I.J. Image, Graphics and Signal Processing, **2023, 3, 60-68**
Published Online on June 8, 2023 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2023.03.05

Enhancing Lte Rss for a Robust Path Loss Analysis with Noise Removal

Seyi E. Olukanni*
Confluence University of Science and Technology/Department of Physics, Osara, 264103, Nigeria
Email: olukannise@custech.edu.ng
ORCID iD: https://orcid.org/0000-0003-1410-8971
*Corresponding Author

Joseph Isabona
Federal University Lokoja/Department of Physics, Lokoja, 260102, Nigeria
Email: joseph.isabona@fulokoja.edu.ng
ORCID iD: https://orcid.org/0000-0002-2606-4315

Ituabhor Odesanya
Federal University Lokoja/Department of Physics, Lokoja, 260102, Nigeria
Email: ituabhor.odesanya@fulokoja.edu.ng
ORCID iD: https://orcid.org/0000-0002-5901-3370

Received: 04 July, 2022; Revised: 24 October, 2022; Accepted: 10 February, 2023; Published: 08 June, 2023

Abstract: Wavelet transform has become a popular tool for signal denoising due to its ability to analyze signals effectively in both time and frequency domains. This is important because the information that is not visible in the time domain can be seen in the frequency domain. However, there are many wavelet families and thresholding techniques (such as haar, Daubechies, symlets, coiflets, meyer Gaussian, morlet, etc) thatare available for the analysis of signals, and choosing the best out of them all is usually time-consuming, thus making it a difficult task for researchers. In this article, we proposed and applied a stepwise expository-based approach to identify the wavelet family and thresholding technique using real-time signal power data acquired from Long-Term Evolution (LTE). We found out from the results that Rigrsure thresholding with the Daubenchies family outperforms others when engaged in practical signal processing. The stepwise expository-based approach will be a relevant guide to effective signal processing over cellular networks, globally. For validation, different datasets were used for the analysis and Rigrsure outperforms the other thresholding techniques.

Index Terms: Path Loss, wireless communication, wavelet transform, noise, LTE signal

1. Introduction

The growth of wireless networks, especially cellular network has been exponential due to their importance in our day-to-day activities. However, the signal produced and afterwards transmitted is always sullied with different types of noise [1]. This is a major limitation to the quality of signal received at the receiver. This is an established problem in signal processing devices [2-4]. Consequently, understanding the properties and effects of noise on wireless communication links is vital for the development of reliable path loss models for accurate planning of the network by engineers and designers [2].

Concerning signal processing, noise is an undesired form of energy or signal that tends to corrupt the needed signal. According to [3], noise can limit the distance of transmission for given transmitter power, can affect the sensitivity of receivers and may compel a bandwidth reduction of a system. As a result of the aforementioned, noise mitigation is very vital for improving the performance of the wireless systems and network planning.

In [3], the sources of noise in telecommunication were classified into internal and external noise. Internal noises are the ones that originated from the components in the communication system and, some of its examples are thermal noise, shot noise, transit time noise. Meanwhile, atmospheric, extra-terrestrial and man-made noise is some of the examples of external noise. These noises hamper the performance of wireless communication.

Meanwhile, researchers have developed different algorithms and transforms to reduce the effects of noise on signals in other to enhance the overall quality of the received signal. Some examples of signal denoising techniques are discussed in [5], however, prominent among them is the wavelet transform [6],

2. Literature Review

There exist many literatures [7-9] that have attempted to denoise a signal in other to enhance the signal quality. The author of [10] used a hybrid slantlet transform, which is a combination of wavelet discrete transform (WDT) and Slantlet transform to mitigate the noise effects on the transmitting signal of the primary user that is received by the secondary user. In [11] the authors termed their approach to signal reduction technique “a new concept”. In their approach, they put into consideration some properties of the human auditory system combined with neural network and rough sets. And, they used their technique to reduce non-stationary noise in audio signal.

In [12], the authors combined wavelet transform and generalized regression neural network and called it Wavelet-GRNN. He used three decomposition levels of discrete wavelet transform for the prediction of spatial electric field strength and argued that his approach – Wavelet-GRNN outperformed median filter and neural networks (MF-GRNN) and GRNN. In [8], the authors argued that noise is a major factor affecting ultraviolet optical communication, and they used wavelet transform to reduce the noise on both simulated data and from a physical experiments. They concluded coif2 of the coiflet family performed better than other wavelet families. Meanwhile, the authors of [13] did a comparative study of discrete wavelet transform (DWT) and discrete Fourier transform (DFT) for signal smoothing and noise removal. And, they conclude through the values of their respective information cost that wavelet transform outperforms Fourier transform.

Meanwhile, in [14], the authors tried to compare the impact of soft and hard thresholding on a voice signal. They concluded that hard thresholding contains more discontinuous shocking points and the signal may lose more useful information if soft thresholding is employed. This made them to develop an algorithm that they claimed is the best compromise between hard and soft thresholding of discrete wavelet transforms.

