Indian Journal of Science and Technology, *Vol 9(29), DOI: 10.17485/ijst/2016/v9i29/94951, Agust 2016*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Efficient Hardware Architecture of EEG Analyzer for Determining the Depressive Disorders

S. Kalvikkarasi and S. Sairabanu*

Department of Electronics and Communication System, Karpagam University, Coimbatore - 641021, Tamil Nadu, India; kalvitpt@gmail.com, sairabanu.ecs@gmail.com

Abstract

Background/Objectives: In this paper, economical hardware design of the Electroencephalography (EEG) is planned for deciding the depressive disorders. The goal of this paper is development of moveable device supported encephalogram analysis targeted at analysis of mental disorders. **Methods/Statistical Analysis:** We presented a modified architecture of the Power Spectral Density (PSD) and also Spectral Asymmetry Index (SASI) for depression detection. **Finding:** The proposed architecture of the PSD computation reduces the computational complexity and hardware requirement due to the adaption of the merging process. SASI algorithm reveals the disturbed state of the brain. **Improvements/Application:** The planned hardware design is meant victimization Field Programmable Gate Array (FPGA). This design is simulated and tested victimization VHDL and synthesized victimization Xilinx ISE fourteen.

Keywords: Electroencephalography (EEG), Field Programmable Gate Array (FPGA), Merging Process, Power Spectral Density (PSD), Spectral Asymmetry Index (SASI)

1. Introduction

Mental disorders are widespread within the population. in line with statistics by National Institute of mental state, close to one quarter of adults is identifiable for one or a lot of disorders within the U.S. Major emotional disorder is one amongst the foremost common mental disorders: about 6.7% of population suffers from depression, and therefore the rate is increasing[1]. Traditional strategies for depression detection[2,3] are primarily based to estimate the subjective clinical symptoms by psychiatrists exploitation questionnaires. This technique is predicated on objective symptoms there numerous strategies determinative depression. During this paper, we have a tendency to propose associate economical FPGA design for graphical record instrument for determinative the depressive disorders[4]. To search out depressive and potential of different mental disorders that are regarding the similar brain imbalances are analyzed in these strategies[5,6]. Useful info for analysis of depression integrated within the graphical record signal beta band (13-30 Hz) and therefore the graphical record alphabetic character band (4-8 Hz)[7,8] is stable and unaffected by a unwellness. A Spectral Spatiality Index (SASI) is calculated as a comparative variation in power of 2 graphical record special frequency bands elite higher and lower of the graphical record spectrum most. Central band of the graphical record signal is expelled from the calculation once the band is round the spectrum most (alpha band at 8-13 Hz). For every individual and regarding the frequency of the graphical record spectrum most the boundary frequencies of the bands are particularly elite. Through the chosen frequency bands are around the normal beta and alphabetic character bands, may be shifted within the case of low or high alpha frequency. Graphical record signal recorded for twenty minutes from one conductor for calculation. SASI calculation algorithmic rule contains digital signal process modules that may be used conjointly for different bio signals analysis tasks. For coming up with hardware architectures Field Programmable Gate Arrays (FPGAs)[9,10] are extremely reconfigurable devices. Over different platforms, admire Application Specific Integrated Circuits (ASICs)[11], Digital Signal Processors (DSPs)[12], and general Central Process Units (CPUs) or

* *Author for correspondence*

Graphics Process Units (GPUs) FPGAs gift numerous blessings. Just in case of space, power, associated speed ASICs supply the most effective implementation however the planning of an ASIC needs terribly high prices and tremendous efforts on circuit verification, and therefore the result's not possible to be modified. Opposite to the present, FPGAs give total flexibility to change the implementation or to correct errors. The progressive FPGAs are famed to be a lot of economical then Digital Signal Processors (DSP) and CPUs. Few numbers of works solely has been analyzed before for determinative the emotional disorder exploitation graphical record instrument.

In[13], subjects {primarily based totally} on aggressiveness score was measured through BPQ (Buss Perry Questionnaire) technique and thus the subject's NAI (Net Aggressiveness Index) values unit of measurement computed pattern the projected task based mean of lay to rest channel constant of correlation technique. Ripple rework may be a operate for ever-changing the time domain signal into time and frequency domain signal by breaking a logo into shifted and scaled versions of the mother wave ψ (t) as a basis operate[14]. As, wise graphical record signals are separate once sampling, separate wave work Discrete ripple rework (DWT) is wide used for these sorts of non-stationary signals.

