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A Low Power and High Performance Hardware Design for Automatic Epilepsy Seizure Detection

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***Abstract*—An application specific integrated design using Quadrature Linear Discriminant Analysis is proposed for automatic detection of normal and epilepsy seizure signals from EEG recordings in epilepsy patients. Five statistical parameters are extracted to form the feature vector for training of the classifier. The statistical parameters are Standardised Moment, Co-efficient of Variance, Range, Root Mean Square Value and Energy. The Intellectual Property Core performs the process of filtering, segmentation, extraction of statistical features and classification of epilepsy seizure and normal signals. The design is implemented in Zynq 7000 Zc706 SoC with average accuracy of 99%, Specificity of 100%, F1 score of 0.99, Sensitivity of 98% and Precision of 100 % with error rate of 0.0013/hr., which is approximately zero false detection.**

***Keywords*—Epilepsy Detection, System on Chip Implementation, Quadrature Linear Discriminant Analysis, Hardware design, seizure detection**

I. INTRODUCTION

THE Brain contains of billions of nerve cells through which the information is communicated by electro chemical discharges. Consequently, these electro chemical discharges produce electrical pulses. The amplitude of the electrical pulses contributes to the information transformation and it is in the order of 100 microvolt's with the frequency range of 0.5Hz to 80 Hz. The brain electrical pulses are measured as Electro Encephalogram (EEG) signals either through surface electrodes or through intracranial electrodes. These EEG signals are classified as delta (1 Hz-3Hz), theta (4 Hz- 7 Hz), alpha (8 Hz-13 Hz), and beta (14 Hz-30 Hz) [1].

The analysis of EEG signal helps in diagnosing brain disorders. Epilepsy is a disease, which is caused by abnormal function of nerve cells in the brain. The world health organisation states that around 50 million people worldwide have been affected by epilepsy. [2]. The seizures are generated due to the sudden abnormalities of electrical activity affecting certain regions of brain. Occurrence of two or more seizures in brain region causes epilepsy. When brain nerve cells losses its control to regularize electrical impulses in some part of brain then epilepsy will develop in that region of brain. Epilepsy can develop in the frontal lobe, occipital lobe or in temporal lobe of the brain. During epilepsy seizure event, the people with epilepsy may lose their body control and consciousness, which may lead to permanent damage in their body.

Hence, it is necessary to design effective hardware to give indications of epilepsy seizure symptoms.

II. RELATED WORK

Epilepsy analysis and Interictal event detection are the two major constraints in the computer based automated epilepsy seizure detection [3]. Epilepsy analysis includes detection of seizure and prediction of seizure. Time domain techniques, Frequency domain techniques, time-frequency domain techniques were utilized to classify the seizure signals. When compared with these three domains, Time Frequency Domain analysis delivers better results as it gives frequency discrimination along with the time details [4-11]. In Time Frequency Domain analysis, wavelet transform method is appreciated by many authors.

Implementation of epilepsy detection algorithm in hardware is important to design standalone system for automatic epilepsy detection. Effective hardware implementation of seizure detection algorithm is necessary to develop low power and cost effective devices. The trade off between detection accuracy, speed and requirement of hardware resources is necessary while implementing in the VLSI systems. Yoo and Altaf developed a hardware design based on Band-Pass Filters (BPFs), Distributed Quad Look Up Table (LUT) based Filters and Support Vector Machine (SVM) to analyze EEG signals [12]. The spectral energy of EEG signals was used as feature for classification. Lichen Feng *et al*, [13] developed a hardware design using wavelet transform and SVM method. The time frequency details were derived from discrete wavelet transform and the classification were obtained using support vector machines. Muhammad Awais *et al*, [14] proposed a hardware design based on non-linear guassian function and non-linear support vector machine. Ta-Wen Kuan et al., [15], applied the sequential minimal optimization method to train the support vector machine. Mushfiq.U et al., [16], developed the Artificial Neural

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network based hardware design. In this design, the statistical variance was employed to train artificial neural network classifier. The sample entropy and SVM based VLSI design was proposed by Yuanfa Wang *et al.*, [17]. The Hjorth variance and coastline features were put to use in detecting the brain signal abnormalities [18]. Maria Hugle [19] introduced convolution neural network based architecture. The discrete wavelet transform and linear classifier based hardware design was implemented by S.Tamilarasi [20]. Lichen Feng *et al.*, [13] proposed a discrete wavelet transform and SVM based VLSI design to detect the abnormalities in EEG.

