International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Adaptive Bayesian Denoising for General Gaussian Distributed Partial Discharge Signals in 11 kV Stator Coil using Wavelet Transform

Madhu S[a]*, Priyashree[a], P B Savitha[b], Vidya H A[c], Raghav Rao[d]

[a]*Dept. of EEE, BNM Institute Technology, Bangalore-560070, Karnataka*
[b]*Dept. of EEE, DSCE, Bangalore, Karnataka*
[c]*HoD, Dept. of EEE, Amrita Vishwa Vidyapeetham, Bangalore*
DOI: https://doi.org/10.55248/gengpi.2023.32475

A B S T R A C T

Noise removal from Partial discharge signal which is corrupted with Gaussian white noise, using Wavelet Transform (WT) based Bayes estimation is presented. Such corrupted partial discharge signal is considered to exhibit Generalized Gaussian Distribution (GGD). Denoising of partial discharge (PD) signals is one of the prime pre-processing stages which help in analyzing the effect of PD on insulation by studying its characteristics and features. The pre- and post-processing of PD signal can be performed significantly using wavelet transform. The WT based adaptive thresholding and coefficients modeling methods for denoising provides a better chance to reduce interferences. The estimation of BayesShrink based estimation of the denoised signal is performed from its noisy wavelet coefficients for the signals with Gaussian distribution. The BayesShrink threshold is independent of the coefficient distribution and is a function of noise and noiseless signal variance. BayesShrink is the most effective thresholding method providing threshold value by reducing the Bayes risk. The coefficient estimation based on Bayes method for GGD signals performs well in removing white noise from the corrupted PD signal. The PD signals are collected by conducting the experiment on damaged 11 kV stator coil which has mica as insulation. The collected signal is processed using WT based Bayes estimation. The result indicate that the optimum Bayes estimator with GGD behave similar to soft thresholding method.

Keywords: Partial discharge; Wavelet Transform; Bayes Estimation; Adaptive thresholding; Generalized Gaussian Distribution.

1. Introduction

For the better and normal operation of the insulation in electrical apparatus, the role of insulation is of prime importance. In order to obtain better efficiency and for safety purposes, assessing the conditions of insulation is essential which helps in condition monitoring as well. The various insulated parts of electrical equipment are subjected to electrical stresses caused by a different factors such as voltage impulses caused by adjustable-speed drives, chemical reactions, thermal overload, mechanical vibrations, etc. [1]. One or combinations of these factors act simultaneously at any instant of time during operation of the equipment and cause deterioration of the insulation. When degradation takes place irrespective of its cause, it results in localized electrical discharges known as PARTIAL DISCHARGES. Once established, partial discharges (PD) are the principal mechanism of insulation degradation. Hence detection and preprocessing of PD activity is a crucial step in condition monitoring of insulation system. PD measurement is an appropriate diagnosis and maintenance tool that provides reliable and timely status identification and it has proved itself in the field on countless occasions.

Even though enough precaution and quality assurance at the stage of production is considered, the presence of foreign particles, surface irregularities, existence of slight defects, etc. are unavoidable or they may be formed while the equipment is in service due to the formation of gas at the point of high electrical stresses, at certain points such as protrusion points, minor cracks, etc. Even at normal operating voltages, presence of these irregularities in the insulation leads to PD due to high electrical stress at such weaker points. Due to this reason, measurements of PD have been accepted as a vital investigative tool as it has an ability to evaluate the condition of insulation for the reliability deficiencies in design during manufacturing and while in service. Thus PD detection is considered to be a major concern in improving the effectiveness of insulation performance for supporting coherent and economical design, ageing process, lifetime prediction and nondestructive testing. This measurement is very important and effective compared to other dielectric measurements when early and timely recognition of sudden faults are needed and it is functional with a considerable amount of accomplishment. Technologies in the field of PD detection have improved significantly with the advancements in hardware and software technology.

According to IEC (International Electro Technical Commission) Standard 60270, “Partial discharge is a localized electrical discharge that does not completely bridge the insulation between the terminals”. Such electrical discharges are called “partial” since their generation in insulation portion where minute cracks, voids and foreign particles are present and the path of such electrical discharges are very small and they have limited magnitude. These are in series with remaining good insulation portion [2].

Partial discharge phenomenon is divided into 3 types: Internal PD, Surface PD and Corona PD.

