International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.2, February 2015 DOI:10.15693/ijaist/2015.v4i2.64-69

Detecting The Epileptic Seizure Using Histogram Features

R.Monisha
PG scholar
M.E.VLSI DESIGN
Sethu Institute of Technology

Dr. R. Ganesan
PG Program Head
M.E.VLSI DESIGN
Sethu Institute of Technology

K.Monisha
Assistant Professor
Department of ECE
Sethu Institute of Technology

***Abstract*— Epilepsy is common chronic neurological disorder involving groups of neuron firing synchronously known as seizures. The efficient detection of seizure is prominent prerequisite for therapy. In coastline method a threshold value determine of the efficiency of seizure detection. The proper value of fixing as threshold value efficiency is improved; otherwise the efficiency would be low. We proposed seizure detection model that does not need patient centric threshold value, feature based seizure detection using histogram and classified seizure and non seizure using minimum distance classifier. This histogram features based detection will be simulated using matlab.**

Key Words **—Epilepsy, low-power VLSI, signal processing.**

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders in which clusters of nerve cells or neurons, in the brain sometimes signal abnormally causing strange sensations, emotions, and behavior or sometimes convulsions, muscle spasms, and loss of consciousness. Generally, the term epilepsy or seizure disorder refers to relatively stereotyped attacks of involuntary behavior. Epileptic seizures are the result of excessive and abnormal cortical nerve cell activity in the brain. Patients are often unaware of the occurrence of seizure due to the random nature of them which may increase the risk of physical injury. A seizure occurs when a burst of electrical impulses in the brain escape their normal limits. They spread to neighboring areas and create an uncontrolled storm of electrical activity. The electrical impulses can be transmitted to the muscles, causing twitches or convulsions. Seizures are a symptom associated with abnormal electrical activity in the brain, sometimes described as an electrical storm in the brain or earthquake in the brain.

Mathematically, seizure detection is similar to that of spike detection. This is a mapping from n EEG points . The morphology of a seizure varied significantly from one rat to the next and from one time period to another. The detection of seizures was significantly easier than that of spikes and the use of many different metrics resulted in good accuracy, as long as the signal-to-noise ratio was large and the amplitude of the signal was relatively large during the seizure compared to the normal EEG activity. Since epileptic seizures occur irregularly and unpredictably, automatic seizure detection in EEG recordings is highly required. For recording of EEG, electrodes will be pasted at some key points on the patient's head.

The majority of the existing seizure detection systems are based on the Electroencephalogram (EEG) which is the neural recording at the surface of the brain. Since the brain is a timevariant non-linear system, the recordings in EEG are a complex combination of all the signals that reach the surface after undergoing many transformations. The main use of electroenchaphalogram (EEG) or electrocorticogram increases detection latency due to their distance from the epileptogenic focus. EEG requires complex signal processing for feature extraction thereby increasing power consumption. Since the goal of seizure detection is to segment the brain's electrical activity in real-time into seizure and non-seizure periods.

For treatment of epilepsy, patients take antiepileptic drugs on daily basis. But about 25% of them again experience frequent seizures. For these patients, surgery is the most important and generally adopted treatment method. Surgery can be done only if epileptogenic focus is identified accurately. For this purpose different types of tracers are used as soon as seizure onset is detected. Hence the seizure onset detection is very important.

Apart from the noise effects in the seizure detection, there are others biological impacts that may degrade seizure detection performance The maximum accuracy with a false detection rate are obtained. The automated diagnosis of epilepsy can be subdivided into preprocessing, feature extraction and classification. Seizure detection can be classified as either seizure onset detection or seizure event detection. In seizure onset detection the purpose is to recognize the starting of seizure with the shortest possible delay. The purpose of seizure event detection is to identify seizures with the highest possible accuracy.

In this paper a method for the analysis of epileptic seizure detection using histogram based features has been proposed. The average energy consumed by the system is dependent on the number of seizures and the duration of baseline. The majority number of signal determines the seizure signal using minimum distance classifier.