In this paper, we have a tendency to propose associate economical FPGA design for graphical record instrument for determinative the depressive disorders. The most contribution of our work includes a changed design for power spectral density computation and a hardware realization of SASI algorithmic rule for depression detection.

2. Related Works

In[15] bestowed an occasional quality algorithmic rule and design to calculate Power Spectral Density (PSD) victimization the Welch methodology. Within the planned novel united FFT approach, the even samples are computed precisely, whereas the odd samples need a shift by a half-sample delay and are calculable employing a duplex fractional-delay filter. Thanks to the approximation used for the implementation of the fractional-delay filter the quality reduction comes at the price of slight performance loss. Additional low-complexity design is bestowed to calculate a special case of the short-time Fourier rework supported the planned PSD computation algorithmic rule.

In[16], exhibited a future alternative energy state of affairs synthesis through power spectral density analysis. The PSD of the alternative energy follows completely different completely different} power laws over different frequency ranges and is approximated by a piecewise operate. For a selected piece scaling exponent of the facility law are often approximated by the slope of Associate in nursing affine operate fastened to an exponent plot of the PSD. Because the slope trends, the primary PSD price, and therefore the last PSD price are hot to forecast the PSD. Then, future alternative energy situations are synthesized from the forecasted PSD.

In[17], bestowed Influence of musicotherapy on mental standing and cognitional operate of patient with depression ill health. Twenty subjects with depression ill health were studied. For every subjects Spontaneous EEG signals and P300 initiated EEG signals were non inheritable and analyzed and once they took musicotherapy. Results explained that inter immusicotherapy have obvious improvement for subjects' in mental standing, however not a lot of authority for his or her memorial or cognitional functions. The influence of depression on deactivation and neural correlates throughout mental arithmetic tasks has been bestowed by[18]. Within the brain depression has been expressed to be related to useful alterations within the resting state property. This study examines whether or not there are variations in neural dynamics measured by Mental Arithmetic Tasks (MAT) between depressed and healthy subjects. To survey the correlates of the brain deactivation regions this study used Associate in Nursing ROI-based purposeful property analysis, Within-Condition Interregional variance Analysis (WICA). Results of this study showed that the corresponding feelingly loop is introspective in healthy subjects and show the management loops of attention and emotion are reduced in depressed subjects throughout MAT, and therefore the patients with depression might manufacture a stronger stress response than the healthy subjects throughout the MAT.

In[19] bestowed a Non Invasive EEG Signal process Framework for Real Time Depression Analysis. This paper identifies the classification of depressed patients from traditional subjects by victimization EEG signal. This paper tries to classify person's status either traditional or depressed with the assistance of EEG signal victimization signal process technique FFT and machine learning technique SVM. For distinctive depressed patients from traditional subjects this work shows that linear

Associate in Nursingalysis of EEG is often an economical methodology. In associate in nursing earlier report[20], bestowed depression level prediction victimization EEG signal process. Victimization EDF browser computer code the EEG signals were scan and therefore the signals were loaded into Matlab to induce logs Power Spectral Density from EEG bands. The results obtained from Matlab are fed into neural network pattern recognition tool and ANFIS tool box that is integrated in MATLAB. The evaluated outputs are useful to differentiate alcoholics from controls and numerous sleep disorders like sleep disorder, narcolepsy, action and nocturnal lobe brain disease.

In[21] bestowed, associate in nursing implementation of a FPGA primarily based model for Associate in Nursing EEG analyzer device. It's a conveyable medical specialty device that executes medical instrument (EEG) signal analysis aimed toward time period in-field medical specialty of human brain disorders that is named depression. The study supported an inventive algorithmic rule for calculation of spectral spatial property index (SASI). In bestowed medical instrument spectral spatial property index for detection of depression. The potency of the SASI was contrasted to the standard EEG inter-hemispheric spatial property and coherence strategies. The SASI expected in Associate in nursing discretional EEG channel differentiated clearly sandwiched between the depressive and healthy cluster. The EEG inhumes neural structure spatial property and unity unconcealed some trends, however no considerable variations are found among the teams of healthy controls and patients through affective disorder.