It is in view of these claims that we make the following contributions:

- Detailed expository of commonly used wavelets families and thresholding techniques has been given
- To find the best wavelet thresholding techniques for enhancing LTE RSS for a robust path loss analysis, and

The remaining of this article is arranged as follows: Section 2 presents the model for a received signal. In section 3 we present a wavelet transform background, and the denoising techniques while in 4, a brief discussion of the performance metrics was discussed. The methodology, result and analysis were presented in section 5 and 6 respectively. Finally, the conclusion was drawn in section 7.

3. Noisy Signal

Noise is one of the factors limiting the performance of the communication system. And, noisy signal is a signal that has been corrupted by unwanted modifications of the original signal before and after transmission.

Assuming that the transmitted signal from an antenna is $t(n)$, the noisy received signal $r(n)$ is expressed as:

$$r(n) = t(n) + e(n) \quad n = 0,1,...(N-1) \tag{1a}$$

where $e(n)$ is an Additive White Gaussian noise (AWGN) with zero mean and variance of σ^2. It is a combination of the thermal noise N_t generated by the components of the electronic devices and the external noise power F_e [15].

$$e(n) = N_t + F_e \tag{1b}$$

N is the number of samples. Using $r(n)$ to develop any path loss model will affect the accuracy of the model, hence the need for signal denoising.

4. Wavelet Transform (WT)

A wavelet denoiser estimates the clean signal from the corrupted signal however; its effectiveness is dependent on the choice of mother wavelets and thresholding applied. Wavelet transform can present signals in both time domain and frequency domain. This ability is what makes it standout from other de-noising techniques [6].

The mathematical representation is given in equation (2):

$$P(b,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi^* \left(\frac{t-b}{a} \right) r(n) dt \tag{2}$$

where a is the dilation parameter, b is the translational parameter and $\frac{1}{\sqrt{a}}$ is a weighting function. ψ^{*}(t) is a complex conjugate of the mother wavelet $\psi(t)$ and $r(n)$is the signal.

$$\psi_{a,b}\left(t\right)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{3}$$

Meanwhile, there exist several wavelets families such as Haar, Daubenchies, Coiflets, Symlets, Morlets, Meyer, Mexican hat, complex wavelets etc.

To accurately apply wavelet transform for the noise reduction process the following steps are followed:

- Select wavelet type: there are countless number of wavelet transform, but the four popular ones are: the Haar, doublets, coiflets, and symmlets
- Select Threshold: the thresholding techniques available in wavelet transform are sqtwolog [16], rigisure, heursure, minimaxi. We shall apply all in this article and present the best.
- Thresholding Methods. Though there exist the hard, soft threshoding methods but, for the sake of this paper, we shall employ the soft thresholding methord.

Soft threshoding

$$x_i^{*}=\begin{cases} 0 & if\left|x_i\right|\le t \\ sign(x_i)\left(\left|x_i\right|-t\right) & if\left|x_i\right|>t \end{cases} \tag{4}$$

Hard thresholding

$$x_i^{*}=\begin{cases} 0 & if\left|x_i\right|\le t \\ x_i & if\left|x_i\right|>t \end{cases} \tag{5}$$

Where $x_i \; and \; x_i^{*}$ are respectively the wavelet coefficients before and after thresholding. Meanwhile to recover back the original signal from the wavelet transform, also known as reconstruction the inverse wavelet transform is employed.

In summary, a signal can be denoised by applying discrete wavelet transform (DWT) on the signal; estimate the noise level, apply soft thresholding to the DWT and take the inverse discrete wavelet transform (IDWT).

5. Performance Measure

The performance of the thresholding methods is estimated with the following statistical metrics: root mean square error (RMSE), mean absolute error (MAE) and the standard deviation (STD).

RMSE: it is the square root of the mean square error. It tells how close the measured received signal strength (RSS), $f(x)$ values are to the values predicted $\bar{f}(x_i)$ by the fitted models. It is given as

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(f(x)-\overline{f}(x))}{n}} \tag{6}$$

where n = total number of measured data

The interpretation of RMSE is a lot easier because its output has same unit as the expected output variables

MAE gives the absolute difference between measured data that is the received signal strength (RSS) values and the predicted values. It is defined as:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left\|f\left(x\right)-\overline{f}\left(x_i\right)\right\| \tag{7}$$

MAE metric is good at handling outliers.

STD is the measure of the amount of dispersion of a set of data. A low STD is an indication that the result is closed to the mean of the data set.

$$STD = \sqrt{\frac{f(x) - \overline{f}(x_i)}{n-1}} \tag{8}$$

6. Methodology

Fig 1 is the blocks diagram of the methodology that guilded this article. The expository work starts by conducting a field measurement of LTE signal around a base station. This is followed by applying the data collected to some wavelets family and thresholding techniques. And, their performance analysis were compared.