II. BACKGROUND

A.COASTLINE METHOD

The different seizure detection techniques were literature examined on human or rat EEG recorded signal.Coastline method, simple seizure detection technique proposed in a literature that's sum absolute difference of current and previous samples in a period of the signal and the summed value compared with a threshold value. The result of comparison is true the seizure presents otherwise not. In each observation, 4 seconds period of samples were examined whether it is seizure not using the method. This method used the fact that during a seizure there was a relatively high-amplitude, high-frequency signal. It failed when there was large amplitude noise. It also failed if the amplitude of the signal during the seizure was less than that encountered during the normal recording.

B. DWT-QA

Recently, [4]proposed method combined of discrete wavelet transform and quasi-averaging (DWT-QA) improve seizure detection efficiency in practical implementation, however not has power efficiency due to carrying out DWT-QA for each observation of 4 sec samples. Proposed two stage algorithm, the first called monitoring stage carried out coastline method and second, examining stage carried out DWT-QA method. The seconds stage execution started by triggering (ON) pulse from first stage. At first stage the trigger pulse issued whenever summed value is greater than threshold value. In this method false detection reduced but miss detection depends on threshold value in first stage of coastline method and power consumption reduced by triggering execution of second stage. Our proposed model, a two stage algorithm achieves power efficiency by implementation low computation histogram feature based algorithm in second stage.

III.PROPOSED METHOD

The proposed model carried out seizure detection with two stage algorithm in order to improve power efficiency in second stage. The first stage is known as monitoring stage of seizure signal and second stage known as analyzing seizure signal to improve efficiency of seizure detection. On monitoring stage, two kind of process carried out coastline method and trigger next stage of the algorithm. On second stage, two kind of process carried out histogram feature extraction and features matching with known features.

The fig.1 shows the input EEG signal. The signal taken from rattus shown below. From a specific time interval the epilepsy signal is taken. All the epileptic signal are gathered together using horizontal and vertical histogram. Finally every signal is compared with the minimum distance classifier whether the signal is seizure or non-seizure.

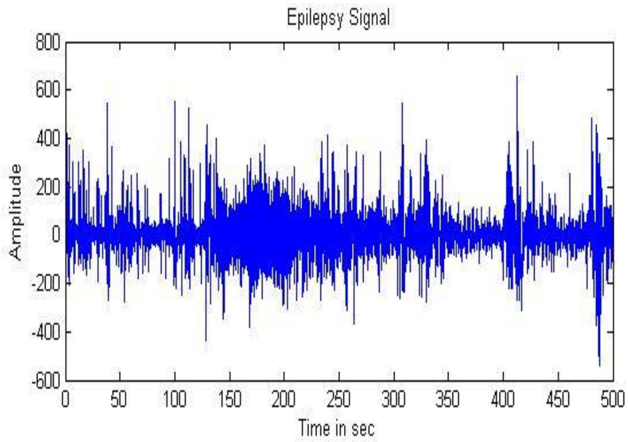

Figure. 1 input EEG signal

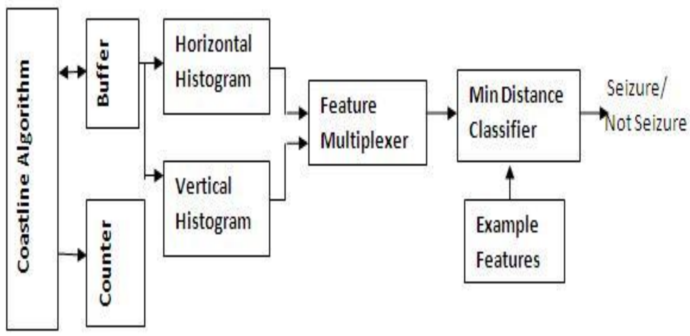

Figure. 2 block diagram of epilepsy seizure

The block diagram shown in fig.2 is model of seizure detection in epilepsy signal. The coastline block connected with buffer and counter block, is accumulates absolute difference of sample and increment the counter by one. The counter value represents index of buffer where the current sample should be stored. Whenever counter value reaches to maximum set sample count, the accumulated value of coastline algorithm is compared with threshold. If the result is greater trigger pulse enable feature extraction block start process using buffered samples, otherwise the counter is reset 0 and buffer cleared.