A main problem during the measurements of PD is the presence of external interventions which will normally have high magnitude as compared with PD signal and it disturbs the reliability and sensitivity of measured PD signal. A foremost issue during PD measurements is the unavoidable appearance of noise and disturbance that are frequently encountered and the magnitude of these noisy signals are higher than the PD signal. If these interferences are not effectively blocked or precisely removed from measured PD signals, they may be considered as PD pulse resulting in false warnings and affecting reliability of measurements. Thus denoising of PD signals has to be considered to remove the noises and analyze the PD signal to know its effect on the insulation.

The most important external disturbances for the period of on-site PD detection/collection are Discrete spectral interferences (DSI), Periodic pulse shaped interferences (PPI), Stochastic pulse shaped interferences (SPI).

In this paper, the Bayesian estimate of the denoised PD signal is estimated from its noisy wavelet coefficients for Generalized Gaussian Distributed (GGD) signal. The wavelet coefficients are assumed to be General Gaussian distributed. The performance is evaluated and compared with the basic Universal thresholding method.

Nomenclature

2. Literature Survey

The emphasis now-a-days is on the pre-processing of PD data for denoising to obtain better protection of the insulation. There are various techniques developed by the researchers in this regard as:

- Analog filtering techniques
- Time domain-based software techniques
- Frequency domain-based software techniques
- Adaptive filtering techniques

Most of the methods mentioned are analysed and observed that it considers the DSI and sinusoidal signal removal. Many a times it has been proved that the narrow band interferences can be easily removed. It can also be seen that the problem still is the removal of noises which are random and pulsive interferences.

In spite of few advantages of these methods, they faced problem of determination of frequency of noise and the method is time-consuming. There is a problem of pulse attenuation which causes waveform distortion which affects the PD pattern recognition at later stages.

Thus it is clearly evident that the time-domain methods are unable to remove disturbances when they are overlapping with the PD pulses whereas frequency-domain approaches cannot remove noise when its frequency spectrum is same as that of PD signal frequency spectrum. In such cases, thus Time and Frequency (TF) domain denoising is of vital importance. The TF domain methods are efficient in noise removal because of their unique feature of identifying signal in both the domains.

To overcome the drawbacks of earlier approaches, the wavelet transform (WT) was introduced. It can be shown from the research done on PD that wavelet based denoising method is well suited for PD signal analysis.

Denoising of signals is an issue in various other fields as well such as image processing, telecommunication signals, biomedical signals, speech recognition, etc. Literature review has been taken up in these fields also to identify the techniques adopted for preprocessing of such signals and which can be implemented for PD signal processing. From the literature review, it is evident that most of the researches have been documented implementing the wavelet transform technique for signal preprocessing in various fields [3-13]. The techniques using statistical parameters for signal denoising have been explored and utilized in the fields of image and biomedical signals, which can be adopted for PD signal denoising with improved performance indices.

D. Gnanadurai et al. developed an effective method for the estimation of adaptive threshold value for image denoising which depends on Generalized Gaussian distribution based on the statistical parameters of the wavelet subband coefficients [3]. S.G. Chang et al. addressed an adaptive BayesShrink threshold for wavelet thresholding images based on the GGD modelling of subband coefficients, a coder has been designed for compression and denoising. The work has been widely referred by many researchers when dealing with BayesShrink thresholding method [14]. M. Hashemi et al. presented a wavelet based denoising methods based on the Bayes estimator for Generalized Gaussian distributed data and optimal wavelet coefficient soft thresholding denoted by Rigorous BayesShrink. The authors have compared these two methods and also have demonstrated that spatially adaptive thresholds improve the performance of denoising method [15].

Hence it has been evidently proved in many cases that the wavelet theory is an influential concept to be used for signal processing. This formed the basis for the current work which involves Generalized Gaussian distribution based Bayeshrink threshold estimation.

3. Wavelet Transform

The WT is a time-frequency signal analysis tool having characteristics of Multi-resolution Analysis. The main strength of WT is that it has ability to denote the partial characteristic of any signal in both frequency and time domain. Therefore, it is considered as a method of time-frequency localization analysis. It is translated and dilated forms of a small wave known as wavelet. The application of this concept in various fields such as science, engineering, medical, etc. is evident to its success. It is widely used in the field of electrical engineering also, especially in the area of High voltage engineering. It has been accepted as a powerful tool for the pre and post processing of PD signal and many researches have already been done in the field.

The WT involves the analysis of the components of a non-stationary signal. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing.

