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# Detection and Separation of EEG Artifacts Using Wavelet Transform

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**Abstract:** Bio-medical signal processing is one of the most important techniques of multichannel sensor network and it has a substantial concentration in medical application. However, the real time and recorded signals in multisensory instruments contains different and huge amount of noise and great work has been completed in developing most favorable structures for estimating the signal source from the noisy signal in multichannel observations. Methods have been developed to obtain the optimal linear estimation of the output signal through the Wide-Sense-Stationary (WSS) process with the help of time invariant filters. In this process, the input signal and the noise signal are assumed to achieve the linear output signal. During the process, the non-stationary signals arise in the bio-medical signal processing in addition to it there is no effective structure to deal with them. Wavelets transform has been proved to be the efficient tool for handling the non-stationary signals but wavelet provide any possible way to approach multichannel signal processing. Based on the basic structure of linear estimation of non-stationary multichannel data and statistical models of spatial signal coherence acquire through the wavelet transform in multichannel estimation. The above methods can be used for Electroencephalography (EEG) signal denoising through the original signal and then implement the noise reduction technique in VLSI to evaluate their parameters such as area utilization, power dissipation and computation time.

**Key words:** Electroencephalography, wavelet transform, signal to noise ratio, mean square error, processing, multichannel estimation, India

## INTRODUCTION

Brain is the most important organ in human beings for controlling the coordination of human muscles and nerves. Human brain is made up of millions of neurons and it is a connected nervous system. The electrical activity of the brain and the language of communication with the nervous system are called as Electroencephalo graphy (EEG) signals. The neurons move in human brain while processing information by changing the flow of electrical currents across their membranes. The neurons movement is observed through electrodes placed on the scalp and the signal is analyzed with respect to change in the electrical properties. Activity of the brain writing process is amplified and recorded from the potentials between different electrodes in Electroencephalogram (EEG) (Tseng *et al*., 1995). The recording is used to investigate the neuron movement of human brain commonly through one EEG. It can be used to evaluate the people having brain disorders and also EEG is used to determine brain death. The continuous signal analysis is more complex. The EEG signal are categorized in different wave length namely alpha ($\alpha$) waves (7.5-14 Hz), beta ($\beta$) waves (14-40 Hz), gamma ($\gamma$) waves (above 40 Hz), theta ($\theta$) waves (4-7.5 Hz), delta ($\Delta$) waves (0.5-4 Hz) (Inuso *et al*., 2007). All the waves represent different movement of neurons in human brain.

The EEG signals have very small amplitude (mV), so, the noise occurs easily or the original signal gets contaminated. During the recording or observation of the EEG signal, various types of noises occur such as noise from baseline movement, EMG disturbance and human body and from other external sources. In EEG signal these types of noise signals are called artifacts and this noise need to be removed from the original EEG signal during the analysis of brain related diseases.

Moreover, during the EEG recording the original signal is also affected by other unknown random signals which can be modeled as additive random noise. These occurrences complicate the analysis and interpretation of the EEGs and the first important processing step would be the elimination of the artifacts and noise. Our goal is to contribute to EEG artifact rejection by proposing an original and more complete automatic methodology consisting if optimized combination of several signal processing and data analysis techniques. There are so many denoising techniques employed to remove the artifacts from the EEG original signal. Some of the denoising techniques used to remove the noises are ICA

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denoising, PCA denoising, wavelet based denoising. The above said techniques employed for denoising the EEG signal and their performance can be evaluated by measuring the parameters like SNR, MSE and computation time, etc.

**Literature review:** In bio-medical signal process, artifacts are unwanted noise caused by the original physiological affair based on the interest. Thus, the aim of analysis depending on the decision should be made as identifying the original and artifact signal. For reliable analysis artifacts classification should be considered which if ignored, might considerably influence the results and therefore, the resulting conclusions. EEGs are typically recorded in conjunction with different physiological signals which can interfere with the exact EEGs. Such artifact like ocular, muscle, electrical field changes, transmission line interference, movements of head and electrodes.

