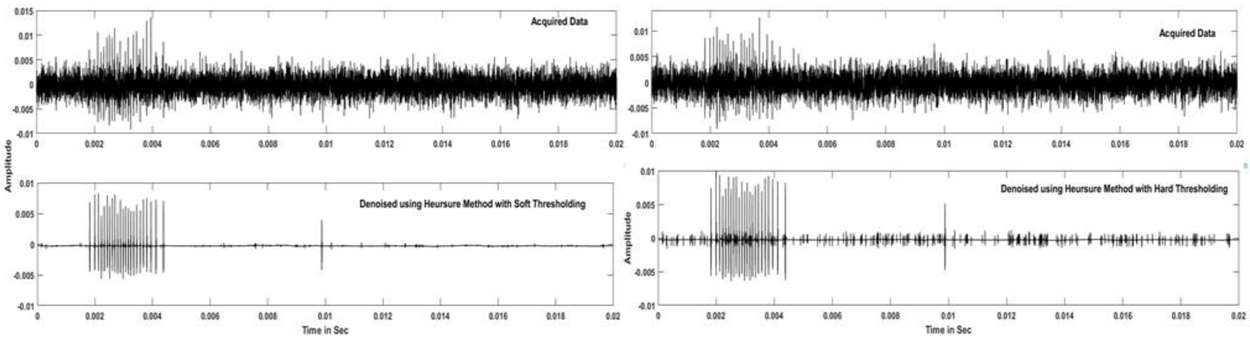

Figure 8.Denoised Corona discharge signal using Heursure Method with Soft and Hard Thresholding

Figure 9 shows the acquired corona discharge, corrupted signal by High magnitude DSI and denoised signals using Minimaxi rule with both soft and Hard thresholding.

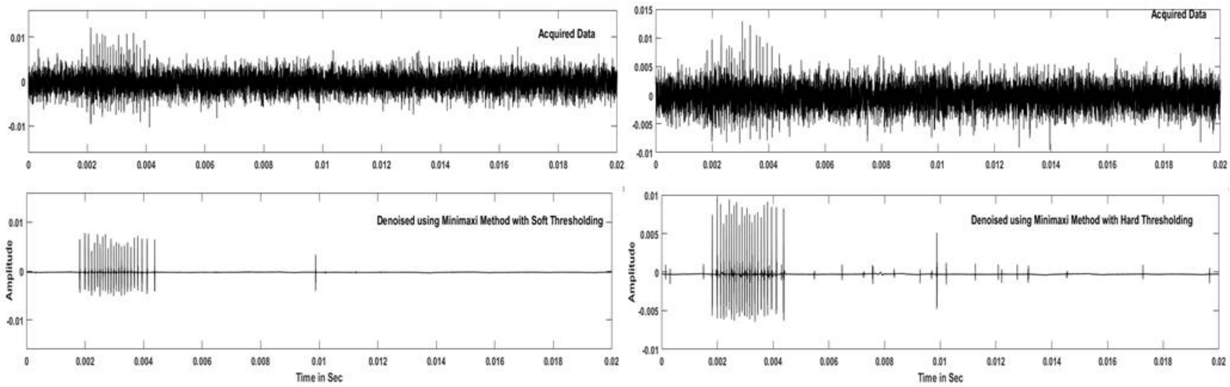

Figure 9.Denoised Corona discharge signal using Minimaxi Method with Soft and Hard Thresholding

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Figure 10 shows the acquired corona discharge, corrupted signal by High magnitude DSI and denoised signals using SureShrink rule with both soft and Hard thresholding.

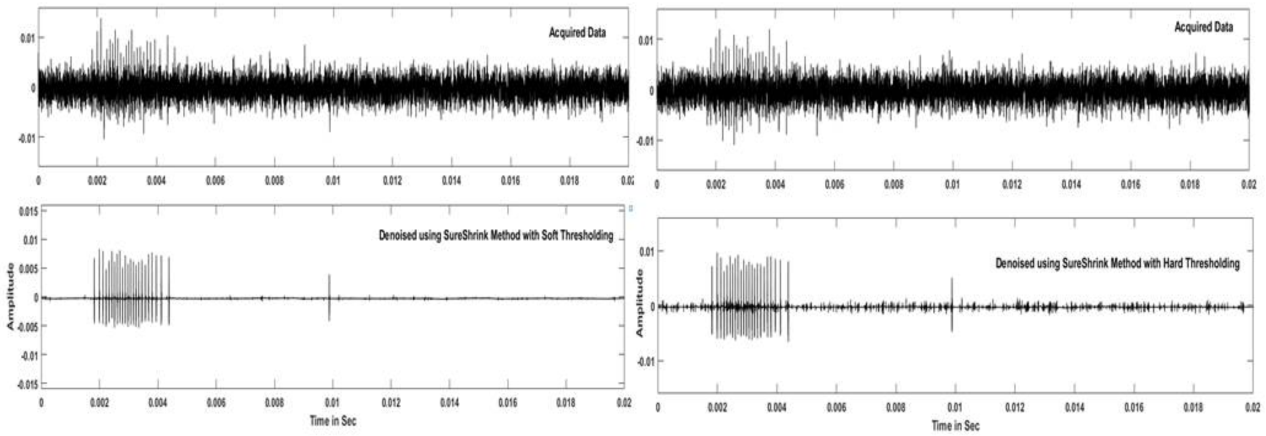

Figure10 .Denoised Corona discharge signal using SureShrink Method with Soft and Hard Thresholding

Figure 11 shows the acquired corona discharge, corrupted signal by High magnitude DSI and denoised signals using VisuShrink rule with both soft and Hard thresholding.