3. Research methodology

This paper determines depressive disorders or alternative mental disorders that are involving similar brain imbalances. SASI is calculable as a comparative distinction in power of 2 EEG special frequency bands selected higher and lowers of the EEG spectrum most. From the calculation of SASI the EEG central waveband round the spectrum most (alpha band) is expelled. The SASI calculation rule has been antecedently enforced as a Matlab program running on a laptop connected to an ad EEG signal capturing instrumentality. Digital Signal process (DSP) modules are utilized in the SASI calculation rule. The DSP modules are often used additionally for alternative analysis tasks. Associate FPGA-based device for health watching are going to be allowed to create that's reconfigured reckoning on the task to be solved.

SASI calculation are often divided into four main steps

- Power spectral density computation of the EEG signal;
- Boundary frequencies choice of the lower and better specific EEG frequency bands;
- EEG signal power estimation within the chosen bands; and
- Estimation of SASI as a uniting of the EEG powers within the chosen bands.

The purpose of Welch's averaged periodogram technique is to search out the facility spectral density of the recorded EEG signal. Since the EEG signals are real valued signals, FFT computation is finished by adopting a true valued FFT processor. Solely forty cycle region of the facility spectrum is needed for SASI calculation, thus solely 256 points of spectrum out of 1024 are calculated. Spectrum comparator module computes the very best spectrum worth as central waveband. Borders calculation module created the ultimate and less complicated calculations. The border calculation module calculates borders for lower and better EEG frequency bands, power calculation unit that finds EEG frequency bands signal powers, and SASI calculation module, that finds the ultimate result to be displayed.

4. Proposed method

4.1 Overview of Proposed EEG Analyzer Architecture

4.2 Preprocessing

Since we have designed the EEG analyzer for digital signals a few preprocessing and post processing tasks are

Figure 1. Block Diagram of the proposed EEG analyzer.

required. The preprocessing steps include the analog to digital conversion, sampling the analog signals in time domain.

Figure 2 shows the sampling process in time domain. Consider the sampling procedure as a time-domain multiplication of the continuous-time signal $x_c(t)$ with a sampling function $p(t)$, which is an episodic impulse function.

$$x_s(t) = x_c(t) \cdot p(t) \quad (1)$$

$$p(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT) \quad (2)$$

The final post processing steps include digital to analog conversion and displaying the output. The processed sequence numbers of $x(n)$ is converted back into a train of impulses $x_s(t)$ (with time interval T_s between two consecutive impulses) and then the time signal of the process signal can be obtained in an ideal low pass filter $h_{lp}(t)$. Conversion from sequence of numbers back to impulse train as,

$$x_s(t) = \sum_{n=-\infty}^{\infty} x[n]\delta(t - nT_s) \quad (3)$$

Interpolation of impulse train to obtain a continuous time signal

$$x_c(t) = x_s(t) * h_{lp}(t) \quad (4)$$

(Or)

$$x_c(t) = T_s \sum_{n=-\infty}^{\infty} x[n]\left[\frac{\operatorname{sinc}(\omega_c(t - nT_s))}{\pi(t - nT_s)}\right] \quad (5)$$

Where, $\omega_c = \omega_s/2$; $\omega_s = 2\pi/T_s$. T_s is the sampling period.

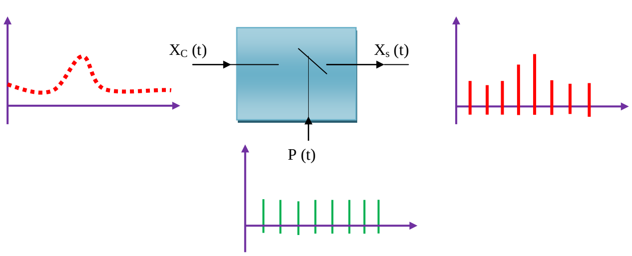

Figure 2. Sampling process in time domain.

4.3 PSD Computation

Our modified computational process for power spectral density includes the following steps.

Step.1: The input discrete signal $\boldsymbol{x(n)}$ is split up into $\boldsymbol{M}+1$- segments with non-overlapping points of length $\boldsymbol{L}/2$. In our cases $\delta = 0$, hence there is no overlap between two successive segments.

Step.2: $\boldsymbol{L}/2$-point FFT process is then performed for each segment separately.

Step.3: The merging of two $\boldsymbol{L}/2$-point FFTs into a single $\boldsymbol{L}$-point FFT is then carried out by adopting a modified merging process with a multiplier less computational unit, which is one of the contributions in this research.

Step.4: Windowing in frequency domain is then performed for each $\boldsymbol{L}$-point FFT using Hanning window coefficients; designed using a 3-tap FIR filter without the use of multipliers, which is another important contribution in this work.

