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Development of Non-Parametric Noise Reduction Algorithm for GSM Voice Signal

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Abstract: *Speech enhancement in Global System for Mobile communication (GSM) is an area of engineering that study different kinds of techniques used in enhancing GSM voice signals. The presence of noise in GSM degrades the quality and intelligible of speech which impedes speaker identification and sound clarity. In this paper, non-parametric noise reduction algorithm which incorporates an adaptive threshold technique is proposed to estimate the adaptive threshold value as a function of first and second order statistics of the voice signal. It uses the cumulative value of minimum mean and maximum standard deviation value and minimum (mean and standard deviation) to minimize the effect of impairments introduced by background noise and GSM channels. The algorithm was implemented in MATLAB environment. The results obtained indicate correlation coefficients of 53.93% and 23 45.52% for maximum and minimum threshold value at 2.95 24 standard deviation of noise and 77.93% and 75.83% for maximum and minimum threshold value at 0.25 standard deviation of noise, respectively. Evaluation of the proposed algorithm was performed on real noisy voice signal and a correlation of 92.15% and 89.24% was achieved for both maximum and minimum threshold values with mean square error of 0.0011% and 0.00033%, respectively. These results have proven the efficiency of the proposed algorithm. The threshold values have satisfied perfect noise reduction when the mean and standard deviation values are selected properly*

Keywords: *Voice signal; threshold value; GSM; Non-parametric; Standard deviation; Mean deviation.*

1. INTRODUCTION

The ubiquitous effect of noise has been known to continue to blight communication systems. These varying noise level lower the quality of speech produced and thereby increasing difficulty in hearing during communication. To address this problem, an approach which quantifies the effects of noise is, therefore, very vital [1]. One of the generalized performance metrics for reformulating noise enhancement problem is the use of speech quality enhancement [2]. Speech quality expresses the clearness of any speaker's words as understood by the audience [3], [4].

Several noise enhancement algorithms such as subjective and objective speech quality measures [5], voice activity detection (VAD) [6], Finite impulse response (FIR) adaptive filter, Recursive least square algorithm (RLS) [7], [8], [9], [10], and many other noise estimation and reduction algorithms have been developed over the years but yet the problems of noise impairment in speech still persist. Techniques such as subspace approach [11], the perceptually-based subspace approach [12], the log minimum mean square error (logMMSE) algorithm [13], and so on have been rated high to tremendously improve the quality of speech. The performances of these techniques were based on the processing time of the signal and the complexity of the practical implementation which depends on the Mean, variance and the Maximum amplitude of the error [11].

Therefore, to allow real time implementation of these algorithms and to achieve a trade-off between high quality noise reduction and low computational load, we propose Non-parametric noise reduction algorithm for GSM voice signals. This technique adopts the use of Non-Intrusive signal denoising algorithms which employs the use of noise suppression algorithms such as, an adaptive threshold algorithm. The algorithm was implemented and used to extract noise components from the signal. It is user-directed and hence offers precise understanding of quality features that lead to better service acceptance from the end users. It is designed to judge the quality of speech alongside with noise distortion as well as overall quality. The proposed algorithm has an advantage of fast processing time, simple complexity of circuit implementation and a high signal to noise ratio (SNR).

The rest of this paper is organized as follows. Section II contains the methodology used. Section III presents the performance evaluation of the algorithms using real world noisy signals. Section IV presents the results obtained and finally, Section V concludes the paper.

2. METHODOLOGY

Non-parametric method of reducing noise from voice data using non-intrusive signal denoising system was employed. A time varying noisy signal was used as the input to the system model. The system has three (3) stages namely; Pre-processing, Threshold and Post-processing as shown in Figure 1.

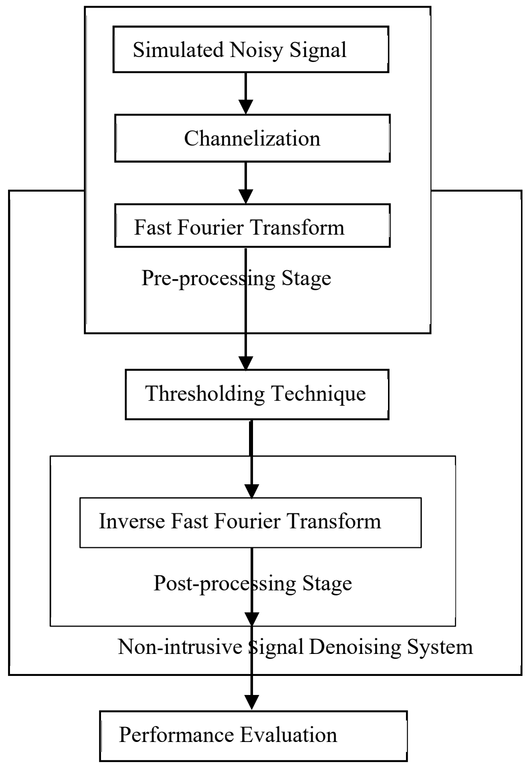

Figure 1: System Block Diagram

2.1 The Simulated Noisy Signal

Time varying signal $x(n)$ of multi-frequencies of N samples was generated. A quantified amount of synthesized Gaussian noise is added with the time-varying signal. The technical conditions adopted were in accordance with the guidelines given in ITU-T recommendation P.800. The noisy speech has been obtained using simulation approach.

2.2 Channelization

Channelization involves the windowing of the noisy signal. The noisy signal is divided into frame block length (L) of five equal sizes of short term. One frame block length (L) of the noisy signal was selected at a time for analysis. The frame block length (L) was passed into the windowing model as illustrated in Figure 2. The windowed frame was then used as an input to the non-intrusive signal denoising system. The equation of the windowed frame can be expressed as;

$$y_m(n) = \sum_{m-n+1}^{m} y(n).h(m-n) \quad (1)$$

where y_m is the windowed signal, $y(n)$ is the noisy signal and $h(m-n)$ is the window function shifted by m samples. The short time transform of these signals can be obtained at a sufficiently high rate (i.e. at or above Nyquist rate of the window) after which the original signal can be recovered within a negligible aliasing error by 'Overlap Add process'.