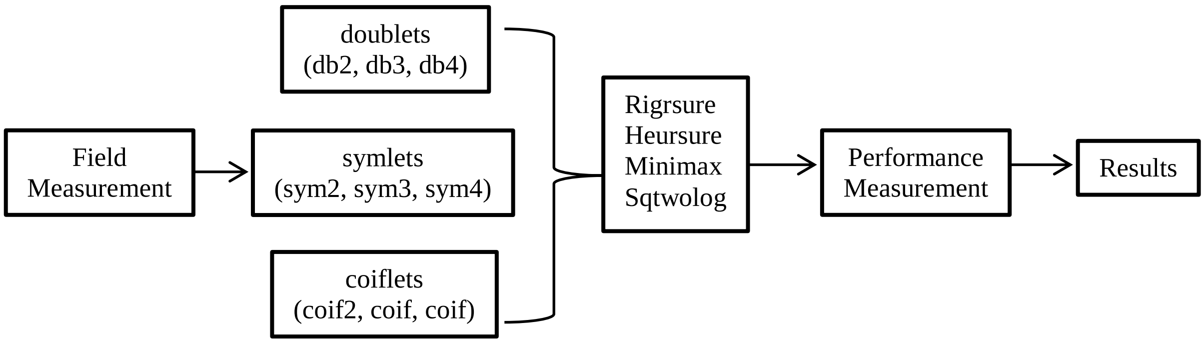


Fig. 1. Block diagram for methodology

A. LTE Data Campaign

The RSS data used in this article is obtained from a drive test (DT) measurement campaigns carried out in Lokoja, the capital city of Kogi State Nigeria around a commercial LTE system network transmitting at a carrier frequency of 2600MHz. The process was accomplished with the help of a laptop preinstalled with TEst Mobile System (TEMS) software, Mobile phone, and a Global Positioning System (GPS) module. The GPS was connected to the laptop to determine the coordinates at every point during the drive test. The mobile phone sends the measured data to the laptop which was stored as log files. The log files were later retrieved for interpretation and analysis.

B. Wavelet Analysis: Signal Decomposition, Thresholding and Reconstruction

The four thresholding techniques – Rigrsure, Sqtwolog, Minimax and Heursure were employed for denoising the measure data so as to compare their impacts on the noisy signal. The process was carried out for the soft threshold methods. The three (3) performance evaluation metrics used to ascertain the performance of the thresholding techniques are, Root mean square error (RMSE), Standard deviation (STD), and mean absolute error (MAE)

7. Result and Discussion

The wavelet analysis and graphing of the original signal (fig 2) used for this work is accomplished using MatLab R2018a. The original signal data were decomposed into three level (N=3) of frequencies employing Daubenchies (db2, db3, db4), the Symlets (sym2, sym3, sym4) and the Coiflets (coif2, coif3, coif4). The soft thresholding method was used, and the results were compared.

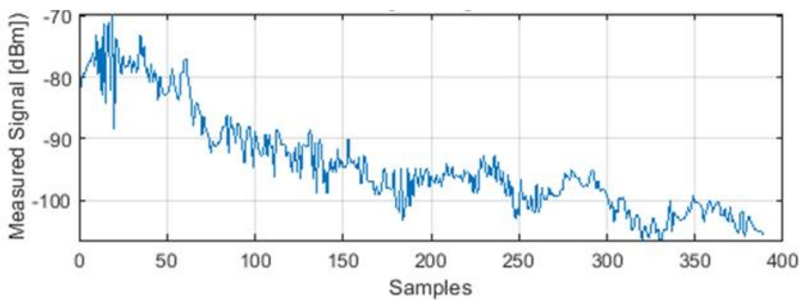


Fig. 2. Original RSS data plot

Fig 3(a-l) displayed the denoising capability of the Rigrsure, Sqtwolog, Minimax and Heursure threshold techniques in a column under the following wavelets families: db2, sym2 and coif2. Table 1 show the performance summary of the 2^{nd} order wavelet families based on the four chosen thresholding techniques. The values of the MAE ranges from (0.7700 - 0.8164), the STD is in the interval of (0.5533 – 0.5638). Fig 4 presents the performance analysis plot. It will be observed from either Table 1 or fig 4 that the Rigrsure techniques outperformed the other techniques under the 2^{nd} order wavelet families.

Table 1. Performance summary of db2, sym2, coif2

Metrics	Thresholding Techniques	db2	sym2	coif2
MAE	Rigrsure	**0.8164**	**0.8164**	**0.7700**
	Heursure	1.2750	1.2750	1.2689
	Minimax	1.1469	1.1469	1.1056
	Sqtwolog	1.2943	1.2943	1.2862
STD	Rigrsure	**0.5638**	**0.5638**	**0.5533**
	Heursure	1.0338	1.0338	1.0501
	Minimax	0.8574	0.8574	0.8693
	Sqtwolog	1.0674	1.0674	1.0794
RMSE	Rigrsure	**0.9921**	**0.9921**	**0.9481**
	Heursure	1.6414	1.6414	1.6471
	Minimax	1.4320	1.4320	1.4065
	Sqtwolog	1.6777	1.6777	1.6791