Step.5: A Modified periodogram process is performed for each of the windowed $\boldsymbol{L}$-point FFT.

Step.6: Finally the PSD is computed by averaging the periodograms of the $\boldsymbol{M}$-segments.

4.4 SASI Computation

Estimation of the SASI consists of following main steps: 1. Selection of boundary frequencies of the lower and higher specific EEG frequency bands; 2. Estimation of the EEG signal power in the chosen bands; and 3. Estimation of the SASI as a union of the EEG powers in the chosen bands.

- The boundary frequencies of the higher and lower specific EEG frequency bands were chosen as follows is shown in Figure 1. At first, the frequency with the highest spectral power f_{max} in the region of alpha band 8–13 Hz of the recorded EEG signal was estimated. Thereafter the parabolic estimate was applied to the spectrum of the EEG central frequency band $(f_{max} \pm B)$ Hz, where B was half-width of the band. The best parabolic fit was expected by applying the Matlab POLYFIT tool, which locates the coefficients of a polynomial function to fits the data in least-squares intelligence. The maximum point of the fitted parabola f_c was in use as a centre of the central band. The frequency limits for the lower and the higher specific frequency bands be related to the predictable central band and verified as follows: the lower frequency band from.

$$F_1 = (f_c - B - 4)\,\text{Hz to } F_2 = (f_c - B)\,\text{Hz}, \quad (6)$$

And the higher frequency band from

$$F_3 = (f_c + B)\,\text{Hz to } F_4 = (f_c - B + 24)\,\text{Hz} \tag{7}$$

The value of the central bandwidth 2B was varied during preliminary estimations. The value of $B = 2\,\text{Hz}$ was finally determined.

- The EEG signal powers P_{lmn} *and* P_{hmn} in the lower and in the higher EEG frequency bands, respectively, were estimated for each EEG channels (indexed by $m \in [1,8]$) and subject (indexed by $n \in [1,8]$) as

$$P_{lmn} = \sum_{f=F1}^{F2} S_{mn}; \qquad P_{hmn} = \sum_{f=F3}^{F4} S_{mn} \tag{8}$$

Where, S_{mn} is the power spectral density of the specific frequency

- At last, the SASI was estimated as

$$SASI_{mn} = \frac{P_{hmn} - P_{lmn}}{P_{hmn} + P_{lmn}} \tag{9}$$

The estimations of the SASI were executed for each subject and EEG channel.

5. Results and Discussions

The proposed architecture of the EEG analyzer is implemented and simulated using VHDL. Results are synthesized using Xilinx ISE 14.5. Figure 3 shows the recorded normal and depressed EEG signal. Using these signals we can analyze SASI value which is computed in Matlab also. From the final result of the SASI value we can finalize whether the signal is normal or depressed that is shown in Table 1 and Table 2.

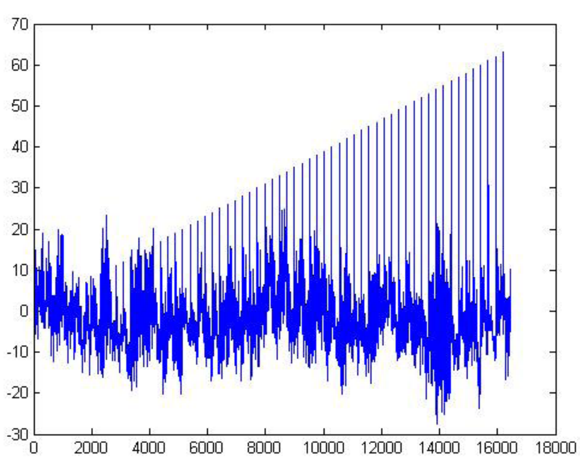

Figure 3. (a). EEG normal signal-1.

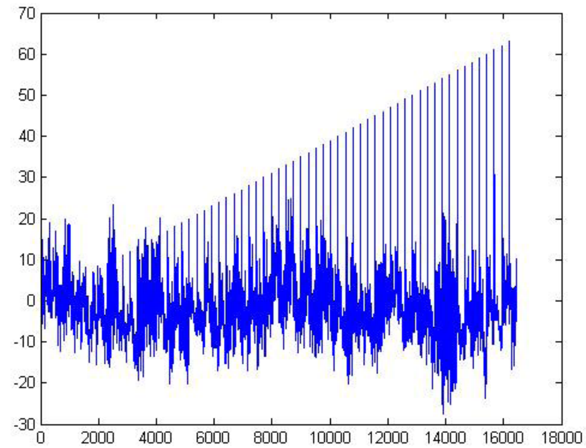

Figure 3. (b). EEG normal signal-2.