Wavelet transforms and Support Vector Machines are widely used in many hardware implementations of automatic epilepsy detection. The SVM learns by solving constrained quadratic programming whose size depends on training sample size [15]. If the samples, which are used for training are high then it needs more iteration and then the implementation of hardware is complicated. Support vector machine requires many processing stages as it implies the hardware requirements. For low power design, there is a balance needed between accuracy and power consumed by the processing units of hardware. The discrete wavelet transform becomes computationally intensive during fine analysis and has less directionality.

The hardware requirements and speed of hardware depends on complexity of algorithm. To be more specific to design hardware with better utilization of its resources and efficient performance, the knowledge about the computational complexity of classification algorithm is necessary. Less computation complexity leads to better hardware design [22]. Some of the popular linear classification models are K-Nearest Neighbourhood (KNN), Support Vector Machine, Multi Layer Perceptron & Linear Discriminant Analysis. The quantity of computing resources required for particular algorithm is described by computation complexity. The computational complexity of the Support Vector Machine is O (n3) and space complexity is O (n2) [23, 24], where n is the size of training data set. The computational complexity of LDA is O(nmt+t3), space complexity is O (mn+mt+nt) where m is the number of samples used to train the classifier and n is the number of feature vector, t=minimum (m,n) [25]. The computational complexity of Multi Layer Perceptron with back propagation learning is O (n.m.hK.o.i) where m is number of parameters, n is number of training samples, K is number of hidden layers, h is number of neurons, o is output neuron, i is number of iterations. The KNN classifier computational complexity is O (nm), where n is the number of training sample and m is number of features.

III. SYSTEM OVERVIEW

Intellectual property core based designs for automatic seizure detection from EEG signal is proposed in this work. The design is implemented in Zynq based SoC. The flow diagram of the design is described in Fig. 1. The proposed hardware design consists of internal stages of Pre processing of signal by Filtering, Segmentation, Statistical Feature Extraction Module, and Classification by Quadrature Linear Discriminant Analysis.

Fig. 1. Flow diagram of proposed design

A. Pre processing

The pre processing unit consists of filtering by Butterworth bandpass filter and data segmentation by sliding window method. EEG data is band limited to 3-29 Hz. Each single channel data is divided into segments of 1.475 seconds duration with over lapping of 0.7375 seconds using sliding window method [26].

B. Feature extraction

The statistical features are extracted from pre processed EEG signal for classification of Seizure Signal. Standardised moments, Root Mean Square, Range, Energy, Coefficient of Variance, are the statistical parameters calculated for each segments as follow:

1) Standardized Moment (SM):
Standardized moment is objective measurement of asymmetry. It is the ratio of Mean to Standard deviation.

$$SM = \frac{\text{Mean}\,(x(n))}{\text{Standard Deviation}\,(x(n))}$$

The standard deviation of each segment is calculated by the equation (1)
Standard Deviation (SD)

$$SD = \sqrt{\sum \frac{(X - X')^2}{N}} \tag{1}$$

2) Root Mean Square value (RMS):
Root Mean Square is quadratic mean of data. It is defined as the arithmetic mean of squares of data as in equation (2).
Root Mean Square (RMS)

$$RMS = \sqrt{\frac{\sum_1^n x^2}{n}} \tag{2}$$

3) *Range* of each segment is the difference of maximum amplitude and minimum amplitude of each segment.