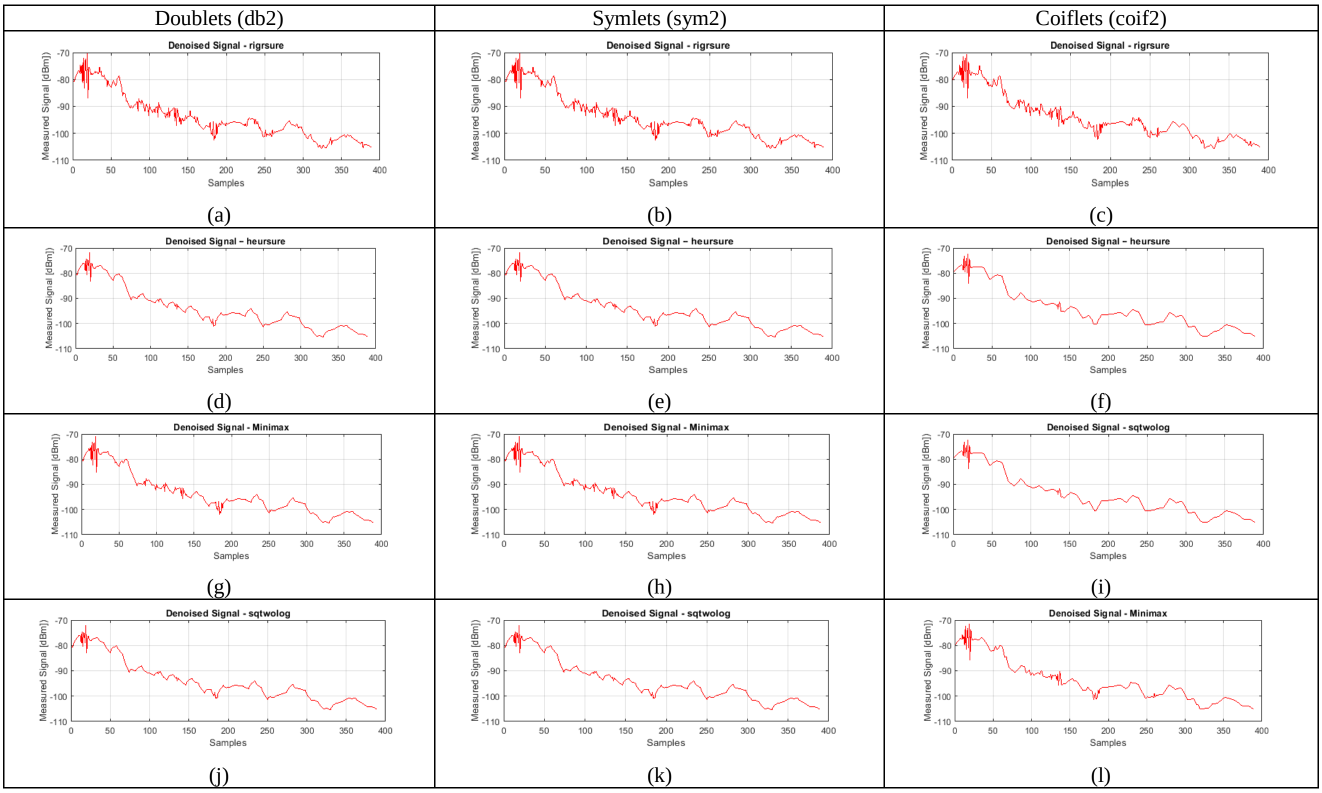


Fig. 3. Comparing of denoising effects of db2, sym2, coif2

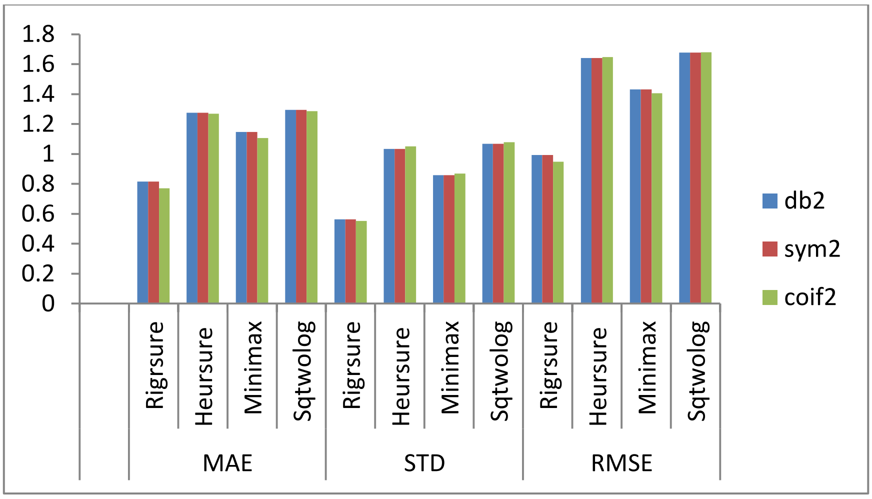


Fig. 4. Error plots of db2, sym2 and coif2

Shown in fig 6(a-l) are the plots of 3rd order wavelets – db3, sym3 and coif3 with the different wavelets methods. Their computed performance summaries are displayed in Table 2 and also shown in fig 5. It is revealed that the Rigrsure performs better than other methods under the soft thresholding.