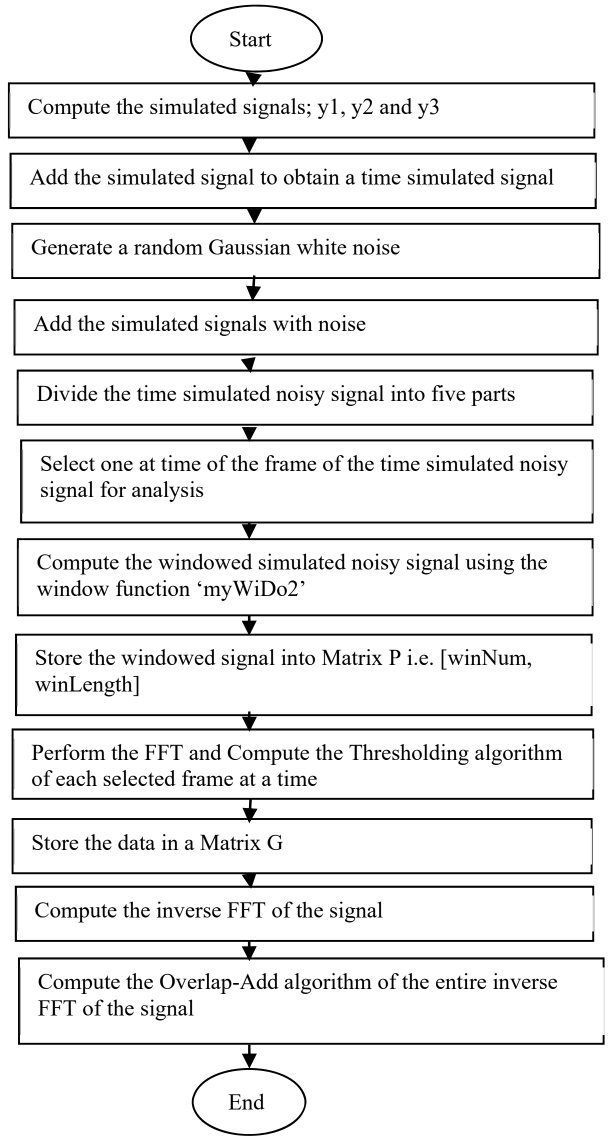

Figure 2: System Algorithm

2.3 Non-intrusive Signal Denoising System (NISDS)

In non-intrusive signal denoising system, the selected windowed noisy signal is analysed, manipulated and the noise in the signal is removed as well as any abnormal variation in the signal considered as degradations. The decomposition of the short time windowed noisy signal is done using Fast Fourier Transform (FFT). The process removes noise, enhances the signal quality and preserves the detailed features of the signal. Non-intrusive signal denoising system converts noisy signal (degraded signal) to clean signal (reference signal).

2.4 Fast Fourier Transform (FFT)

Fourier Transform provides spectral information about a signal and only works for stationary signals. Many real-world signals are non-stationary and need to be processed in real time. Meaning, the signal statistics such as the mean, power and power spectrum are time-invariant. The Fast Fourier Transform (FFT) is applied to the selected windowed noisy signal to compute the Discrete Fourier Transform (DFT) of each of the overlapping short time windowed noisy signal as represented mathematically in (2).

$$Y(f) = \int_{-\infty}^{\infty} y_m(t) e^{-j\omega t} dt \qquad (2)$$

where $Y(f)$ is the Fourier windowed signal, f represent the frequency (in Hertz), y_m is the windowed noisy signal, t represent the time (in seconds) and ω is the harmonic frequency.

Applying the DFT to the short time overlapping windowed noisy signal, where

$$Y(k) = \sum_{k=0}^{N-1} y_m(n) \; e^{-j\omega k}, \qquad n = 0,1,2,......N-1 \tag{3}$$

$$y(n) = y(nT_s), \quad and \quad \omega = 2\pi n / N \tag{4}$$

where $Y(k)$ is the kth harmonic (*i.e* $k = 0....N-1$), $y_m(n)$ is the nth windowed noisy signal sample $(n = 0.....N-1)$, T_s is the sampling period, N is number of samples and n is the sample index.

2.5 Adaptive Threshold Algorithm

The threshold function in (NISDS) is an adaptive threshold employed to improve the performance of the noisy signal. The adaptive threshold uses two processes; first, it fluctuates with the signal and secondly, computes the optimal version which is estimated as a single value for all the signal [14], [15], [16], [17]. In this research, the adaptive threshold is used to smoothen out or to remove some coefficients of FFT sub signals of the measured signal. This reduces the noise content of the signal under the non-stationary environment [18] .

This algorithm uses two statistical properties of the signal, Mean and Standard deviation of the FFT windowed noisy signal as illustrated in Figure 2. The adaptive threshold algorithm is illustrated in (5).

$$\lambda_n = \min(\mu(n)) + \max(\sigma(n)) \tag{5}$$

where

$$\mu(n) = \frac{1}{n} \sum_{k=1}^{n} Y(k) \tag{6}$$

$$\sigma(n) = \sqrt{\frac{1}{n} \sum_{k=1}^{n} \left(Y(k) - \mu(n)\right)^2} \tag{7}$$

$\mu(n)$ and $\sigma(n)$ are the mean and standard deviation of each of the FFT windowed noisy signal. λ is the adaptive threshold.

2.6 Inverse Fast Fourier Transform (IFFT)

The Inverse Fast Fourier Transform (IFFT) transforms a spectrum (amplitude and phase of each component) into a time domain signal. An IFFT in this paper, converts back each of the thresholded FFT signals from frequency domain to time domain in order to obtain a clean (denoised) signal. Each data point in frequency spectrum used for an FFT operation is transformed back to the time domain in the form of windowed signals using inverse discrete Fourier transform (IDFT) as in Equation (8). The realized time signal is the denoised signal x^r which is similar to the original time varying signal x ,

$$x^r(n) = \frac{1}{N} \sum_{n=0}^{N-1} X(k) \; e^{\frac{-j2\pi nk}{N}} \tag{8}$$

where $x^r(n)$ *and* $X(k)$ were the reconstructed signal and corrupted signal, respectively.

2.7 Overlap Add Algorithm

The overlap add algorithm sums up the entire reconstructed windowed time varying signals $x_m^{\;r}$ to obtain the vector form (whole) of time varying signal similar to the initial time varying signal x .