The WT as applied for PD signal denoising is divided into 3 stages:

A. Application of Wavelet transform

B. Calculation & application of Threshold value

C. Application of Inverse Wavelet Transform

4. Formulation of Problem

Consider a noiseless signal with data length N having vector

$$\bar{y}^N = [\bar{y}_1, \dots \dots, \bar{y}_N]^T \qquad (1)$$

This noise-less signal is degraded by an additive white Gaussian random process

$$\bar{\omega}^N = [\bar{\omega}_1, \dots \dots, \bar{\omega}_N]^T \qquad (2)$$

having zero mean and variance of σ_ω^2.

Let the data obtained be $y^N = [y_1, \dots \dots, y_N]^T$ is

$$y_i = \bar{y}_i + \omega_i \qquad (3)$$

The noisy signal represented in equation (3) can be expressed in terms of a desired orthonormal wavelet basis in the following form:

$$\theta_i = \bar{\theta}_i + v_i \qquad (4)$$

where θ_i denoted the i^{th} noisy coefficients, $\bar{\theta}_i$ denotes the i^{th} noiseless coefficient and $v_i$are the wavelet coefficients of noise.

v_i also represent additive white Gaussian random variables having same mean and variance since orthonormal bases are used.

Assume that the coefficients of noiseless signal have zero mean General Gaussian distribution

$$f(\bar{\theta}) = C(\sigma_{\bar{y}}, \beta)\exp\{-[\alpha(\sigma_{\bar{y},\beta})|\bar{\theta}|^\beta\} \qquad (5)$$

where β is the shape parameter.

$$\alpha(\sigma_{\bar{y}}, \beta) = \sigma_{\bar{y}}^{-1}\left[\frac{\Gamma\left(\frac{3}{\beta}\right)}{\Gamma\left(\frac{1}{\beta}\right)}\right]^2, C(\sigma_{\bar{y}}, \beta) = \frac{\beta\alpha(\sigma_{\bar{y}})}{2\Gamma\left(\frac{1}{\beta}\right)} \; and \qquad (6)$$

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t}\, dt \qquad (7)$$

When β=1, the distribution represented by equation (5) is Laplacian and when β=2, it is Gaussian distribution. The main objective is to provide the soft threshold value, T which minimizes the Bayes risk.

4.1 Estimation of Bayesian for Generalized Gaussian Distribution Signals

The Bayes estimate of the required denoised parameter $\bar{\theta}$

denoted by $\hat{\theta}$, minimizes the mean square error. $\widehat{\theta_B} = arg_{\hat{\theta}} \min E\left(\hat{\theta} - \bar{\theta}\right)^2 \qquad (8)$

The value of the estimator is the equivalent of the mean of the posterior distribution which gives an unbiased least squares estimate of $\bar{\theta}$ for a given measurement of θ [15].

$$\hat{\theta}_B = \int \bar{\theta}\, f_{\bar{\theta}/\theta}(\bar{\theta}/\theta)d\bar{\theta} = \frac{\int \bar{\theta} f_{\bar{\theta}/\theta}(\bar{\theta}/\theta) f_{\bar{\theta}}(\bar{\theta})d\bar{\theta}}{\int f_{\theta/\bar{\theta}}(\theta/\bar{\theta})d\bar{\theta}} \qquad (9)$$

Due to the additive noise having Gaussian distribution,

$$f_{\theta|\bar{\theta}}(\theta|\bar{\theta}) = f_v(\theta - \bar{\theta}) = \frac{1}{\sqrt{2\pi}\sigma_\omega} e^{-\frac{(\bar{\theta}-\theta)^2}{2\sigma_\omega^2}} \quad (10)$$

The above equation can be written as

$$\hat{\theta}_B = \frac{\int \bar{\theta} f_v(\bar{\theta}-\theta) f_{\bar{\theta}}(\bar{\theta}) d\bar{\theta}}{\int f_v(\theta-\bar{\theta}) f_{\bar{\theta}}(\bar{\theta}) d\bar{\theta}} \quad (11)$$

The Bayes estimator with β=2 gives

$$\widehat{\theta_B} = \frac{\sigma_{\bar{y}}^2}{\sigma_{\bar{y}}^2 + \sigma_\omega^2}\,\theta \quad (12)$$

5. Mean Square Error Soft Threshold fitting for the Bayes Estimator

The Bayes estimator of noisy GGD signals as given in equation (9) is presented as a function of noise variance, noise-free variance and the shape parameter. The analysis clearly indicates that the estimator is similar to the soft thresholding algorithm. Fig 1 shows the variation of the coefficient estimator with respect to the WT coefficients. As the value of the noise variance increases, it is zero up to a particular point and it exhibits the slope of one. Similar behavior can also be shown for different noiseless variance keeping the noise variance as constant. These two concepts gives the confirmation that the estimation using Bayes risk is an odd function of the noisy coefficients that is zero at zero, grows slightly non-linearly and later it asymptotically exhibits a linearity property for larger coefficients.