The pre-processing technique SMOTE is an over-sampling method which combines the informed over-sampling of minority class with random under-sampling of the majority class. It involves a mathematical procedure which transforms a number of possibly correlated variables into smaller number of uncorrelated variables called principal components (Deepa *et al*., 2010). Based on removing high frequency noise in wavelet analysis, the PCA algorithm is used to process the EEG signals to reduce the data dimension (Kang and Zhizeng, 2012). A noise rejection method with wavelet transformation was proposed which is used to eliminate noises such as electrode disturbance, baseline movement, EMG noise and so on (Yu, 2009).

Figure 1 illustrates sections of graphical record contaminated by typical samples of artifacts. Once some of knowledge corrupted by an artifact has been with successfully known then there are different ways which may be adopted, betting on the shape of that artifact. In extreme cases the whole epoch that contains the artifact might have to be discarded, various normal artifact detector is used and therefore, the signals that is contaminated by the artifact is known and discarded. As an alternative in some instances there is a potential to estimate the original EEG signal using appropriate signal process techniques by suppressing the artifact.

The efficiency of ICA algorithm is evaluated by applying contaminated EEG signals. Its performance was compared to 3 fixed-point ICA algorithms using MSE, peak SNR, signal to distortion ratio (Walters-Williams and Li, 2011). The characterization ability of seven nonlinear features due to time reversal are compared with two linear features namely the Autoregressive (AR) reflection coefficients and AR Model coefficients (Balli and Palaniappan, 2010). Brain-Computer Interfaces (BCIs) aim at providing a non-muscular channel for sending commands to the external world using the Electroencephalographic activity or other Electrophysiological measures of the brain function (Bashashati *et al*., 2007). The classification algorithms used to design Brain-Computer Interface (BCI) systems based on Electroencephalography (EEG) (Lotte *et al*., 2007).

An automated method for Electrocardiogram (ECG) artifact detection and elimination is proposed for application to a single-channel Electroencephalogram (EEG) without a separate ECG channel for reference (Park *et al*., 2002). Segmentation of the EEG into stationary lengths can be carried out on a fixed-interval basis with clustering or classification according to the features of each interval and concatenation of adjacent similar

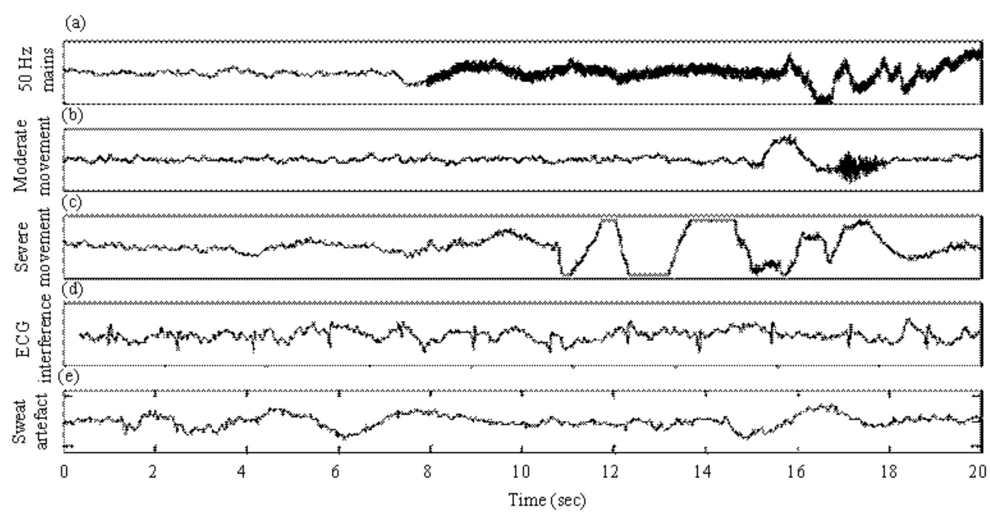


Fig. 1: a-e) EEG recording corrupted by artifacts

intervals (Barlow, 1985). If the respective optimization problems are generalized for nonquadratic criteria, so that, higher-order statistics are taken into account their solutions will in general be different. The solutions define in a natural way several meaningful extensions of PCA and give a solid foundation for them (Karhunen and Joutsensalo, 1995).