Table 2. Performance summary of db3, sym3, coif3

Metrics	**Thresholding Techniques**	**db3**	**sym3**	**coif3**
MAE	Rigrsure	**0.9038**	**0.9038**	**0.9703**
	Heursure	1.2804	1.2804	1.2669
	Minimax	1.1534	1.1534	1.1353
	Sqtwolog	1.2943	1.2943	1.2831
STD	Rigrsure	**0.6472**	**0.6472**	**0.7034**
	Heursure	1.0988	1.0988	1.0354
	Minimax	0.9012	0.9012	0.8665
	Sqtwolog	1.1266	1.1266	1.0596
RMSE	Rigrsure	**1.1116**	**1.1116**	**1.1985**
	Heursure	1.6872	1.6872	1.6362
	Minimax	1.4638	1.4638	1.4282
	Sqtwolog	1.7159	1.7159	1.6640

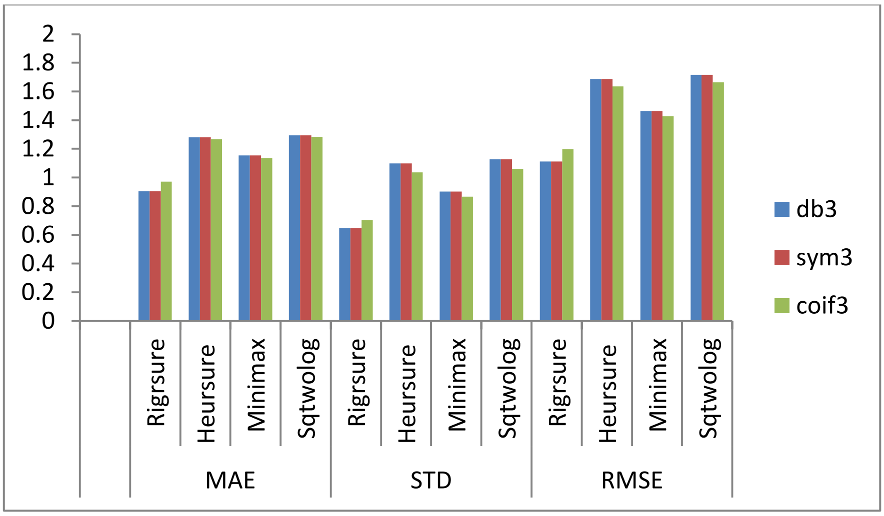
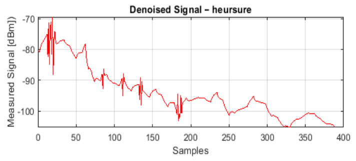
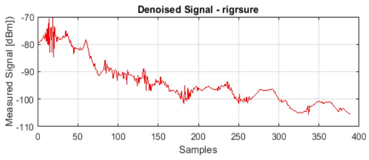
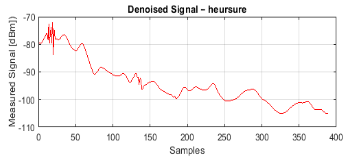
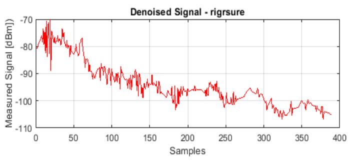
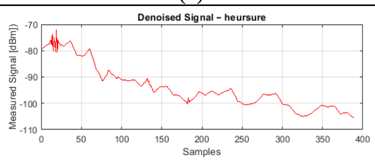
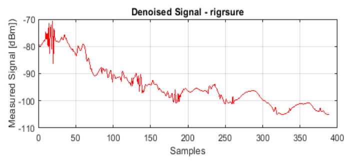
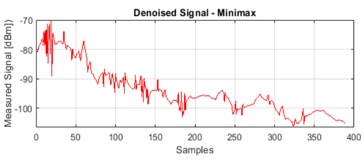
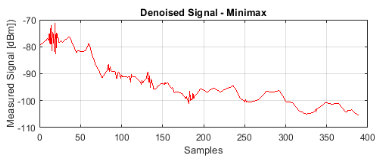
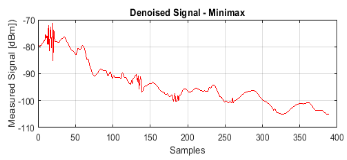


Fig. 5. Error plots of db3, sym3 and coif3

Doublets (db3)	Symlets (sym3)	Coiflets (coif3)
 (a)	 (b)	 (c)
 (d)	 (e)	 (f)
 (g)	 (h)	 (i)