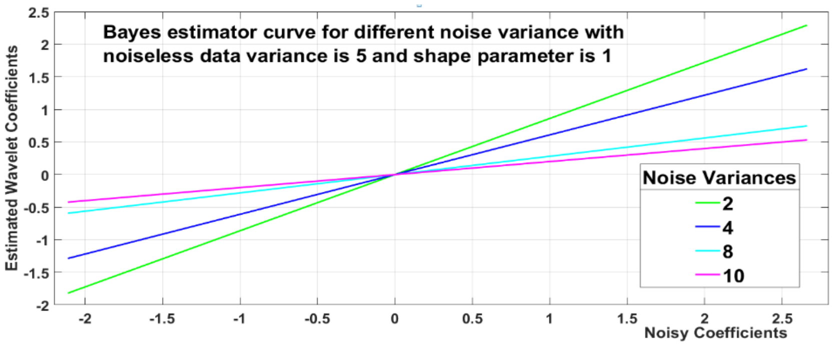

Fig 1 - Bayes estimator for different noise variance with noiseless data variance as 5 and the shape parameter as 1

Fig 2 shows the variation of threshold value for different values of signal standard deviation with σ_w being constant and fig 3 represents the variation of threshold value with the change in standard deviation of the noisy signal keeping estimator of σ_y constant.

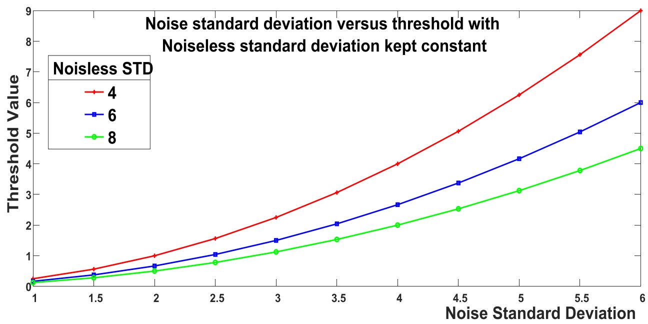

Fig 2 - Threshold value versus Noiseless standard deviation with noisy standard deviation being constant

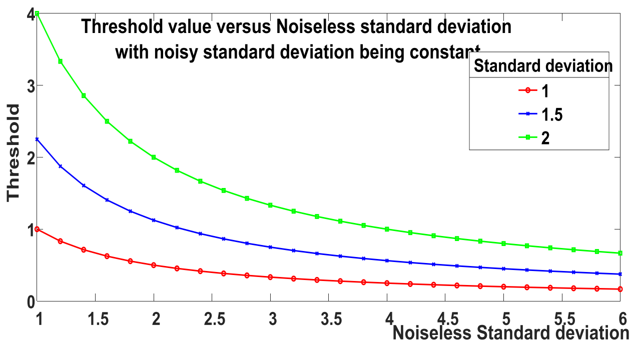

Fig 3 - Threshold value versus Noise standard deviation with noiseless standard deviation being constant

The Bayes estimator for GGD signals is similar to a soft thresholding method. For such cases, the WT based BayesShrink method is an effective technique in order to remove the noise from the PD signal. This method finds the optimum value for minimizing the mean square error. The numerical analysis gives the following relation for computing the threshold.

$$T_B = \frac{\sigma_\omega^2}{\sigma_{\bar{y}}} \quad (13)$$

5.1 Parameter Estimation of GGD

The various parameters can be estimated using the equations mentioned below.

The estimates of the parameters required for Bayeshrink are

i. Noise variance σ_w^2 : Median Absolute Deviation is the standard noise variance estimator.

$$\hat{\sigma}_{MAD} = \frac{Median\ (|\theta|)}{0.6745} \quad (14)$$

Where, θϵ approximate coefficients

ii. Noiseless data variance (σ_θ^2): The variance of the noisy signal is given by

$$\sigma_\theta^2 = \sigma_\theta^2 + \sigma_w^2 \quad (15)$$

6. Partial Discharge experimental Set-up

Fig 4 shows the connection diagram of the experimental setup. The set up for measuring PD signals provides a framework to ascertain the different characteristics involved in PD measurements using the guidelines mentioned in IEC 60270.