4) *The coefficient of variation* is a statistical parameter, which measures the relative variability between data. It is the ratio of standard deviation to Mean as in equation (3). i.e.

$$CV = \frac{SD}{Mean} \tag{3}$$

5) The Energy of the each segment of data set is calculated by Parsevel's Energy formula, as

$$\frac{1}{N}\sum_{k-0}^{N-1} x(n)^2 \tag{4}$$

The feature vector, which is to be assigned to the classification module, contains five features of each segment. The Feature vector size of the single channel data of 23.6 seconds consists of 31* 6 elements.

C. Classification

In this analysis, Quadrature Linear Discriminant Analysis (QLDA) method is adapted for normal/Seizure data classification. The feature vector is used as input to the classification module. From the feature vector, the classification rules corresponding to Normal and Seizure cases were formed. Quadrature Linear Discriminant analysis maximizes the difference between classes. Based on the differences the discriminant score is formed for each class.

The QLDA algorithm:

Consider the training data set consists of two classes. {Normal & Seizure} referred as {X & Y}.

i) Prepare the training data set E = {X;Y} where X belongs to normal EEG data and Y belongs to Seizure EEG data. X and Y contains all features from all samples,

$$\text{Let } X= \begin{pmatrix} x11 & x12 \ldots x1F \\ x21 & x22 \ldots x2F \\ xm1 & xm2 \ldots xmF \end{pmatrix}$$

$$\text{Let } Y= \begin{bmatrix} y11 & y12 \ldots y1F \\ y21 & y22 \ldots y2F \\ ym1 & ym2 \ldots ymF \end{bmatrix}$$

x_{ij} refers to an i^{th} feature vector of j^{th} segments in normal data set. y_{ij} refers to an i^{th} feature vector of j^{th} segments in Seizure data set.

Where m is the number segments of each single channel EEG data and F is number of feature vector. In this design, m=31 x 80 and F=5.

ii) Calculate the Mean Values of each class as µ1, µ2 and Mean of entire class as µ, which is calculated by merging X & Y together. In the case of two class problem of Quadratic Linear Discriminant method, the probability (p) is assumed as 0.5.

iii) Calculate zero mean feature vector X^0 & Values of ^{0}. The mean value is subtracted from feature values. The apriori probability of this problem is considered as P= {(p1,p2)}. In this design, the value of p1=0.5 & p2=0.5.

iv) The scatter matrix for each class is calculated as follows: Scatter matrix is calculated for class c_1 and c_2 is given in equations (5) and (6).

$$C_1 = \frac{(X^o)^T.(X^o)}{l} \tag{5}$$

$$C_2 = \frac{(Y^o)^T.(Y\ \ ^o)}{l_i} \tag{6}$$

Covariance matrix is calculated in equation (7)

$$\text{as } G\,(r,s) = \frac{1}{l}\sum_{i=1}^{g} l_i\, c_i\,(r,s) \tag{7}$$

v) Pseudo inverse is calculated for G(r,s) in order to derive better discriminant rules for Normal and Seizure classes.

vi) The Quadrature Linear Discriminant Analysis (QLDA) discriminant function is calculated as

Fi=µiG-1xiT-0.25 µiG-1µiT+ln(pi). (8)

Transforming all data into discriminant function {F1F2}, the sample data and the training data can be presented in new coordination. The discriminant line is all of {F1 F2} values of all data.

vii) The class of the sample set is determined as follows:
if F1>F2 then
the classification output = Normal
else,
Classification output = seizure.

IV. EXPERIMENTAL RESULT

We designed the automatic deduction system with real time feature extraction and epilepsy seizure deduction. The performance of this system is validated by using BONN database [27]. Five sets of data are used to validate the performance of proposed method. Each data set consisted of single channel EEG of 100 segments with the duration of 23.6 seconds and 173.6 Hz sampling frequency.

The data sets A and B contained segments acquired from surface EEG recordings, which were executed on five normal persons in awaken and relaxed state with eyes open in set A and eyes closed in set B using a standardized electrode placement scheme.