Wavelet-based statistical signal processing techniques such as denoising and detection typically model the wavelet coefficients as independent or jointly gaussian. These models are unrealistic for many real-world signals. The development of a new framework for statistical signal processing based on wavelet-domain Hidden Markov Models (HMMs) that concisely models the statistical dependencies and non-gaussian statistics encountered in real-world signals (Crouse *et al*., 1998).

The effortless way to eliminate artifacts is to find at the period of occurrence and recorded data is eliminated. One technique that is used to take artifact as any important deviation from the traditional is to permit detection by seeking variations (non-stationaries) within the measured signal. This technique should be applied with care, since, the original EEG is itself non stationary, therefore, major parameters have to be designated, so, the entire connected non-stationaries are detected. Energy operators may be helpful markers of sudden changes (e.g., spikes) as they are sensitive to instant fluctuations (Arvaneh *et al*., 2011) however will require more sensitivity to record accurate changes within the signal spectrum.

A set of mathematical functions that transforms number of correlated variables into a smaller number of unrelated variables is known as principal component. The Principal Component Analysis (PCA) is a primary element that accounts for the maximum amount of the variability within the data as possible and every succeeding element accounts for the maximum amount of the remaining variability as potential. Principal components are absolute and independent to provide the recording dataset that is normally circulated. PCA is more accurate to the relative level of the initial variables. Depending on the application, it is additionally named as distinct Karhunen-Loeve transform, the hotelling transform or proper orthogonal decomposition.

The mathematical method utilized in PCA is termed as eigen analysis. It tends to solve the eigen values and eigenvector of a square symmetric matrix with sum of square and cross product. The eigenvector is related to the biggest eigen values and has constant direction because it is the first principal element. The eigenvector related to the second largest eigen values determine the direction of the second principal component. The addition of the eigen values equals the trace of the matrix and therefore the most numbers of eigenvectors equals the quantity of rows (or columns) of this matrix (Babu and Prasad, 2011). An alternative approach is obtained using ICA (Independent Component Analysis) that makes the multichannel character of most EEG record signals to decompose the information into a collection of random variables that are maximally independent (Inuso *et al*., 2007). This decomposition is thought to be representing the supply signals that underlie in the measured data set. The magnetism nature of EEG signals implies that these signals fulfill the assumptions of the ICA algorithmic rule, i.e., ones supported by a right away mixture model. Consequently EEG analysis normally has been a fruitful application space for ICA (Davies and James, 2007).

Devising a method for successful removal of artifacts from EEG recordings is still is a major challenge Fig. 1 shows a segment of EEG signals corrupted with artifacts. From the EEG artifacts Fig. 1a 50Hz mains interference waves on the EEGs Fig. 1b moderate movement causes from the EEG Fig. 1c severe movement that can clip the EEG. Figure 1d ECG interference appears as a pulsed EEG and Fig. 1e EEG with the artifacts due to sweat.

The ways rely on the assumption that the artifact and EEG may arise from completely different (statistically independent) sources. Therefore by estimating those supply parts one can, determine that parts relate to the artifact and it relates to the EEG signal. This permits the reconstruction of the sensing element signals mistreatment, solely the EEG signal connected sources and thus, eliminating the artifact. A key drawback with ICA is that the study and automatic identification/separation of parts with reference to graphical record and artifact. Further, if the signal is temporally metameric then the ICA decomposition lacks consistency between sections and care must be exercised once recombining the information across segment boundaries (Vigario *et al*., 1998).

## MATERIALS AND METHODS

**Wavelet denoising:** The implementation of Wavelet Transform (WT) time-frequency representation helps to present the frequency and time in sequence with respect to time. The difference of information between the approximation of a signal at the resolutions 2/sup j+1/ and 2/sup j/(where j is an integer) can be extracted by decomposing this signal on a wavelet orthonormal basis of L/sup 2/(R/sup n/), the vector space of measurable, square-integrable n-dimensional functions (Mallat, 1989). In time-frequency representation the time domain signal is passed through two different filters namely low pass and high pass filters, here both portion are considered. The filters are used to eliminate the artifacts and noise signals from original signal and the process is called as decomposition. The operation is continuously repeated until the signal is decomposed to a cutoff level or to a certain level. A group of different frequency bands obtained from the EEG recording signals representing in the same. The high frequency components are enhanced to improve with respect to time and the low frequency components are enhanced to determine the frequency. The wavelet transform is defined as Eq. 1:

$$W(a, b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

The above equation is said to be a mother wavelet transform (Chui, 1992). The equation contains two different variables (a, b) used to transform the signals. Both variables are representing translation and scaling parameters and the denoising function is obtained through the mother wavelet transform. The low frequency components are matched with detailed view and the high frequency components are matched with non-detailed view. In scaling process either the input signal is to be compressed or expanded. The high frequency components (large signals) are always stretched out and low frequency components are compressed.

During the denoising process the synthesis and analysis of original signal and sufficient information is obtained through the Discrete Wavelet Transform (DWT) and it provides the maximum reduction with minimum computation time. The different frequency bands of input signals are analyzed with different resolution that is used to decompose the signals to get detailed information. The DWT functions are same in the mother wavelet transform associated with low pass and high pass filters in time domain signals. The original input signal x[n] is first processed through a half-band high-pass filter g[n] and a low-pass filter h[n]. The signal can be sub-sampled by dividing it by 2, simply by discarding every other sample. This constitutes one level of decomposition and can be expressed as follows Eq. 2 and 3:

$$Y_{high}[k] = \sum_n x[n].g[2k-n] \tag{2}$$

$$Y_{high}[k] = \sum_n x[n].h[2k-n] \tag{3}$$

where, $y_{high}[k]$ and $y_{low}[k]$ are the output of the high pass and low pass filters after the sub-sampling divided by 2. These decomposition techniques have time resolution and only half the number of samples describes the entire signal (Fig. 2).

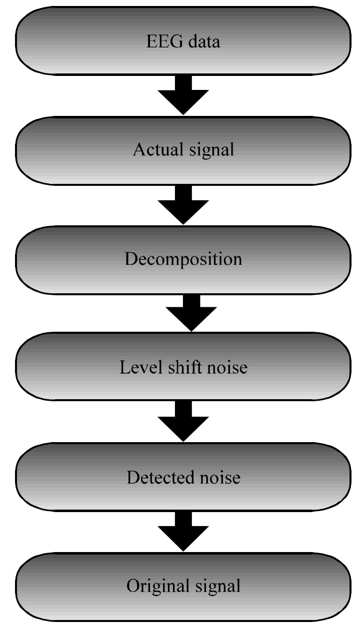


Fig. 2: Block diagram of proposed system

EEG Data decomposition level shift with detected noise and original signal. However, this procedure doubles the frequency resolution because the half of the frequency is spanned effectively by reducing the uncertainty in the frequency band and repeats the second half of the frequency band to reduce the noise. The above procedure is also called as sub-band coding and it can be frequently used for additional decomposition. At each level sub-sampling filtering results is obtained with half the frequency band span. The following statistical features were utilized to represent the time-frequency distribution of the EMG signals: Standard deviation, mean, average power and ratio of absolute mean of the coefficients in each sub-band samples.

## RESULTS AND DISCUSSION

The research study was to find out the possibility of minimizing the artifacts and noises in EEG signal using wavelet denoising technique. The main objective of the study was to minimize the artifacts and noise level without affecting the original EEG signal. Since, the EEG recording requires clinical information from many channels (standard channels 32-44), the input sources high so a critical design is used during the analysis using real time multichannel artifacts and noise detection system. The result of the study currently shows that the utilization of the WT significantly decreases the input size, lacking in