A PD measuring system consists of:

- An Insulation sample or the object under test
- Coupling capacitor with low inductance value
- A HV supply having less background disturbances
- HV connections
- A HV filter to decrease disturbance/noise from the power supply
- A PD detector
- Computer based software for analysis

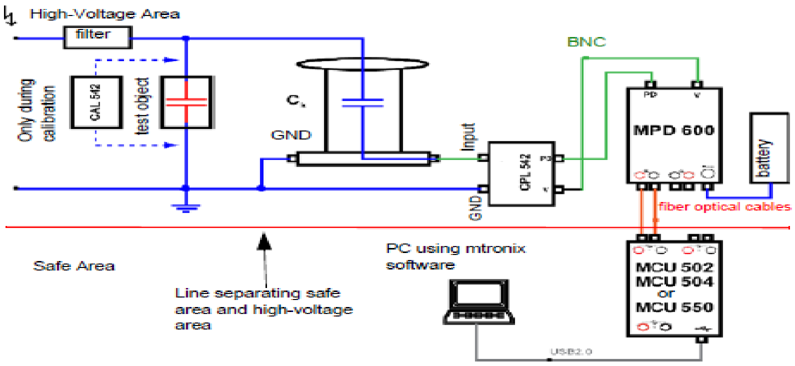

Fig 4 - Partial Discharge measuring Set-up

The measurement in the present work has been performed in a regulated environmental set up known as Faraday’s Cage which has an electromagnetic shielding along with employing digital software filters and noise thresholding to remove the noises. The experimental set up has a HV PD free transformer rated 36 kV, 160 kVA for supplying HV to the test set up, which is controlled by the autotransformer.

Input impedance Z_m(CPL 542) is connected in series with a coupling capacitor having value of 1000 pF.Z_m forms the detector circuit. Collection of PD data is done by using MPD 600 PD measuring system manufactured by OMICRON Mtronix technology and recorded in Mtronix software in a shielded area. PD pulses are produced by the test object which are detected by Z_m and are sent to the detector through a cable in the form of apparent charge in pC.

Fig 5 shows the data acquisition room for PD measurements where the collected PD signal is processed using Mtronix software. Fig 6 shows the photo of the 11 kV stator coil connected for PD measurements. This setup is done in an enclosed chamber to avoid the disturbances being included while measuring.

Fig 5 - PD data acquisition chamber

Fig 6 - Connected stator coil for PD measurement

7. Partial Discharge experimental Set-up

Fig 7 shows the denoised signal when corrupted with white noise collected by conducting experiments on damaged 11 kV stator coil using adaptive Bayesian Denoising for General Gaussian Distributed (GGD) Signals in Wavelet Domain. This method out performs other thresholding methods when the signal is corrupted by white Gaussian noise.

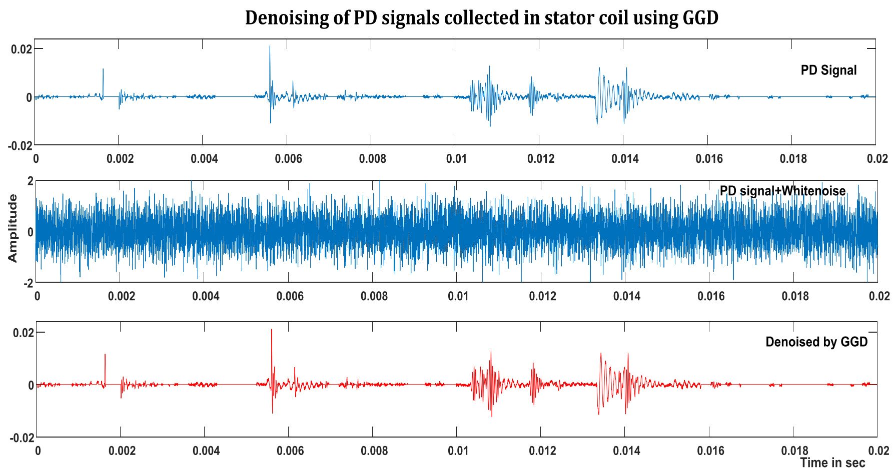

Fig 7 - Acquired PD signal, noisy signal (white noise) & denoised signals for stator coil using adaptive Bayesian with GGD

Table 1 gives the values of SNR at different levels of decomposition with Bayes estimator for GGD signals. From the values, it is observed that, at level-7. When the same signal is denoised using Universal thresholding method, the SNR obtained is 38.27.