2.8 Experiment on Non-Parametric Noise Reduction Algorithms Using Real-World Noisy Signal

An experiment was carried out to evaluate the proposed algorithms using a noisy speech corpus (NOIZEUS). The database consists of thirty (30) IEEE sentences produced by both the male and female speakers. The corrupted sentences were obtained using eight different real-world noises at different SNRs which are babble, exhibition hall, sub-urban train noise, restaurant, car, train-station, street, and airport noise signal [19]. The sentences were originally sampled at 25 kHz and down sampled to 8 kHz [20]. The noisy speech was read and stored in .wav file on MATLAB 2012 installed on a laptop with window 7 operating system. First, 50% overlaps of windowed signals were obtained using the channelization process described. Fourier representation of each overlapped windowed signals were obtained using N sample points of FFT as in (2). Then, one frame block length of FFT windowed signal was selected at a time for thresholding and lastly, the conversion back to time domain was done using inverse FFT as in (8). The Overlap-Add algorithm summed the signals in order to obtain the reconstructed GSM voice signal.

2.8.1 Performance Evaluation

The performance of most noise algorithms from literature, uses SNR, mean square error, correlation coefficients, standard deviation, Noise variance, probability of false alarm and histogram intersection distance [21], [22], [14]. But, in this paper, three evaluation metrics were used to determine the performance of the non-parametric noise reduction algorithm namely; Correlation coefficients, Mean square error and Standard deviation, respectively.

i. Correlation Coefficients

The correlation coefficient measures the similarity between the reconstructed signal and the time varying signal. The more the estimated result matches the signal, the closer the correlation approaches a value of 1. This can be expressed using the equation below.

$$R(x^r, x) = \left(\frac{C(x^r, x)}{\sqrt{C(x^r, x^r)\, C(x, x)}} \right) \tag{9}$$

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Where (x^r, x, C & R) are; reconstructed signal, original signal, Covariance and correlation coefficient, respectively.

ii. Mean Square Error (MSE)

The mean square error was used to calculate the error difference between the reconstructed signal and the time varying signal and also between the noisy signal and the time varying signal. The MSE expressed the reliability of the reconstructed signal. The equation is expressed below,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i^r - X_i) \qquad (10)$$

where (X_i^r , X_i, N) are the reconstructed signal, time varying signal and total number of samples, respectively.

iii. Standard Deviation

The standard deviation indicates the dispersion level of the spectral data around the mean value. If the data fluctuate much, the dispersion of the noisy signal will change faster and the threshold will also vary faster. If the fluctuation is less, then threshold will change slowly. The mathematical expression is depicted in Equation (7) above.

3. RESULTS AND DISCUSSION

The results obtained illustrate our technique performance on simulated signals and human voice signal for each section of the algorithm. The algorithm was trained using 1024 samples of noisy signal simulated using a quantified amount of white Gaussian noise of standard deviation of 2.95 and 0.25 respectively. The results of both the time varying signal without the noise and the noisy signals are displayed in Figure 3 - Figure 7. The observations deduced from the Figure 3-7 shows the effect of noise as the standard deviation of noise signal increases. The signal to be recovered get more buried in the noise which makes it more difficult to recover due to the abnormalities introduced by the noise.

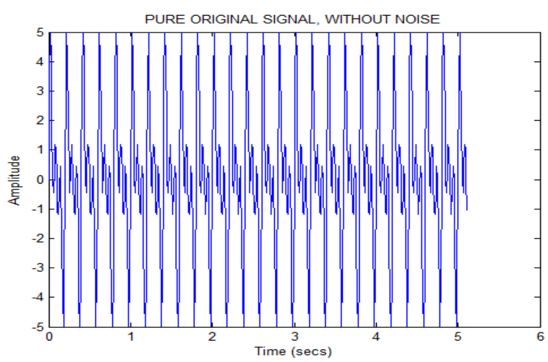

Figure 3: Image of Time signal without the Noise

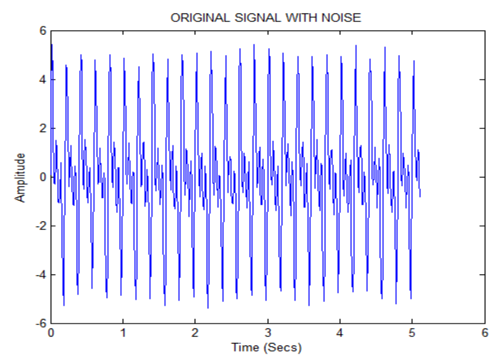

Figure 4: Image of noisy signal at 0.25 standard deviation

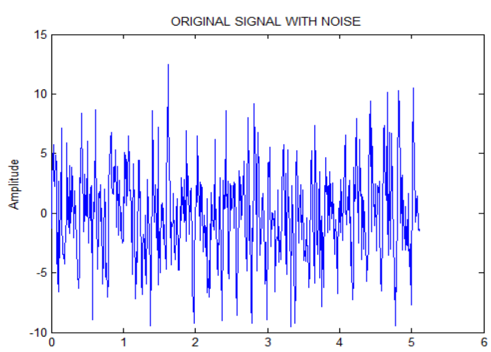

Figure 5: Image of time noisy signal at 2.95 standard deviation

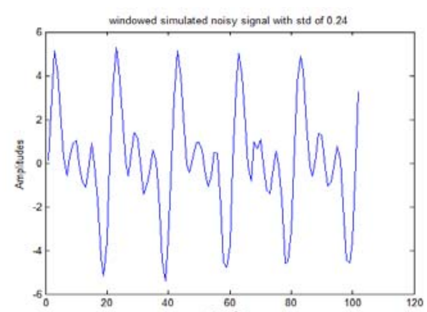

Figure 6: Image of Windowed Noisy Signal with STD of 0.25

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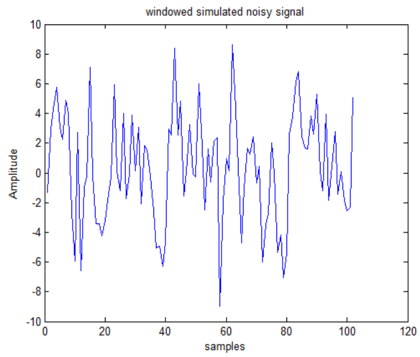