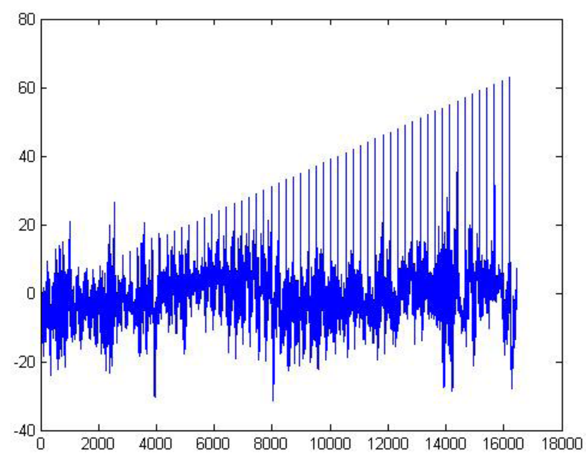

Figure 3. (c). EEG normal signal-3.

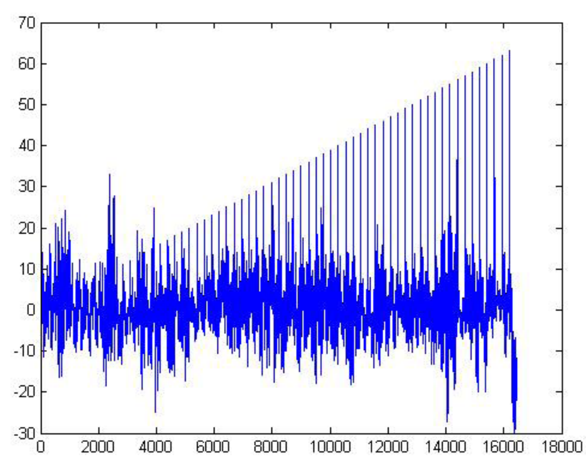

Figure 3. (d). EEG normal signal-4.

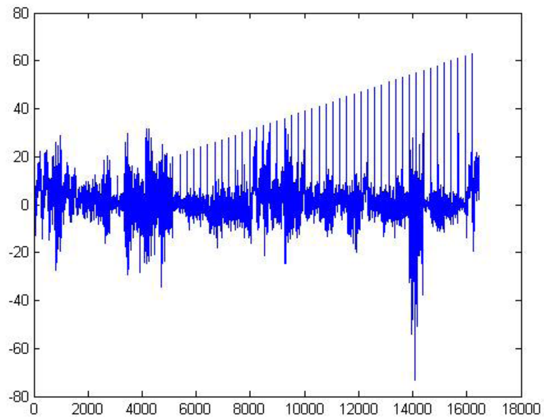

Figure 3. (e). EEG normal signal-1.

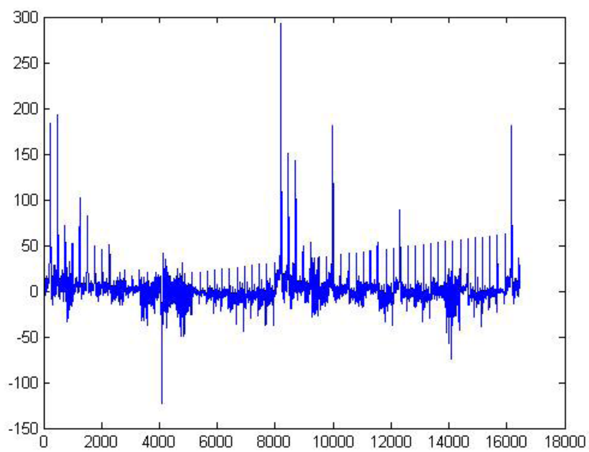

Figure 3. (f). EEG normal signal-2.

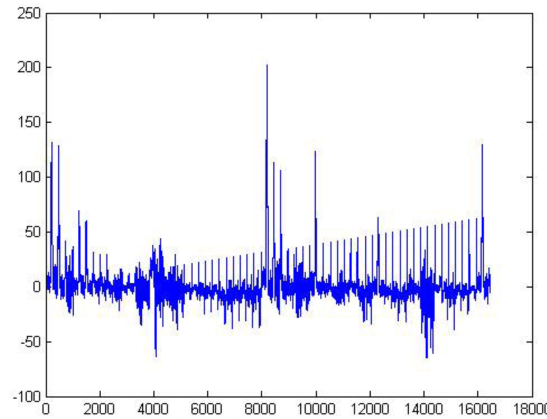

Figure 3. (g). EEG depressed signal-3.