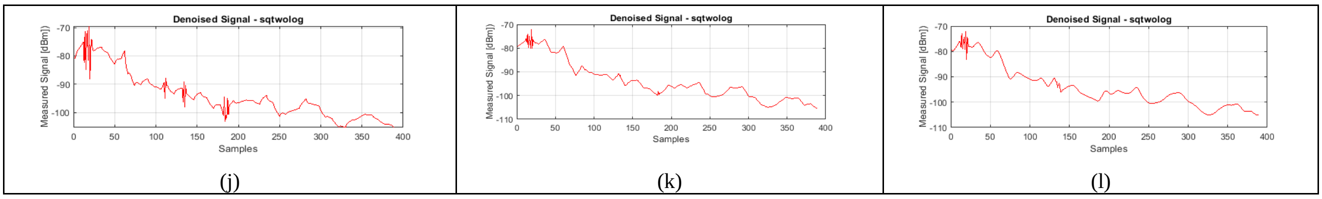


Fig. 6. Comparing of denoising effects of db3, sym3, coif3

Likewise, from Table 3 and the plots in figure 7 and figure 8, we can conclude that rigrsure is the best denoising techniques under soft thresholding.

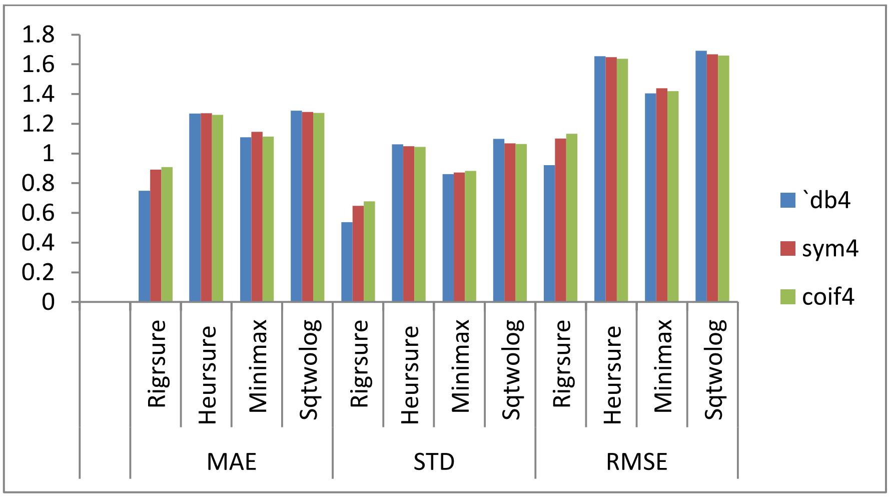


Fig. 7. Error plots of db4, sym4 and coif4

Table 3. Performance summary of db4, sym4, coif4

Metrics	Thresholding Techniques	`db4	sym4	coif4
MAE	Rigrsure	**0.7482**	**0.8906**	**0.9080**
	Heursure	1.2685	1.2709	1.2607
	Minimax	1.1094	1.1456	1.1135
	Sqtwolog	1.2876	1.2795	1.2722
STD	Rigrsure	**0.5377**	**0.6464**	**0.6769**
	Heursure	1.0610	1.0483	1.0446
	Minimax	0.8599	0.8714	0.8818
	Sqtwolog	1.0973	1.0676	1.0647
RMSE	Rigrsure	**0.9213**	**1.1005**	**1.1325**
	Heursure	1.6538	1.6474	1.6373
	Minimax	1.4036	1.4394	1.4204
	Sqtwolog	1.6917	1.6664	1.6590

Table 4. Performance summary of db2, sym2, coif2

Metrics	Thresholding Techniques	`db2	Sym2	Coif2
MAE	Rigrsure	**1.5445**	**1.5445**	**1.5884**
	Heursure	2.0071	2.0071	2.0765
	Minimax	1.7041	1.7041	1.8193
	Sqtwolog	2.1061	2.1061	2.1432
STD	Rigrsure	**0.9235**	**0.9235**	**1.0052**
	Heursure	1.4470	1.4470	1.5771
	Minimax	1.0706	1.0706	1.3074
	Sqtwolog	1.5860	1.5860	1.6656
RMSE	Rigrsure	**1.7996**	**1.7996**	**1.8797**
	Heursure	2.4743	2.4743	2.6076
	Minimax	2.0125	2.0125	2.2403
	Sqtwolog	2.6365	2.6365	3.7144

To verify the outcome of the test dataset on the thresholding techniques, we employed another dataset for analysis of db2, sym2 and coif2. Table 4 presents the results. Rigrsure still performs better than the other thresholding techniques affirming the outcome of the test datasets.