Table 1 - SNR values at different levels using Bayes Estimation

Levels	SNR	MSE
1	5.9386	0.482
2	15.9948	0.395
3	24.0419	0.239
4	32.0797	0.150
5	38.1079	0.086
6	44.1266	0.026
7	**45.1368**	**0.012**
8	43.1404	0.019

8. Conclusion

A wavelet transform based denoising technique; Bayesian estimation for Generalized Gaussian Distributed data has been presented. It has been also showed that for such signals, the Bayes estimation is well suited. The threshold value of the BayesShrink is a function of noise variance and noise-free data variance. The Bayesian estimator is comparable with the soft thresholding technique. The method has been applied to the PD signal collected from the 11 kV stator coil. The collected signal is added with the white Gaussian noise to make it resemble the GGD signals. The method performs well in removing the random noise from the corrupted PD signal. The values of SNR at different levels of WT decomposition is also presented and the value is compared with the universal thresholding method.

Acknowledgements

We express our sincere thanks and gratitude to all the authorities, engineers, and HR department of T D Power systems, Dabbaspete, Bangalore, a Generator manufacturing company for giving us the opportunity to conduct experiments on measurements of Partial discharge signals using a damaged 11 kV stator coil.

References

Naidu, M. S., Kamaraju, V.: 'High Voltage Engineering' (New Delhi: Tata McGraw Hill Education Private Limited, 2012

Dr. F.H. Kreuger, “Discharge detection in High Voltage Equipment”, Temple press Books Ltd.,

D. Gnanadurai& V. Sadasivam, “An efficient adaptive thresholding technique for wavelet based Image denoising”, World Academy of Science, Engineering and Technlogy, IJECE, Vol.2, No. 8, 2008.

Zahra Sadeghipour, MassoudBabaie-Zadeh, Christian Jutten. An adaptive thresholding approach for image denoising using redundant representations. T. Adali, J. Chanussot, C. Jutten, J. Larsen. IEEE International Workshop on Machine Learning for Signal Processing (MLSP 2009), Sep 2009, Grenoble, France. Proceedings of the 19-th international IEEE workshop on Machine Learning for Signal Processing (MLSP 2009), 6 p., 2009.

M. G. Sumithra and B. K. Thanushkodi, “Performance Evaluation of Different Thresholding Methods in Time Adaptive Wavelet Based Speech Enhancement,” IACSIT International Journal of Engineering and Technology, vol. 1, no. 5, pp. 439–447, 2009, pp 42-51, ISSN: 1793-8236439–447.

Sachin . D. Ruikar, Dharmpal D Doye, “Wavelet Based Image Denoising Technique,” International Journal of Advanced Computer Science and Applications, vol. 2, no. 3, pp. 49–53, 2011.

R. K. Rai and T. R. Sontakke, “Implementation of Image Denoising using Thresholding Techniques,”, International Journal of Computer Technology and Electronics Engineering (IJCTEE) , vol. 1, no. 2, pp. 6–10.

D. Jana, “Wavelet Thresholding for Image Noise Removal Different Techniques of Thresholding Used for Wavelet Image Denoising,” no. June, pp. 1400–1405, 2014.

S. G. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression,” IEEE Trans. Image Process., vol. 9, no. 9, pp. 1532–1546, 2000.

L. I. U. En-hai, L. I. U. Hong-pu, Z. Yan, and G. U. O. Zhi-tao, “An Improved Method of Image Denoising Base on Stationary Wavelet,” 2009 WRI Glob. Congr. Intell. Syst., vol. 4, no. 413027, pp. 379–383, 2009.

Manel LIMEM and Mohamed Ali HAMDI, “Uterine Electromyography signals denoising using discrete wavelet transform” pp. 101–103 ICABME 2015,

ShemiP.M.andShareena E.M., “Analysis of ECG Signal Denoising Using Discrete Wavelet Transform” pp. 916–920 2nd IEEE International Conference on Engineering and Technology (ICETECH), 17th & 18th March 2016,

Hari Om, Mantosh Biswas “An Improved Image Denoising Method Based on Wavelet Thresholding”, pp. 109-116, Journal of Signal and Information Processing, 2012.

S. G. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression,” *IEEE Trans. Image Process.*, vol. 9, no. 9, pp. 1532–1546, 2000.

Masoud Hashemi, Student Member, Soosan Beheshti, and Senior Member, “Adaptive Bayesian Denoising for General Gaussian Distributed (GGD) Signals in Wavelet Domain,” , IEEE Transactions on Signal Processing, March 2014.