The data sets C, D, & E were recorded from five seizure affected patients. The data set C was documented during the hippocampal formation of the opposite hemisphere of the brain. The data set D was taken from the epileptogenic zone. The data set E was recorded during the seizure activity. The performance of the classification model is enhanced by filtering the EEG signal in the range 3-29 Hz. During training process out of 100 data segments, 80 were used to train the classifier, and 20 were utilized to test the performance of the classifier. The result were obtained by working on a Windows 7 computer system with an Intel i3 CPU 4GB RAM.

The band limited EEG is segmented to 1.475 seconds duration. Overlapping window method is used to segment the band limited EEG signal. Each segment is of 1.475 seconds duration with overlapping of 0.7375 seconds with adjacent segment. For each segment, five statistical features are calculated.

The variations in statistical values of seizure and non-seizure signals are discriminated in Fig. 3. The statistical parameter standardized moment is used to test the asymmetry property of time sequence data. Standardized moment value is zero for perfect symmetric data. The asymmetry function of the EEG signal is measured by Standardised Moment Calculation. The asymmetry value of seizure EEG signal is lower than the healthy signal because during epileptic period the normal pattern of electrical impulses are disturbed. As a result, neurons rapidly fires electrical impulses all at once. This causes electrical pattern of the EEG signal to change into symmetrical pulses. The randomness of EEG signal is reduced during seizure event due to the abnormal pattern of electrical impulses. To be more precise, the epilepsy seizure signals are less random and stationary with variable amplitude [51, 52]. Hence, Standardised Moment value of seizure signal is less than non-seizure EEG signal.

The amplitude of the EEG signal during seizure is high when compared with the healthy EEG signal due to the abnormal activity of neurons in course of seizure event. Hence, the Root Mean Square, Energy and Range values of the seizure EEG signals are higher than the non-seizure EEG signals parameters. The epilepsy signals have higher level of dispersion around its Mean Value. As consequence, the Coefficient of Variance of seizure signals is higher when compared with non-seizure signals.

With our proposed design, the seizure deduction is obtained within 0.17 seconds. To validate the classifier we have formulated five kinds of problems as P1,P2,P3,P4,P5 where P1 is the classification between the data set A and E , P2 is defined