Table 1. SASI value for normal signal

Normal EEG Signals	SASI value using matlab		SASI value using xilinx	
	[19]	Proposed	[19]	Proposed
EEG-1	-0.4396	-0.5293	-0.4276	-0.596
EEG-2	-0.4434	-0.7173	-0.4322	-0.756
EEG-3	-0.4263	-0.3648	-0.4151	-0.396
EEG-4	-0.1833	-0.3530	-0.1513	-0.352

Table 2. SASI value for depressed signal

Normal EEG Signals	SASI value using matlab		SASI value using xilinx	
	[21]	Proposed	[21]	Proposed
EEG-1	0.5056	0.7530	0.5206	0.652
EEG-2	0.1327	0.2316	0.1263	0.247
EEG-3	0.1326	0.2117	0.1225	0.267
EEG-4	0.5003	0.6526	0.5135	0.682

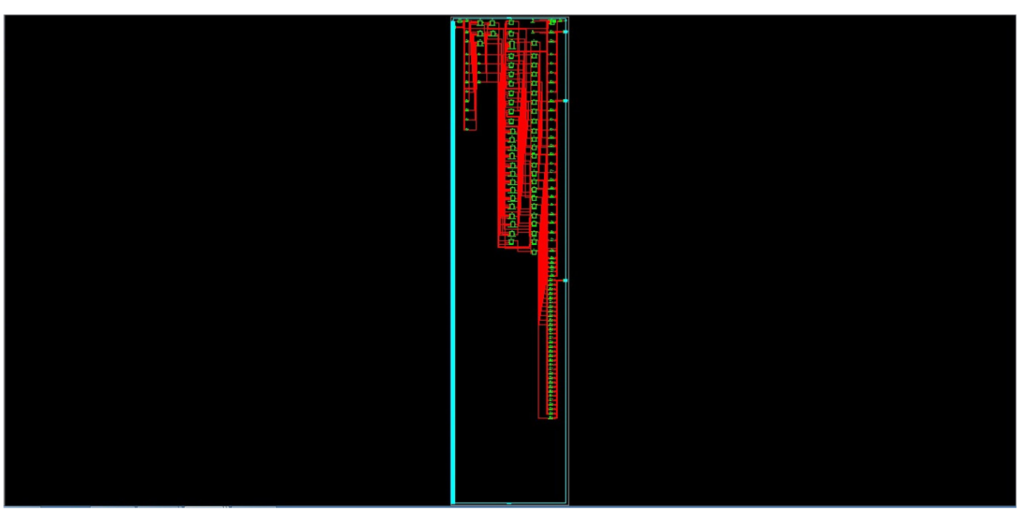

Figure 4. Schematic diagram of EEG analyzer.

From Table one, if the resulted SASI price is negative the electroencephalogram signal are going to be think about as a standard signal. Equally from Table two, if the resulted SASI price is positive the electroencephalogram signal are going to be thinking about as a depressed signal. Figure 4 shows the schematic diagram of the electroencephalogram analyzer and Figure 5 shows the simulation results of the electroencephalogram analyzer that is simulated within the target device xc4vfx12-12sf363 mistreatment xilinx ISE 14.5. From the simulation results of electroencephalogram analyzer, to process complexness SASI out thought of as within the kind of IEEE 754. Since thought of IEEE 754, 1st bit is taken as sign bit and next eight bits square measure accustomed specific the exponent. The ultimate twenty three bits square measure accustomed specific the exponent.

- **Area**
  The proposed design occupies 940 among available 10,944 slice Flip Flops utilizing about 8% of the available resources and utilizes 764 among available 10,944 LUTs thereby utilizing about 6% of the resources. About 584 out of 5472 available slices are occupied by our proposed design utilizing about 10% of the resources.
- **Power**
  Our implemented EEG analyzer consumes a dynamic power of 0.025W and Quiescent power of 0.167W. Hence our proposed architecture of EEG analyzer needs a total power supply of 0.192W. The power consumption by the sub modules in on-chip is shown in Figure 6. Also Figure 7 shows the power consumption by the proposed PSD architecture.