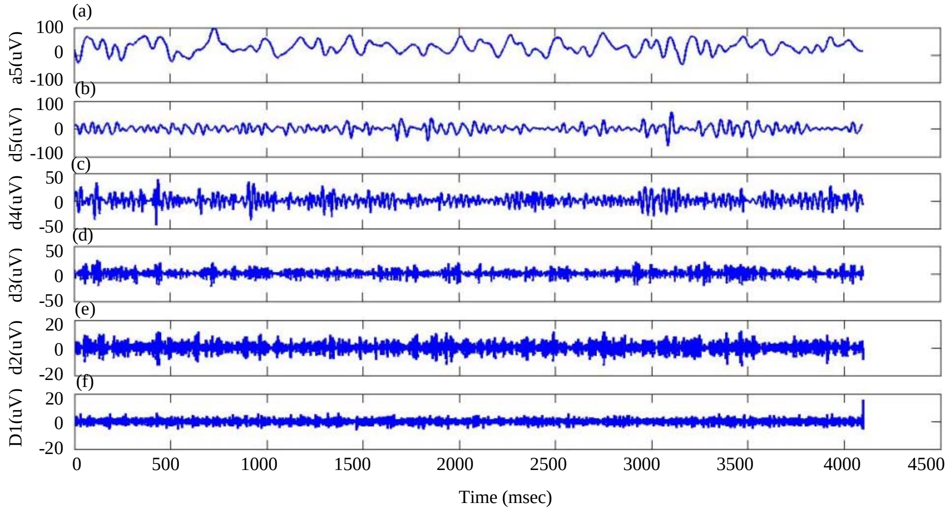


Fig. 3: a-f) Decomposition waves of D1-D5 and A5

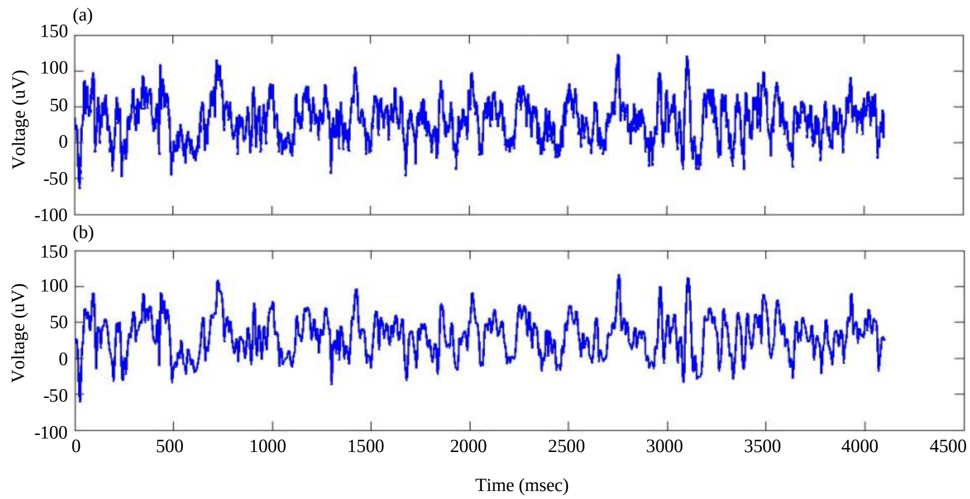


Fig. 4: The input noise signal and the corresponding output signal from DWT: a) Niose signal and b) Output signal

performance while not maximum compromise on the performance. The foremost vital consideration of performance was the correct choice of the scale in the input signal. Wavelets were found appropriate for analysis as a result of the compact support. Programs are developed to show the sample waveforms for various channels and also for decomposition of the undulation mistreatment DB-1 and DB-5 in addition the original signal is denoised and compressed into waveforms for every channel. The sampled outputs of first high-pass and low-pass filters provide the detail D1-D5. We have extracted 6 different values from the frequency bands to calculate D-D5 and A5 of DWT. Figure 3 shows the extracted output wave form of the DWT and Fig. 4 shows the input noise signal and output signal obtained from the wavelet transform. In this figures the 4097 input samples are taken to extract the different resolution in wavelet transform.

Table 1: Cell and area utilization of DWT based denoising architecture

| ANC | Cell and area utilization<br>Cell | Area (µm) |
|---|---|---|
| Ssequential | 104 | 1685 |
| Inverter | 43 | 98 |
| Logic | 498 | 5911 |
| Total | 645 | 7694 |

Figure 5 shows the output waveform of the discrete wavelet transform which are obtained for EEG signals using xilinx ISE Simulator. Figure 6 shows the RTL view complied from the Verilog HDL of DWT using cadence encounter view complier.