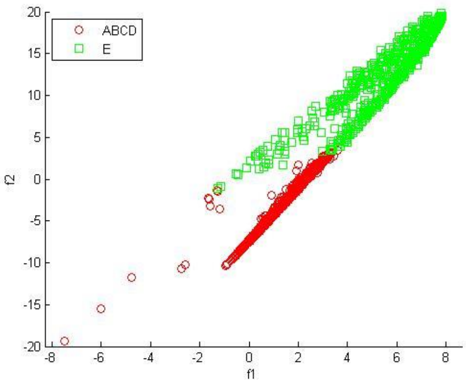

Fig. 2. The classification between seizure and non seizure signals

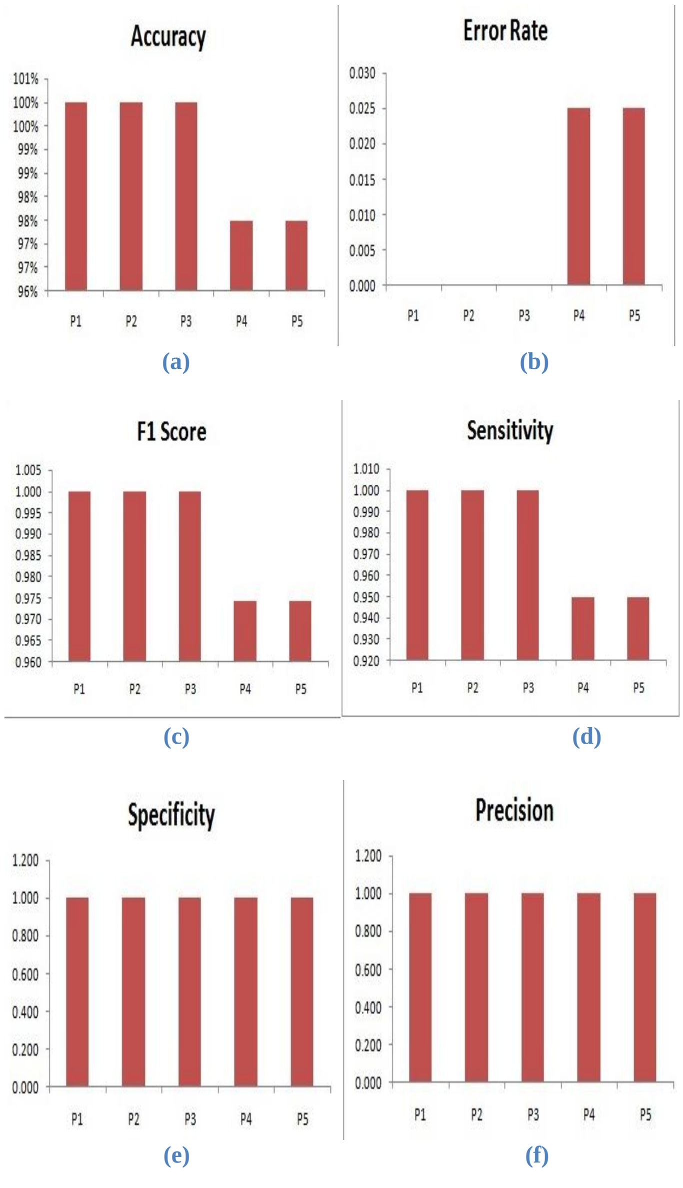

Fig 3 : Performance analysis of proposed classifier .(a) Accuracy ,(b)Error Rate (c)F1 Score (d)Sensitivity (e)Specificity, (f) Precision

as classification between B data set and E data set ,P3 is data set C and E ,P4 is defined as D and E and P5 is defined as ABCD and E . Five types of classification problems are tested by using this proposed method. The classification output is shown in Fig 2. The overall classification performance is described in Fig. 3. and performance metrics for each classification problem is given in the table 4.During the testing phase, out of 100 seizure data sets, 98 data sets were successfully detected as epilepsy seizures. Performance metrics used to validate the proposed classifier are accuracy, Error rate,Precision,Sensitivity,F1 score, Specificity.. As a result, we obtained an average accuracy of 99%, Specificity of 100%, F1 score of 0.99, Sensitivity of 98% and Precision of 100 % with error rate of 0.0013/hr., which is approximately zero false detection.

The Online process of feature extraction and seizure classification are implemented in hardware. The discriminate coefficients which are required for classification is calculated on off-line. The hardware implementation of seizure detection algorithm is simplified by this off-line process. The methodology of hardware implementation is discussed in the following section.

HIGH LEVEL SYNTHESIS BASED DETECTION DESIGN

HLS (High level Synthesis) is method which uses high level languages (i.e. C /System C/C++) to design hardware systems. It mainly used in Application specific integrated design and Field Programmable Gate Array design.HLS tool will convert the algorithms in to RTL level and it gives estimation of registers and digital signal processor in the micro architecture.

The proposed algorithm is realized in hardware using the Vivado software. The discrimanat co efficient and input EEG signal uses floating point with single precision format. The floating point arithmetic operations are synthesized by math library of Vivado HLS math library. The discriminate co efficient is stored in external memory because of patient specific property of classification algorithm. The utilization of resources of hardware is reported after placement and routing in Vivado implementation process. The implementation is needed AXI interconnects and Direct memory access blocks and Zynq 7 processing system. The target FPGA is Zynq board with clock frequency of 100MHz. The block diagram of generated IP is named as My_design_0 and shown in Fig. 6. This integrated design consists of Pre processing module, Feature extraction and Classification modules. The interconnection diagram of IP with Zynq processing system of proposed design is given in Fig. 4. The resource utilization of proposed algorithm implementation is given in Table I.