Figure 7: Image of Windowed simulated noisy signal with 2.95 STD

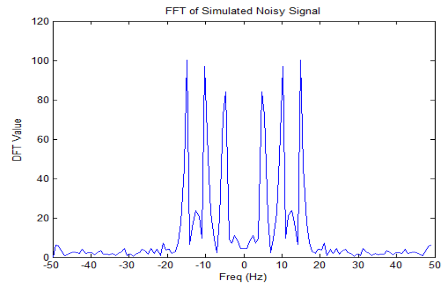

Figure 9: Image of FFT Windowed Noisy Signal of 0.25 STD

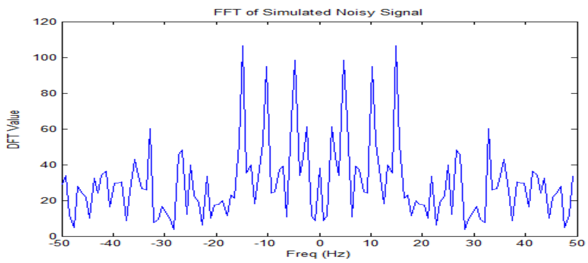

Figure 8: Image of FFT Windowed Noisy Signal of 2.95 STD

The FFT program in this paper uses 128 sample points' transforms to compute the DFT of each selected frame block of the windowed noisy signals that were divided into ten equal segments using Equation 11.

$$N = nextpow2(N) \tag{11}$$

The results in Figure 8 and Figure 9 illustrate some of the FFT image obtained. This result depicts different noise peaks and signal peaks present in each FFT noisy signal as illustrated in Table 1. The information provided by this sub-section was used to compute the threshold value. It was amazing to note that, some frequency of the simulated signal has been lost due to noise effect. It was also deduced from Figure 10 that, the signal peak decreases with increase in standard deviation of noise as noticed in the case of 2.95 when compared with 0.25 standard deviation of noise in Figure 11.

Table 1: Different variation of signal peak and noise peak due to the value standard deviation

Noise Peak @ standard dev. of 2.95	**Signal peak @ standard dev. of 2.95**	**Noise Peak @ standard dev. of 0.25**	**Signal peak @ standard dev. of 0.25**
60	105	12	100
55	139	6	100
42	120	7	100
62	105	3	100

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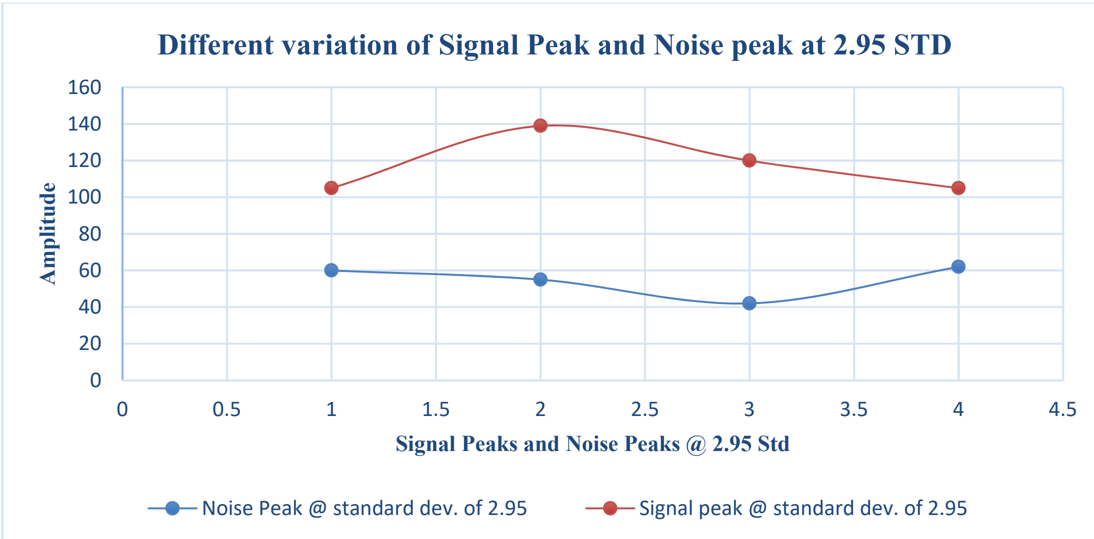

Figure 10: Noise Peak and Signal Peak @ 2.95 Standard Deviations

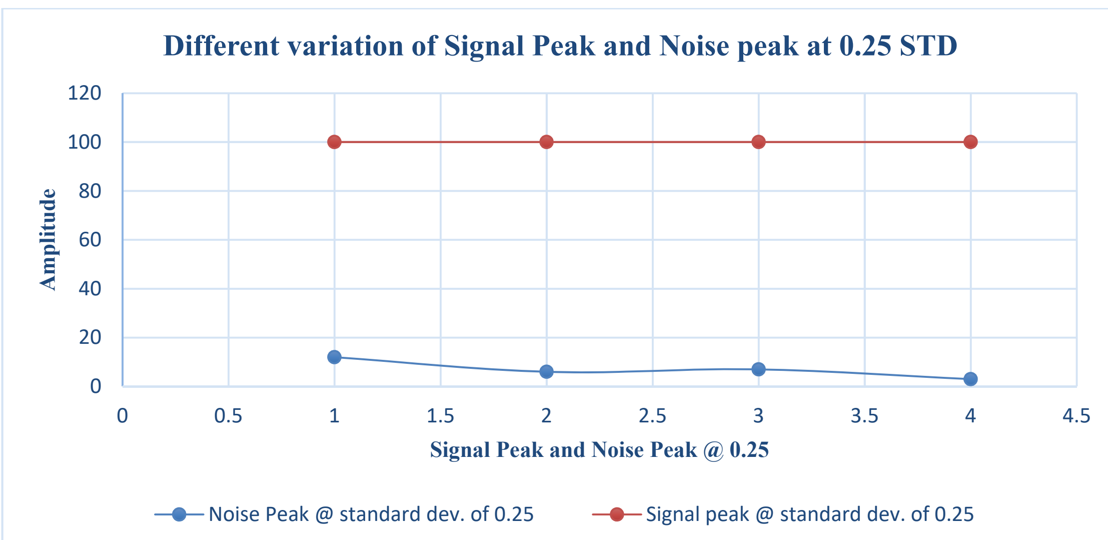

Figure 11: Noise Peak @ 0.25 Standard Deviations

At the thresholding Section, some of the image results obtained are depicted in Figure 12 and Figure 13. The adaptive threshold algorithms compute the threshold value as a cumulative value of minimum mean and maximum standard deviation and minimum (mean and standard deviation) respectively as it fluctuates with the signals. The threshold line drawn across each image demarcates the area occupied by noise from signal noise. It was observed that, the threshold values computed for maximum threshold perform better than the threshold value at the minimum threshold. Table 2 in the appendix illustrate the computation of mean, standard deviation and the threshold value for each segment of the selected sub-divided FFT windowed signals.