From Table 1, it shows the area utilized with respect to the number of cells for DWT based denoising architecture and the corresponding graphical representation are shown in Fig. 7. From Table 2, it shows the power utilization of DWT architecture and the

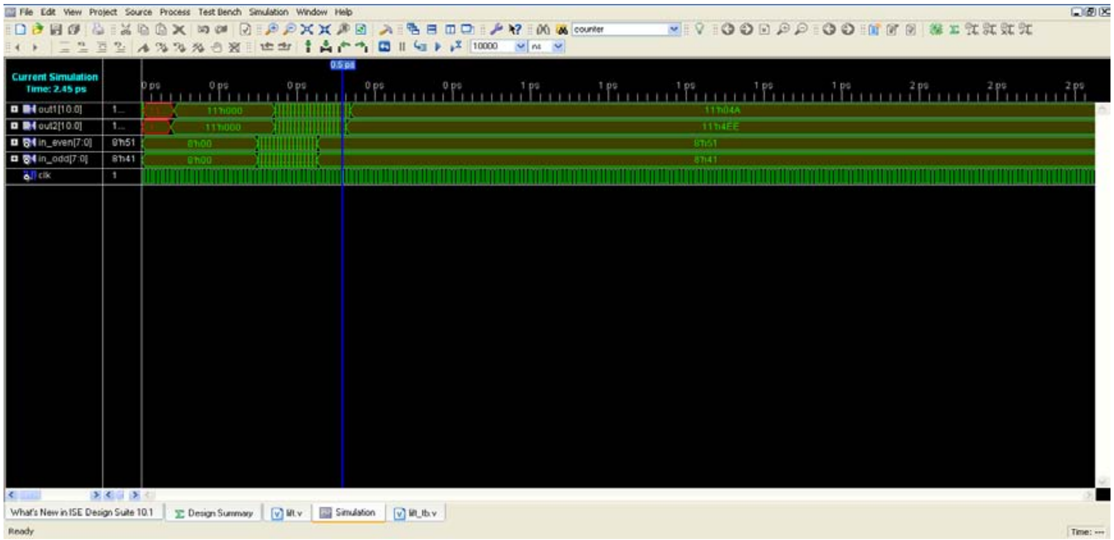


Fig. 5: Simulated output waveform of wavelet transform

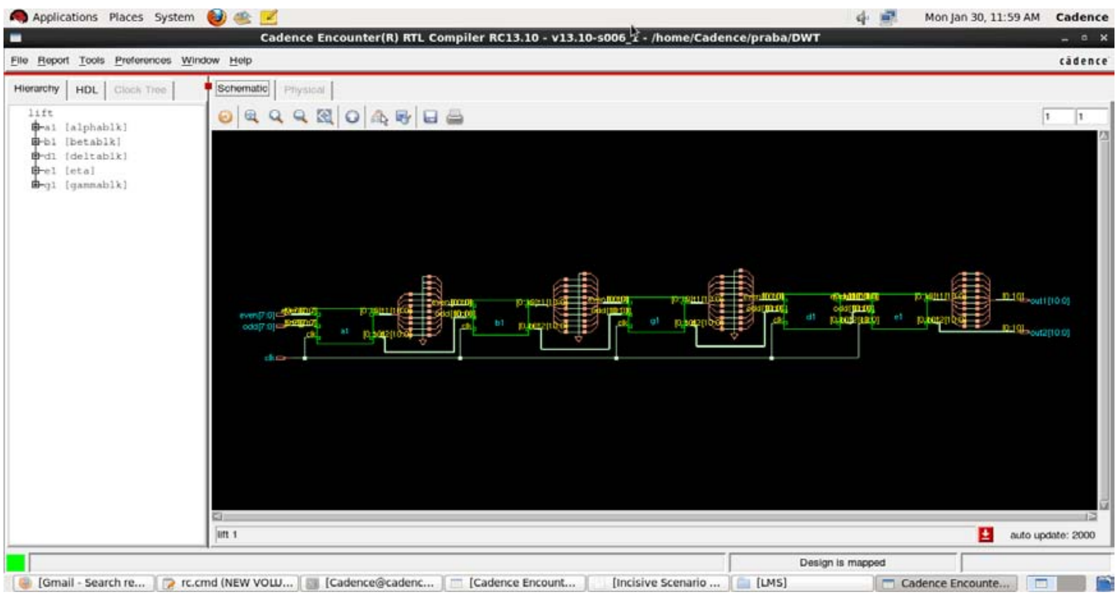


Fig. 6: RTL view of wavelet transform

Table 2: Power utilization of DWT based denoising architecture

| | Power utilization | | |
|---|---|---|---|
| Cells | Static power (nW) | Dynamic power (nW) | Total power (nW) |
| 645 | 37397 | 191928 | 229325 |

Table 3: Time utilization of DWT based denoising architecture

| | Time utilization | |
|---|---|---|
| Fall time (pS) | Rise time (pS) | Total time (pS) |
| 5276 | 1772 | 7048 |

graphical representation shown in Fig. 8 and Table 3 contains time utilized for DWT architecture with corresponding graphical representation shown in Fig. 9. The above result was obtained in TMSE 90 nm technology cadence environment.

Figure 7 shows the number of cells and areas utilized for the denoising the artifacts using DWT method simulated by Verilog HDL in the Cadence 90 nm technology for the FPGA implementation.

The static power, dynamic power and total power dissipated by the hardware implementation of DWT method, for the removal of artifacts, in the cadence tool using Verilog HDL is shown in Fig. 8 and the corresponding values are tabulated in Table 2.

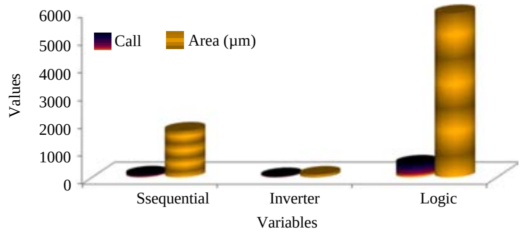


Fig. 7: No. of cells and area utilized for DWT based denoising

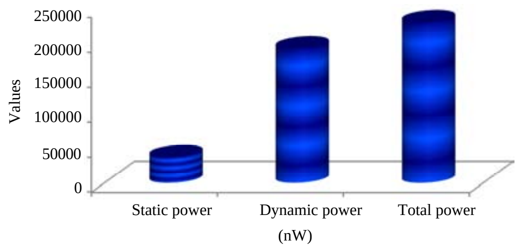