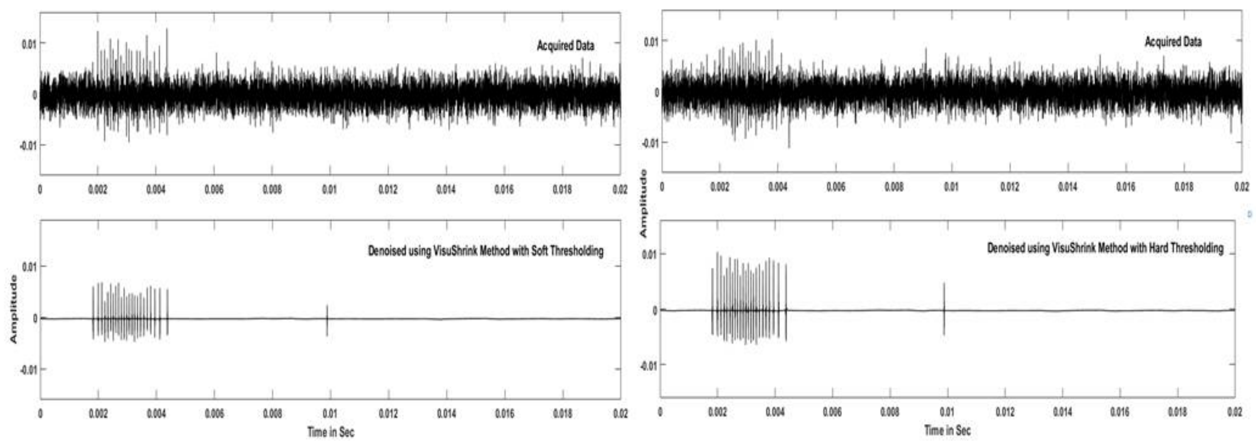

Figure 11.Denoised Corona discharge signal using VisuShrink Method with Soft and Hard Thresholding

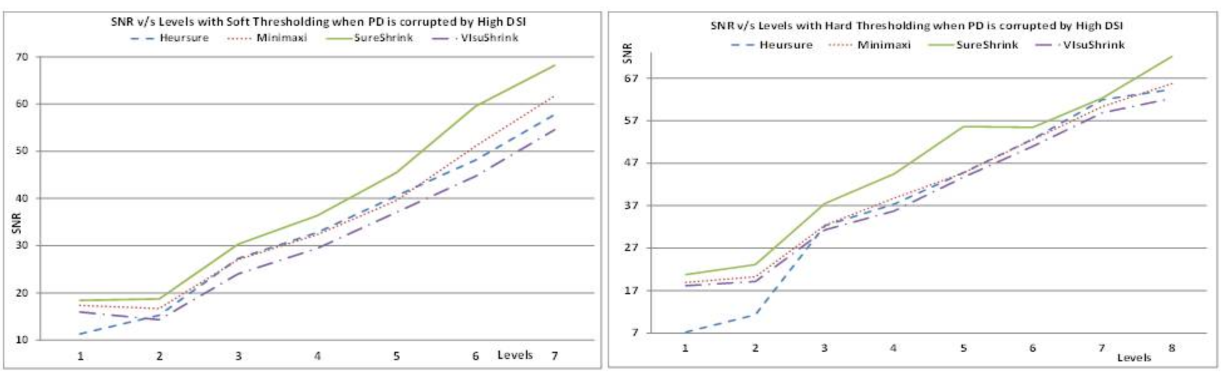

Figure 12.SNR v/s Number of Levels When PD is corrupted by High magnitude DSI with Soft and Hard thresholding

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Figure 12 shows theSNR v/s Number of Levels When PD is corrupted by High magnitude DSI with Soft and Hard thresholding. It is clear that the noisy corona discharges collected from the insulations can be denoised well with the adaptive thresholding methods. The graphs also indicate that the VisuShrink method of thresholding using WT denoises the corona discharge signals corrupted by high magnitude DSI.

VII. CONCLUSION

This paper presents the several adaptive thresholding techniques such as Heursure, Minimaxi, VisuShrink, and SureShrink thresholding methods for denoising of the experimental corona discharge signals obtained in a sharp needle which was used as the point electrode. With the applied voltage being 7.1 kV, the corona discharges are obtained along with the DSI from DSO. The developed adaptive thresholding algorithm suitably removes the interferences from the practical Corona discharge signals. The SNR values are evaluated which justifies the strength of the algorithm in denoising of experimental PD data. The developed denoising algorithm selects the optimal mother wavelet based on the several performance parameters. In the present work, db2 is selected as the optimal mother wavelet for denoising of experimental corona discharges. The selected optimal mother wavelet is used with various adaptive thresholding techniques and best thresholding method is selected. From the results obtained and the values of SNR, it is clear that the VisuShrink method is better suited for the denoising of experimental corona discharge data.

It is observed that the edge information is well restored with Soft thresholding method, when experimental corona signals are corrupted by DSI. Though, the result may change for the real corona signals on-site, but the algorithm can find the best mother wavelet, optimal level of decomposition of PD signal and check the performance of the thresholding rules.

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