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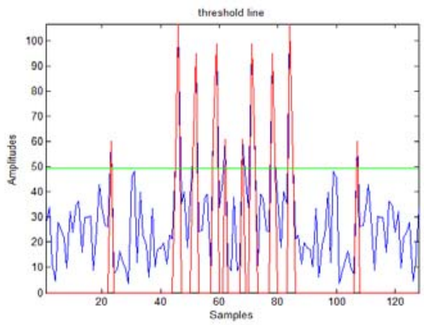

Figure 12: Result of image of an Adaptive Threshold of FFT Windowed Noisy Signal

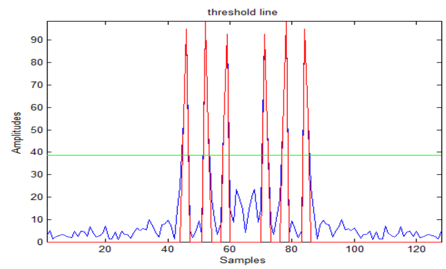

Figure 13: Result of image of an Adaptive Threshold of FFT Windowed Noisy Signal

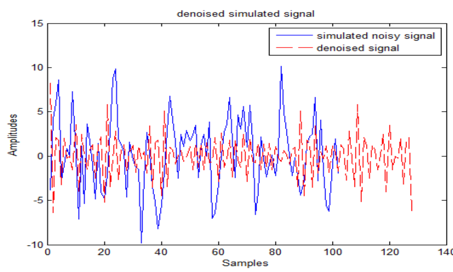

Figure 14: Image result of IFFT

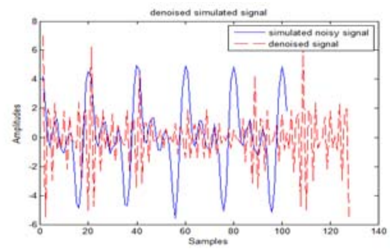

Figure 15: Image result of IFFT

From Figure 12 and Figure 13, it was observed that despite the amount of white Gaussian noise available in the noisy signal; the algorithm was still able to filter out the noise and keep the signal using the threshold values in the Table 2 in appendix.

At the Inverse FFT section, it was observed that, the reconstructed signal (denoised signal) has more samples than the simulated noisy signal. This was because of the sample points of FFT used. It is also clear from the Figure 14 and Figure 15 that the amplitudes of each of the reconstructed signal were shorter compared with the noisy signal. This is because the algorithm filtered out all other signal buried in the noise to obtain a signal free from noise. The inverse FFT signal obtained is a replica of the simulated signal but with small amplitudes.

The overlap add section summed-up the entire inverse FFT signal to vector form as illustrated in Figure 16 and Figure 17 respectively. Figure 16 is the overlap adds of image result of IFFT signals with 2.95 standard deviation while Figure 17 is the image result of IFFT signals with 0.25 standard deviationn. The reconstructed signal has more samples of signals due to the sample points of FFT used as compared with the discrete signal samples.

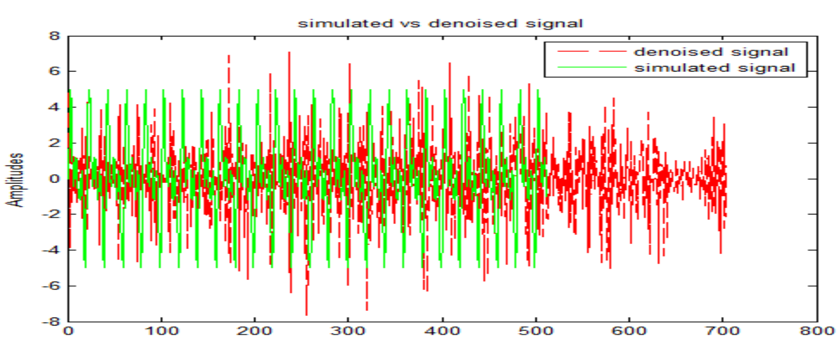

Figure 16: overlap adds of IFFT signals for 2.95 STD to vector form.

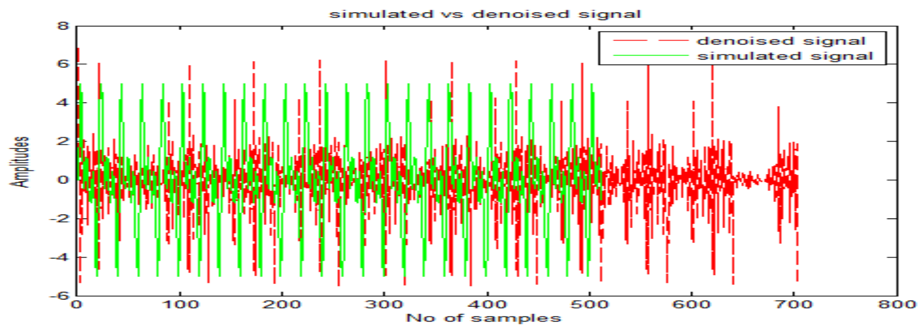

Figure 17: overlap adds of IFFT signals for 0.25 STD to vector form.

3.1 Results Obtained Using Voice Signal

This section displays the image results obtained from the proposed algorithm when a noisy voice signal of 10 SNR was used. The noisy voice signal has 40000 samples. The signals were overlapped and windowed to obtain 50% overlap, which were Fourier transformed into frequency domain. The results of each stage of the algorithm is presented in Figure 18 to Figure 22.