Fig. 8: Power utilization of DWT based denoising

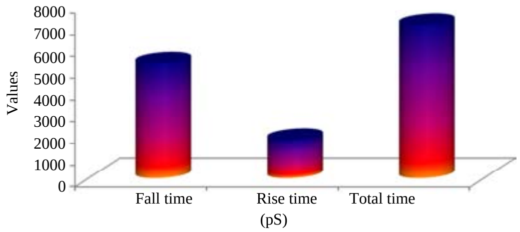


Fig. 9: Time utilization of DWT based denoising

The propagation delay taken between the input and output signal is calculated and it is shown as time utilization by the hardware implementation of DWT for the removing of artifacts in the EEG signal is shown in Fig. 9 and the corresponding values are shown in Table 3.

## CONCLUSION

Wavelets function is a robust tool used for the task of signal denoising. The ability to decompose a signal into a totally different scale is extremely vital for denoising and it improves the analysis of the signal considerably. A real-time denoising VLSI based wavelet transform technique is employed in this study to remove the artifacts and power-line interferences from EEG signal. Wavelet functions square measure is used for denoising. The results of denoising are evaluated for SNR, RMSE and computation time in MATLAB. Finally, the implementation of the wavelet transform in the VLSI is carried out and estimated the area utilization, power dissipation and computation time. Careful analysis of the graphical record signals will provide data associated to patients affected with brain disorders. In future, additional advanced ways will be explored for denoising of the EEG signal corrupted with the different sources of interference. Additionally, these methods are going to be implemented and tested on real EEG signals. The implementation and prototyping of the proposed technique are simulated in Verilog HDL with Cadence 90 nm environment.

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