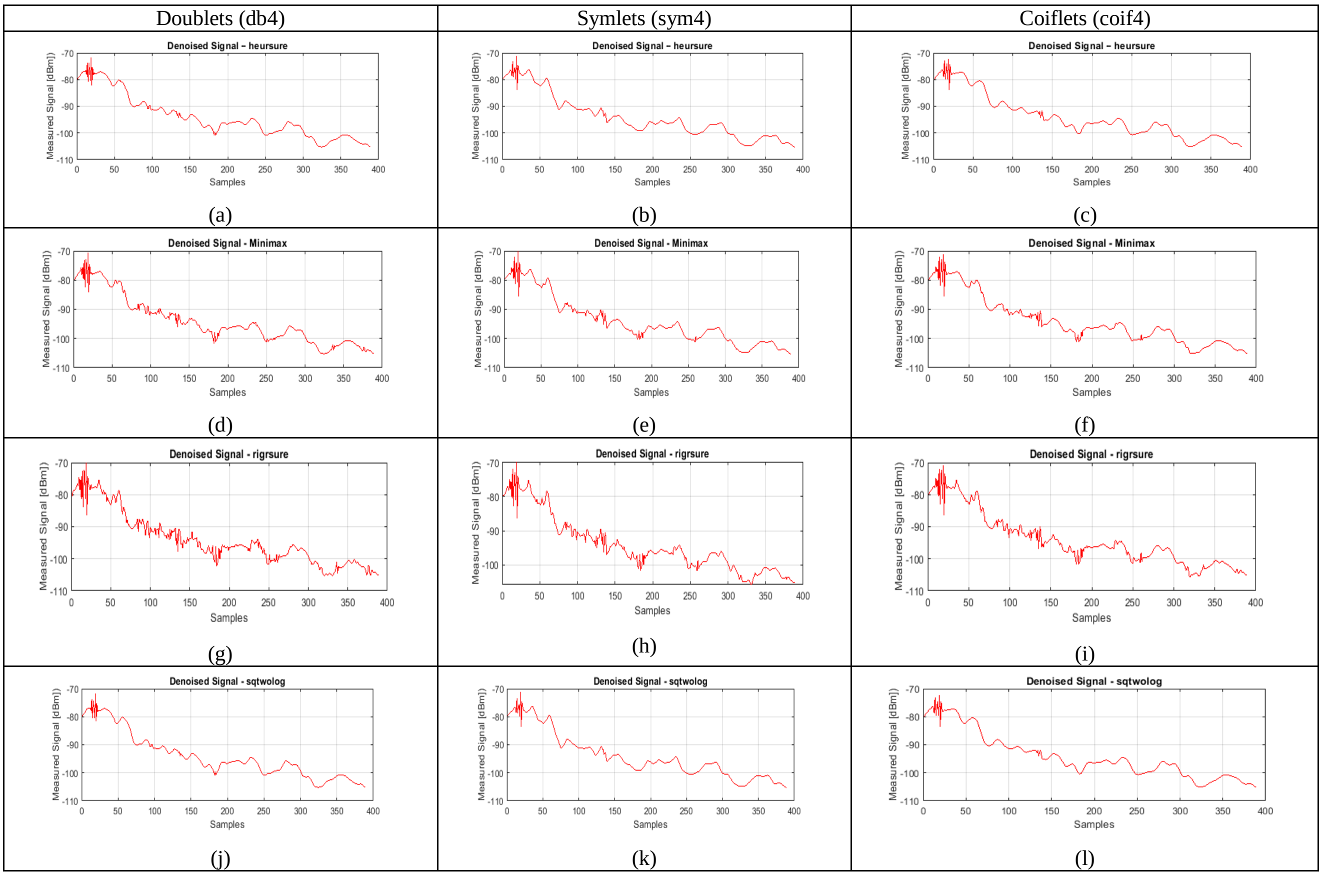


Fig. 8. Comparing of denoising effects of db4, sym4, coif4

8. Conclusion

To develop a reliable path loss model, there is a need to reduce the noise in the training data set. Wavelets transform is a popular tool that can be used to 'clean' the data. But, there are many available wavelet families which makes it difficult to know the one to choose. In this work, four wavelets denoising techniques namely, Rigrsure, Sqtwolog, Minimax and Heursure under soft thresholding for Daubenchies (db2, db3, db4), the Symlets (sym2, sym3, sym4) and the Coiflets (coif2, coif3, coif4) were examined on an LTE signal dataset. The MAE, STD and RMSE were used to ascertain their performances, and it is found that the rigrsure outperforms the other three and Sqtwolog performed the least.

References

[1] D. Sundararajan, *DISCRETE WAVELET TRANSFORM DISCRETE WAVELET TRANSFORM A SIGNAL PROCESSING APPROACH*. India: John Wiley & Sons Singapore Pte. Ltd. Registered, 2015.

[2] Kalyan; Viswanathan, "Noise and Telecommunications Systems," *Telecommun Syst Manag.*, vol. 3, no. 1, pp. 1–2, 2014, doi: 10.4172/2167-0919.1000e112.