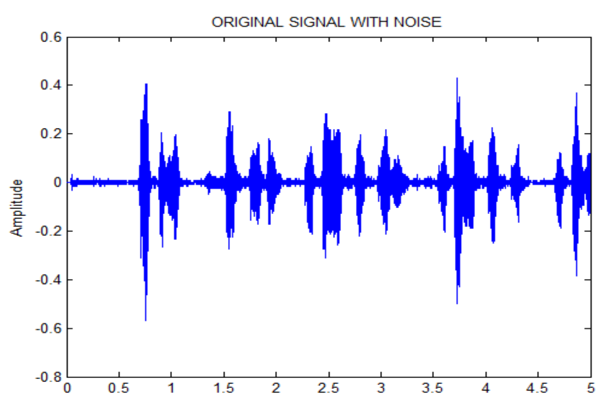

Figure 18: Image result of noisy voice signal

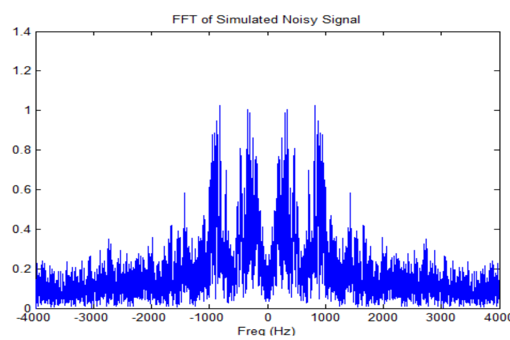

Figure 19: Image result of FFT windowed noisy voice signal

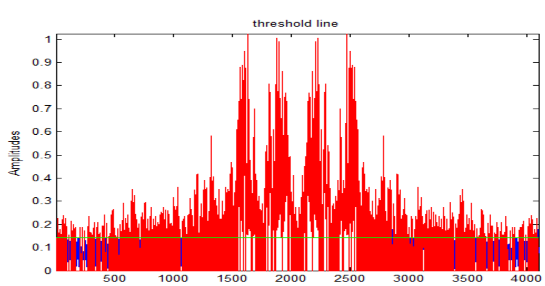

Figure 20: Image result of thresholded FFT windowed noisy voice signal

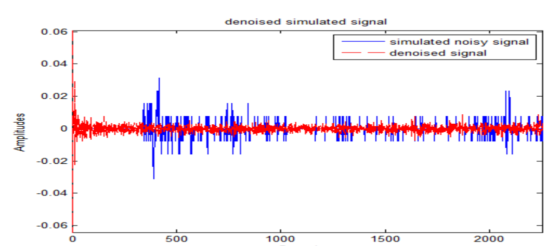

Figure 21: Image result of IFFT voice signal IFFT voice signal

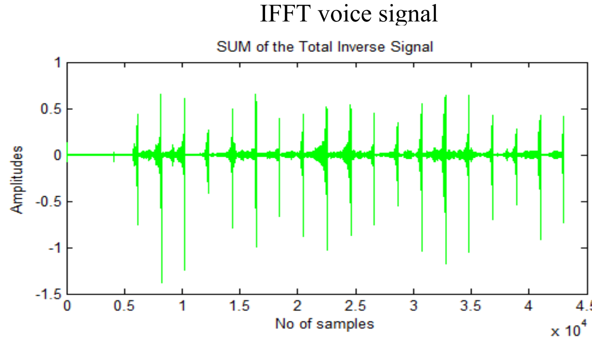

Figure 22: Image result of overlap add signal of entire IFFT voice signal

It is clear from Figure 22 that, the noise present in the signal has been reduced and the signal tends to be elongated when compared with the Figure 18.

3.2 Performance Evaluation

The performance of the algorithm using standard deviation of 2.95 showed a correlation of 53.93% for threshold value of minimum mean and maximum standard deviation. The experiment was repeated on the same noisy signal with 2.95 standard deviation using a minimum mean and minimum standard deviation as threshold value and 45.52% of correlation was obtained. Similar performance was carried out on noisy signal with 0.25 standard deviation using both minimum mean and maximum standard deviation & minimum (mean and standard deviation) as the threshold value. A correlation of 77.93% and 75.83% were obtained respectively. Table 3 and Table 4 confirmed the results obtained for the correlation coefficients, mean square error (MSE) and standard deviation at threshold values of minimum mean & maximum standard deviation and minimum (mean and standard deviation) for both values of noise at 2.95 and 0.25 standard deviation respectively.

Table 3: Adaptive threshold Algorithm value obtained at 2.95 standard

	Correlation Coefficients value at		**M S E at**		**Standard deviation at**	
Signal	Maximum Threshold Value	Minimum Threshold Value	Maximum Threshold Value	Minimum Threshold Value	Maximum Threshold Value	Minimum Threshold Value
Reconstructed signal	0.5393	0.4552	-0.6813	-0.4326	1.8033	2.2662
Original signal					1.7104	1.7104
Reconstructed signal	0.7274	0.8139	-0.8251	-0.6513	1.8033	2.2662
Noisy Signal					3.173	3.173
Original signal	0.549	0.6256			1.7104	1.7104
Noisy Signal			-0.1438	-0.2187	3.173	3.173

The 53.93% correlation coefficients value obtained between the reconstructed signal and the original signal (simulated signal) at maximum threshold value indicates the performance of the algorithm to recover the signal after the noise have been increased by 8.5% (i.e. from 0.25 standard deviation to 2.95 standard deviation). It was observed that, the magnitude of the noisy signal was quite huge with a standard deviation of 3.17. Noise of this magnitude has eroded most of the signals leaving behind less than 30% of the original signal (simulated signal). 72.74% correlation between the reconstructed signal and the noisy signal confirmed the analysis above on Table 3. The mean square error and standard deviation of the obtained reconstructed signal at maximum threshold value were -0.6813 and 1.8033. This has proven the ability of the proposed algorithm to reduce noise from standard deviation of 3.17 to 1.8 as shown on Table 3. The same performance was carried out on the noisy signal at minimum threshold value and the results indicates a correlation of 45.52%, mean square error of -0.4326 and 2.2662 standard deviation. The correlation coefficients, mean square error and standard deviation between various sets: reconstructed signal & original signal; reconstructed signal & noisy signal and original signal & noisy signal for maximum and minimum threshold value were also computed as shown on Table 4. It can therefore, be deduced that, despite the huge amount of noise introduced in the discrete signal, the proposed algorithm was able to reduce the noise from 3.17 to 1.8, which is about 57% accuracy.