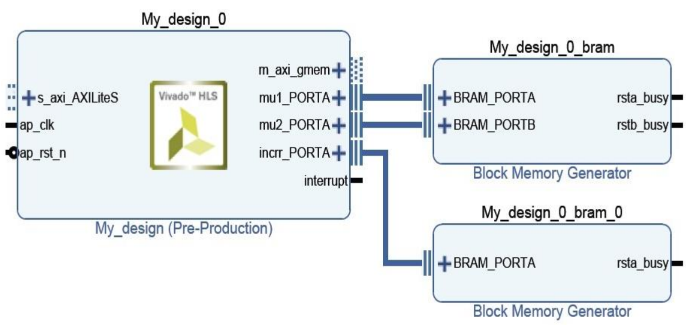

Fig. 4. Block diagram of generated IP.

After the customized IP interconnect with Zynq processing system, the Synthesis and routing is performed .and bit stream is generated for this design .Finally the generated bit file is downloaded in to FPGA board by using Xilinx SDK. The detailed power consumption report of the FPGA implementation is given Table II.

V. DISCUSSION

This epilepsy seizure detection algorithm is executed and verified on BONN, Germany database. The inclusive performance of this design is aligned with various existing works with high accuracy and very low false detection rate. The comparison between existing hardware algorithms and proposed algorithm is given in the Table III, which shows that this proposed algorithm exhibits better classification accuracy when compared with existing algorithms. Therefore, high classification accuracy ensures enhanced performance of the automatic detection system.

CONCLUSION

The computational complexity performs a vital role in designing the hardware for the automatic epilepsy seizure detection from EEG signals. The working probability of the design involves in the utilization of hardware resources, which in turn depends upon number of features extracted from EEG signal and classification algorithm. In this design, we have developed Intellectual Property core integrated design based on Zynq FPGA for automatic epilepsy detection. The EEG signal is band limited to 3-29 Hz and five statistical features are extracted for classification of epilepsy seizure using Quadrature Linear Discriminant Analysis (QLDA) classifier. We have validated this design using open EEG database of University of BONN, Germany. To prove the reliability of this work, we have tested five different types of seizure detection problems and performance measures of detection results are listed. It is observed that the design gives average detection accuracy of 97.2 % with error rate of 0.03.

The program l logic utilizes 0.09 watt dynamic power and DSP operation uses 0.010 watt power in the hardware implementation.

Due to reduced memory space and less dynamic power this design can be used to develop low power devices for automatic epilepsy detection application. For further research, the reduction of IOB is to be considered in order to design low cost integrated circuit for classification of epilepsy seizure.

TABLE I
RESOURCES UTILIZATION REPORT OF ZYNQ ZC706 PROCESSING SYSTEM IMPLEMENTATION

Resources	Estimation	Available	Utilization%
LUT	20281	218600	9.28
LUT RAM	424	70400	0.60
FF	18735	437200	4.29
BRAM	78.50	545	14.40
DSP	33	900	3.67
IO	258	362	71.27
BUFG	1	32	3.13

TABLE II
POWER REPORT OF FPGA UTILIZATION

Particulars	**Zc706 device**
Device on chip power	2.13 watt
Static power	0.225 watt
Signals	0.098 watt
Logic	0.090 watt
BRAM	0.081 watt
DSP	0.010 watt
IO	0.019 watt
Processing system	1.567 watt
Junction temperature	28.8˚ C

TABLE III
COMPARISON WITH EXISTING ALGORITHMS

Reference work	Hardware	Classifier	Accuracy	Memory used	Data set used to validate
[16]	SoC 180µm CMOS	SVM	84.4%	64KB SRAM	CHB MIT database
[18]	SoC 180µm CMOS	NLSVM	95.1%	96KB SRAM	CHB MIT database
[21]	FPGA Virtex 6 XC6VCX75T	Sample Entropy & voting	95.9%	-	BONN database
[17]	FPGA Altera cyclone II	SVM	96.8%	297 KB DDR2 SDRAM	BONN database
[28]	FPGA Spartan6 XC65LX150T	SVM	80%		BONN database
[25]	FPGA Xilinx Virtex 5 XC5VLX110T	NLSVM	94.2%	86 *36KB –Block RAM	BONN database
This work	FPGA Zync 7000 SoC ZC 706	Quadrature Linear Discriminant Analysis	97.2%	78.50 Block RAM	BONN database

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