[3] S. C. M. M. F. A. M. G. Sadeque, "Study of Different Types of Noise and Its Effects in Communication Systems," *Int. J. Eng. Manag. Res.*, vol. 5, no. 2, pp. 410–413, 2015.

[4] A. Mirzaev and S. Zoteev, "Noise in Telecommunication: Different Types and Methods of dealing with Noise," *J. La Multiapp*, vol. 01, no. 05, pp. 25–28, 2020, doi: 10.37899/journallamultiapp.v1i5.275.

[5] D. K. R. Shubhojeet Chatterjee, Rini Thakur, R.N. Yadav, Lalita Gupta, "Review of noise removal techniques in ECG signals," *IET Signal Process*, vol. 14, 2020, doi: 10.1049/iet-spr.2020.0104.

[6] C. S. Burrus, R. A. Gopinath, and H. Guo, *Introduction to Wavelets and Wavelet Transforms A Primer*. Prentice-Hall, Inc., 1998.

[7] J. O. O. D. ISABONA, "WAVELET SELECTION BASED ON WAVELET TRANSFORM FOR OPTIMUM NOISY SIGNAL PROCESSING," *BIU J. Basic Appl. Sci.*, vol. 3, no. 1, pp. 52–61, 2017.

[8] Y. Tan, X. Geng, and T. Zhao, "Noise Reduction on Received Signals in Wireless Ultraviolet Communications Using Wavelet Transform," *IEEE Access*, vol. 8, 2020, doi: 10.1109/ACCESS.2020.3009944.

[9] R. Krolikowski and A. Czyzewski, "Noise Reduction in Telecommunication Channels Using Rough Sets and Neural Networks," pp. 100–108, 1999, doi: 10.1007/978-3-540-48061-7_14.

[10] H. Al-hmood, S. Member, and S. Member, "Signal Denoising Using Hybrid Slantlet Transform Based Energy Detector in Cognitive Radios," *IEEE*, vol. 1, pp. 7–9, 2013.

[11] R. K. A. Czyzewski, "Noise Reduuction in Telecommunication Channels Using Sets and Neural Networks," *Springer-Verlag Berlin Heidelb.*, pp. 100–108, 1999.

[12] J. Isabona, "Wavelet Generalized Regression Neural Network Approach for Robust Field Strength Prediction," *Wirel. Pers. Commun.*, no. 0123456789, 2020, doi: 10.1007/s11277-020-07550-5.

[13] R. J. Barsanti and J. Gilmore, "COMPARING NOISE REMOVAL IN THE WAVELET AND FOURIER DOMAINS," *IEEE*, pp. 163–167, 2011, doi: 10.1109/SSST.2011.5753799.

[14] Z. pengtu Wang chunli, Zhang Chunlei, "Denoising algorithm based on wavelet adaptive threshold," *Elsevier Int. Conf. Appl. Phys. Ind. Eng.*, 2012, doi: 10.1016/j.phpro.2012.02.100.

[15] F. K. Jondral, "White Gaussian Noise – Models for Engineers," *Commun. Eng. Lab*, pp. 1–7, 2017, doi: 10.1515/freq-2017-0064.

[16] A. Bruce, D. Donoho, and G. Hong-Ye, "Wavelet analysis," *IEEE Spectr.*, pp. 26–35, 1996.

Authors' Profiles

Seyi E. Olukanni is a Ph.D student in the Department of Physics, Federal University Lokoja, Kogi State, Nigeria. He received his M.Sc degree in 2017 and B.Sc degree in the year 2008. Both degrees are in physics from University of Ilorin and University of Abuja respectively. His area of interest includes Electromagnetism, Signal Processing, Internet of Things and Radio communications.

Joseph Isabona (Associate Professor), Ph.D, received Ph.D. and M.Sc. degrees in Communication Electronics, 2013 and 2007 respectively, and a B.Sc in Applied Physics in 2003. He is the author of more than 120 scientific contributions including articles in international refereed Journals and Conferences in the area of Wireless Mobile communications. The Author is a Postdoctoral Research Fellow of the Department of Electronic Engineering, Howard College, University of KwaZulu-Natal, Durban, South Africa. His area of interest includes Signal Processing, RF Propagation Modelling and Radio Resource Management in Radio Telecommunication Networks. He can be reached with joseph.isabona@fulokoja.edu.ng.

Dr. Ituabhor Odesanya is a lecturer in the Department of Physics, Federal University, Lokoja, K ogi State, Nigeria. She obtained her B.Sc in Applied Physics from Ambrose Ali University, Ekpoma and her M.Sc and PhD in Physics Electronics from the University of Benin, Edo State, Nigeria. Her area of interest is in artificial Intelligence and Telecommunications. ituabhor.odesanya@fulokoja.edu.ng

How to cite this paper: Seyi E. Olukanni, Joseph Isabona, Ituabhor Odesanya, "Enhancing Lte Rss for a Robust Path Loss Analysis with Noise Removal", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.15, No.3, pp. 60-68, 2023. DOI:10.5815/ijigsp.2023.03.05