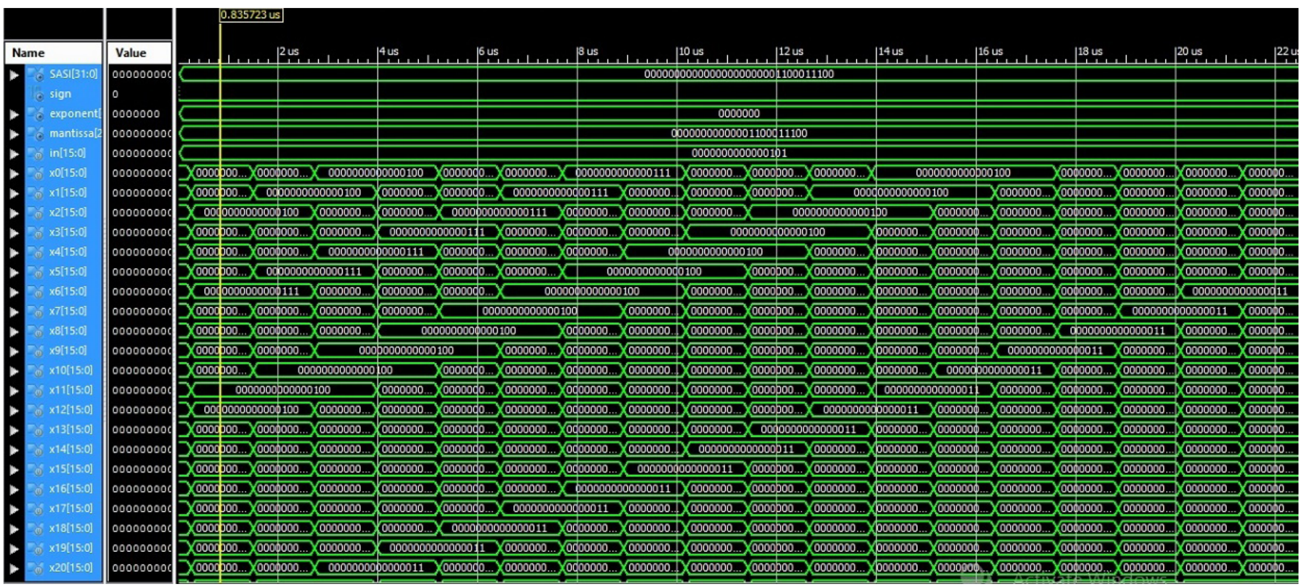

Figure 5. Simulation result of the EEG analyzer.

Supply Summary		Total	Dynamic	Quiescent
Source	Voltage	Current (A)	Current (A)	Current (A)
Vccint	1.200	0.093	0.021	0.072
Vccaux	2.500	0.031	0.000	0.031
Vcco25	2.500	0.001	0.000	0.001
		Total	Dynamic	Quiescent
Supply Power (W)		0.192	0.025	0.167

Figure 6. Power consumption of the proposed architecture.

Supply Summary Source	Voltage	Total Current (A)	Dynamic Current (A)	Quiescent Current (A)
Vccint	1.200	0.077	0.006	0.072
Vccaux	2.500	0.031	0.000	0.031
Vcco25	2.500	0.001	0.000	0.001
		Total	Dynamic	Quiescent
Supply Power (W)		0.173	0.007	0.167

Figure 7. The power consumption by proposed PSD architecture.

- **Comparison of our work with other work**

  Compared to [1] proposed PSD architecture utilizes 1% out of 10,944 slices flip flops and utilizes 1% of occupied slices out of 5,472. Total power supply of our proposed PSD architecture is reduced to 0.173W compared to [1]. Compared to [1] number used as logic for PSD computation also reduced in our proposed.

Paper implemented in Xilinx spartan 3 but our proposed architecture is implemented in Xilinx virtex 4. So that speed grade of the our proposed architecture is -12. Compared to number of cccupied slices reduced to 10% in our proposed architecture. Power consumption of our proposed also reduced to 0.192W compared[21].