Table 4: Adaptive threshold Algorithm value obtained at 0.25 standard deviation

	Correlation Coefficients value at		**MSE at**		**Standard deviation at**	
Signal	Maximum Threshold Value	Minimum Threshold Value	Maximum Threshold Value	Minimum Threshold Value	Maximum Threshold Value	Minimum Threshold Value
Reconstructed signal	0.7793	0.7583			1.6676	1.7102
				-0.6308		
Original signal			-0.5944		1.7104	1.7104
Reconstructed signal	0.5852	0.5851			1.6676	1.7102
Noisy Signal			-0.5928	-0.6421	1.7411	1.7495

Original signal	0.9938	0.9935			1.7104	1.7104
Noisy Signal			0.0017	-0.0113	1.7411	1.7495

The performance evaluation of the proposed algorithm at 0.25 standard deviation of noise was also carried out as shown on the Table 4. 77.93% correlation between the reconstructed signal and the original (discrete) signal was obtained. The improvement of the proposed algorithm was proven with the increase in correlation value obtained with lower value of standard deviation of noise as shown above. The correlation coefficients, mean square error and standard deviation (STD) between various sets: reconstructed signal (RS) & original signal (OS); reconstructed signal (RS) & noisy signal (NS) and original signal & noisy signal for maximum and minimum threshold value were also computed for 0.25 STD as shown on Table 4. It was observed that the correlation between the original signal and noisy signal was 99.38% as compared to 54.90% on Table 3. This means that, the noise magnitude difference between the correlation of original signal and noisy signal on Table 3 & 4 is 44.48%. It can therefore, be deduced that, the lower the standard deviation of the noise in the signal, the best the efficiency of the proposed algorithm and vice versa. Figure 23 shows the relationship between the Max. Threshold value and Min. Threshold value at both 0.25 STD and 2.95 STD for various set of signals.

3.3 Performance of the algorithm on real voice signal

The performance of the algorithm on real voice signal was quite impressive at maximum threshold value, as 92.15% correlation was obtained. Table 5 confirmed the results obtained. The mean square error and the standard deviation at maximum threshold were 0.0011% and 0.53% respectively. These values have proven the efficiency of the proposed algorithm.

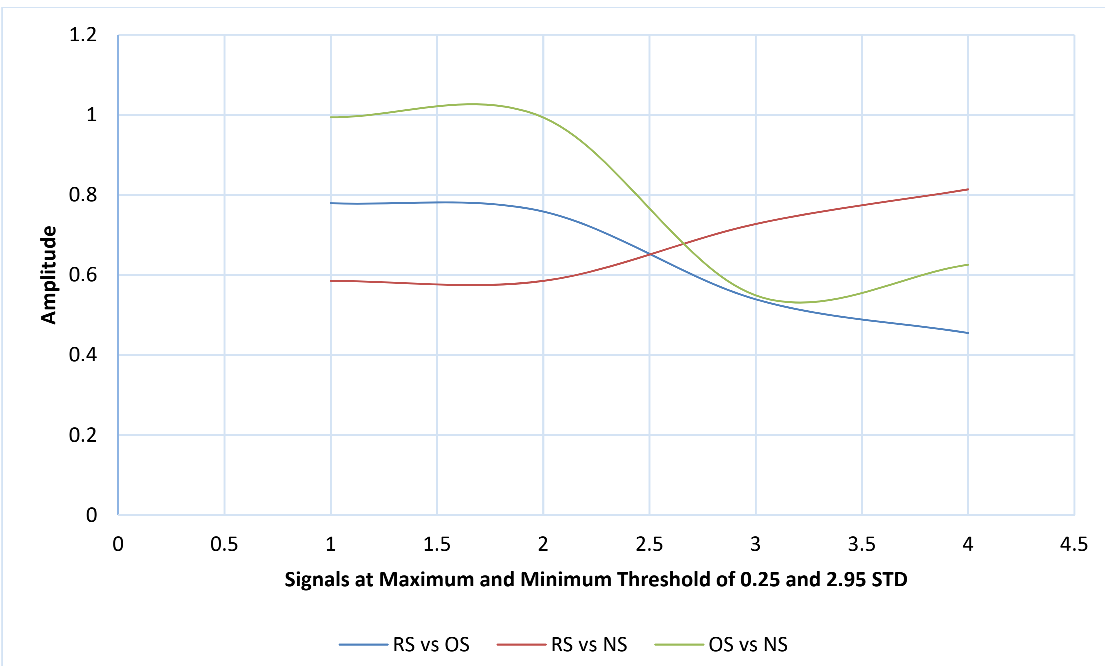

Figure 23: Relationship Between Max. Threshold and Min. Threshold Value for Various Sets at both 0.25 STD & 2.95 STD

Table 5: Adaptive threshold Algorithm value obtained for voice signal

Correlation Coefficients value for real voice signal at			Mean Square Error at		Standard Deviation at	
Signal	Maximum Threshold Value	Minimum Threshold Value	Maximum Threshold	Minimum Threshold	Maximum Threshold	Minimum Threshold
Reconstructed signal	0.9215	0.8924		0.0000033	0.0053	0.0072
Original voice signal			0.000011		0.0048	0.0048

It can therefore, be concluded that, the proposed algorithm performed better at maximum threshold value as compared to the values obtained at minimum threshold value. The correlation coefficients, mean square error and standard deviation between the reconstructed voice signal & original voice signal for maximum and minimum threshold value was also computed as shown on Table 5. The mean square error between the reconstructed voice signal and the original voice signal was almost in non-existent. This was because the algorithm was able to recover almost all the voice signal from the noise.