6. Conclusion

In this paper FPGA based efficient hardware architecture of EEG analyzer for determining the depressive disorders is proposed. The proposed modified architecture of the Power Spectral Density (PSD) used to reduce the computational complexity. Depressed state of the mind is detected by the presented Spectral Asymmetry Index (SASI). Utilization of hardware is reduced and also power consumption of the propose architecture is reduced to 0.192W. Our system when coded, synthesized and simulated in Xilinx ISE exhibited an efficient SASI values

7. References

1. WHO - World Health Organization. Available from: http://www.who.int
2. Yang Y, Fairbairn C, Cohn J. Detecting depression severity from vocal prosody. IEEE Trans Affective Computer. 2013; 4(2):142-50.
3. Low LSA, Maddage NC, Lech M, Sheeber LB, Allen NB. Detection of clinical depression in adolescents. Speech During Family Interactions. 2011 Mar; 58(3):574-86.
4. Kim J, Nakamura T, Kikuchi H, Yoshiuchi K, Sasaki T, Yamamoto Y. Conversation of depressive mood and spontaneous physical activity in major depressive disorder: Toward Continuous monitoring of depressive mood. IEEE Journal of Biomedical and Health Informatics. 2015; 19(4):1347-55.
5. Hinrikus H, Suhhova A, Bachmann M, Aadamsoo K, Vohma U, Lass J, Tuulik V. Electroencephalographic spectral asymmetry index for detection of depression. Medical and Biological Engineering and Computing. 2009; 47(12):1291-9.
6. Hinrikus H, Bachmann M, Lass J, Suhhova A, Aadamsoo K, Vohma U, Tuulik V. Method and device for determining depressive disorders by measuring bio-electromagnetic signals of the brain. US: Patent Publication; 2009.
7. Muthuswamy J, Sherman D, Thakor N. Higher-order spectral analysis of burst patterns in EEG. IEEE Transactions on Biomedical Engineering. 1999; 46(1):92-9.
8. Choi J, Hwang E, Lee C. Opto-EEG: A novel method for mapping brain networks in freely moving mice using combined optical neuro-modulation and EEG. Brain Stimulation. 2015; 8(2):347.
9. Huang WK, Meyer F, Chen XT, Lombardi F. Testing configurable LUT-based FPGA's. IEEE Transactions on Very Large Scale Integration (VLSI) Systems. 1998; 6(2):276-83.
10. Iglesias V, Grajal J, Sanchez M, Lopez-Vallejo M. Implementation of a real-time spectrum analyzer on FPGA platforms. IEEE Trans Instrum Meas. 2015; 64(2):338-55.
11. De Geronimo G, Bolotnikov A, Carini G, Fried J, O'Connor P, Soldner S. Characterization of an ASIC for CPG sensors with grid-only depth of interaction sensing. IEEE Trans Nucl Sci. 2006; 53(2):456-61.
12. Xu J, Zhang W, Liu C. A Novel Method for Filling the Depressions in Massive DEM Data. 2007; p. 4080-3.
13. Xu TK, Paulraj MP. Aggressiveness level assessment using EEG inter channel correlation coefficients. Indian Journal of Science and Technology. 2015 Sep; 8(21). doi:10.17485/ijst/2015/v8i21/79136.
14. Ziaratban SM, Shaligram AD. Improving capabalities

of the adaptive recrusive least-square filter in the ocular artifact removal from EEG Signal. Indian Journal of Science and Technology. 2016 Mar; 9(13). doi:10.17485/ijst/2016/v9i13/85908
15. Parhi K, Ayinala M. Low-complexity welch power spectral density computation. IEEE Trans Circuits Syst I. 2014; 61(1):172-82.
16. Lee D, Baldick R. Future wind power scenario synthesis through power spectral density analysis. IEEE Trans Smart Grid. 2014; 5(1):490-500.
17. Zhou P, Lin D, He W, Li G, Shang K. Influence of Musicotherapy on Mental Status and Cognitional Function of Patient with Depression Disease. IEEE; 2009. p. 1-4
18. Feng S, Wang W, Chen L, Fan H, Abraham A, Wu J. The influence of depression on deactivation and neural correlates during mental arithmetic tasks. 13th International Conference on Intelligent Systems Design and Applications; 2013 Dec 8-10. p. 359-63.
19. Mantri S, Agrawal P, Patil D, Wadhai V. Non-invasive EEG Signal Processing Framework for Real Time Depression Analysis. 2005. p. 518-21.
20. Mallikarjun HM, Suresh HN. Depression Level Prediction using EEG Signal Processing. 2014. p .928-33.
21. Jenihhin M, Gorev M, Pesonen V, Mihhailov D, Ellervee P. EEG Analyzer Prototype based on FPGA. 2011. p .101-6.