4 Conclusion

A new algorithm using first and second order statistics of the voice signal was developed. The results obtained from the developed non-parametric noise reduction algorithm showed that there is a correlation of 0.5393 and 0.4552 between the simulated noisy signals generated and the reconstructed signal for maximum threshold and minimum threshold value at 2.95 standard deviation of noise. While the performance of the algorithm at 0.25 standard deviation of noise indicates a 0.7793 and 0.7583 correlation for both maximum threshold and minimum threshold. The results obtained gave a good account of the robustness of the proposed method in the reduction of noise.

The result of the performance evaluation of the algorithm on the noisy voice signal was also carried out to test its capability on real signal. The result indicates a correlation of 92.15% with a mean square error of 0.0011% for maximum threshold value and 89.24% correlation with mean square error of 0.00033% for minimum threshold value obtained as illustrated on Table 5. Therefore, the results confirmed the stability of the reconstructed signal using the proposed algorithm. The proposed algorithm can be deployed in the following areas to reduce the effect of noise; Image processing; signal processing; cognitive radio for sensing signals and speech communication area.

References

[1] Gbadamosi, A. S., Aibinu, A. M., Ugweje, O. C., Onumanyi, A. J., Onwuka, E. N., and Aderinola, M. (2015). “Non-Intrusive Noise Reduction in GSM Voice Signal Using Non-Parametric Modeling Technique,” IEC conference 2015, pp. 264–269.

[2] Barile, M., Camarda, P., Aquila, R. D., Vitti, N., Politecnico, D. E. E. and Orabona, V. E. (2006). “Parametric Models for Speech Quality Estimation in GSM Networks,” 2006.

[3] Mahdi, A. E. and Picovici, D. (2009). “Advances in voice quality measurement in modern telecommunications,” Digit. Signal Process. A Rev. J., vol. 19, no. 1, pp. 79–103.

[4] Premananda, B. S. and Uma, B. V. (2014). “Speech Enhancement in Presence of Near-end Noise by Incorporating Auditory Masking in Frequency Domain,” vol. 5, no. 11, pp. 621–627, 2014.

[5] Ben Aicha, A. and Ben Jebara, S. (2012). “Perceptual speech quality measures separating speech distortion and additive noise degradations,” Speech Communication, vol. 54, no. 4. pp. 517–528, 2012.

[6] Shrawankar, U. and Thakare, V. (2014). “Noise Estimation and Noise Removal Techniques for Speech Recognition in Adverse Environment,” 2014.

[7] Taal, C. H., Jensen, J. and Leijon, A. (2013). “On optimal linear filtering of speech for near-end listening enhancement,” IEEE Signal Process. Lett., vol. 20, no. 3, pp. 225–228.

[8] Mirza, A., Kabir, S. M. and Sheikh, S. A. (2016). “Reduction of impulsive noise in OFDM systems using a hybrid method,” Int. J. Signal Process. Syst, vol. 4, no. 3.

[9] Chauhan, P. R. (2014). “Comparitive Study of Different Active Noise Cancellation Methods & Transfer Function Method,” vol. 3, no. 2, pp. 207–211.

[10] Tripathi S. and Ikbal, M. A. (2015). “Step Size Optimization of LMS Algorithm Using Aunt Colony Optimization & Its comparison with Particle Swarm optimization Algorithm in System Identification,” vol. 2, no. 7, pp. 599–605.

[11] Hu Y. and Loizou, P. C. (2004). “Speech Enhancement Based onWavelet Thresholding the Multitaper Spectrum,” IEEE Trans. Speech Audio Process., vol. 12, no. 1, pp. 59–67.

[12] Jabloun, Firas, and Benoît Champagne. (2002). "A perceptual signal subspace approach for speech enhancement in colored noise." In Acoustics, Speech, and Signal Processing (ICASSP), 2002 IEEE International Conference on, vol. 1, pp. I-569. IEEE, 2002.

[13] Ephraim Y. and Malah, D. (1984). “Speech enhancement using a minimum mean square error short-time spectral amplitude estimator”, IEEE Transaction on Acoustic, Speech, Signal Processing, vol. ASSP-32, pp. 1109–1121.

[14] Dan, M., Zhiyong, F., Huying, C. and Yanjun, Y. (2009). “An adaptive threshold method for data processing in spectrum occupancy measurements,” in IEEE Vehicular Technology Conference, 2009.

[15] Sanam, T. F. and Shahnaz, C. (2014). “A semisoft thresholding method based on Teager energy operation on wavelet packet coefficients for enhancing noisy speech,” Eurasip J. Audio, Speech, Music Process., vol. 2013, no. 1, 2014.

[16] Sanam, T. F. and Shahnaz, C. (2011). “An approach for noisy speech enhancement by employing the teager energy operation on wavelet packet,” in IEEE Region 10 Annual International Conference, Proceedings/TENCON, 2011, pp. 1135–1138.

[17] Sanam, T. F. and Shahnaz, C. (2013). “Noisy speech enhancement based on an adaptive threshold and a modified hard thresholding function in wavelet packet domain,” Digit. Signal Process. A Rev. J., vol. 23, no. 3, pp. 941–951.

[18] Aggarwal, R., Rathore, S., Karan S. J., Tiwari, M., Gupta, V. K. and Dr. Anubhuti K. (2011). “Noise Reduction of Speech Signal using Wavelet Transform with Modified Universal Threshold,” Int. J. Comput. Appl., vol. 20, no. 5, pp. 975–8887.

[19] Hu Y. and Loizou, P. C. (2008). “Evaluation of objective quality measures for speech enhancement,” IEEE Trans. Audio, Speech Lang. Process., vol. 16, no. 1, pp. 229–238.

[20] Gandhimathi G. and Jayakumar, S. (2012). “Efficient method of pitch estimation for speech signal using MATLAB,” Spec. Issue IICCT, no. 1, pp. 107–111.

[21] Khoa, P. C. and Siong, C. E. (2012). “Spectral local harmonicity feature for voice activity detection,” in International Conference on Audio, Language and Image Processing, Proceedings (ICALIP), 2012, pp. 407–413.

[22] Zhuan, Y., Memik, G. and Grosspietsch, J. (2008). “Energy Detection Using Estimated Noise Variance for Spectrum Sensing in Cognitive Radio Networks,” in Wireless Communications and Networking Conference, 2008. WCNC 2008. IEEE, 2008, pp. 711–716.