A. Monitoring Stage

Coastline method on monitoring stage draws more attention due to simplicity and hence implemented in this stage.

$$= \quad - \qquad (1)$$

The problem with it is setting threshold value. If it is set high value, the chance of seizure miss detection would increase whereas if it is set with low value, the chance of seizure detection would increase and increase cost of power consumption because of execution of second stage frequently.

$$= \quad 1, \quad > 0 \qquad (2)$$

The coastline method output would be 1/0 represents triggering pulse ON/OFF stage which is transferred to second stage of histogram feature extraction.

B. Analysis Stage

The second stage of seizure detection process ensures whether the period of signal contains seizure presence or not and is carried out by feature extraction and matching feature with known class of features.

In feature extraction, proposed histogram based features extraction techniques, since it is fast and low power consumption. In horizontal histogram, sample's amplitude is discredited as histogram bins and frequency of sample's amplitude is counted for each bin. While for vertical histogram time-axis is discredited as its bins and for each bin count value is measured as sum of sample's amplitude of the bin period. The figure (3) and (4) shown represents seizure and non-seizure samples of horizontal and vertical histogram features.

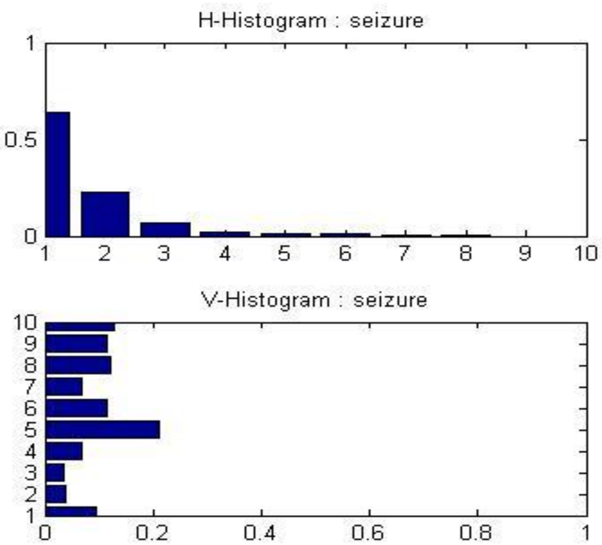

Figure. 3 seizure samples horizontal & vertical histogram

When comparing these two histogram features, the seizure samples bin value spread out in horizontal histogram (H_s^h) and more value in vertical histogram (H_s^v) higher bin and while for non-seizure signal, bin value accumulated highly in lower bin of horizontal (H_{ns}^h) and vertical histogram (H_{ns}^v). These histogram feature presented here provide better separation between seizure and non seizure samples.

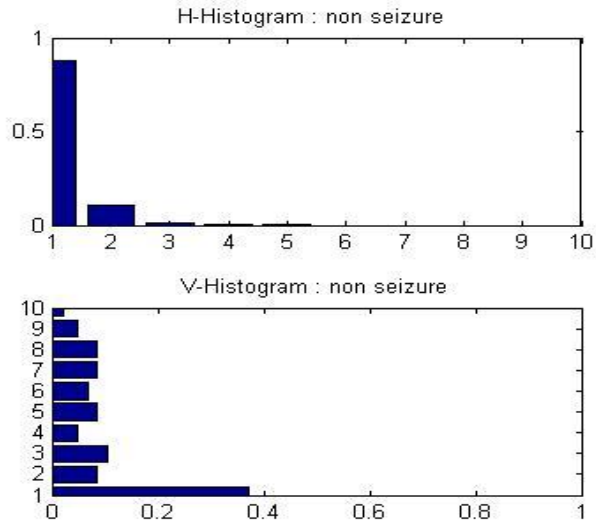

Figure.4 seizure samples horizontal & vertical histogram

C. Feature Matching

The proposed feature matching method is carried out between periods of samples of histogram features and known classes (seizure and non-seizure) of histogram features with different weight, w value. The sample contains seizure or not is concluded with feature matching technique. The value of D_s(distance of seizure) greater than D_{ns} (distance of non seizure), the samples are seizure otherwise not.

$$= \times \quad h - h \quad + \times \qquad (3)$$

$$= \times \quad h - h \quad + \times \qquad (4)$$

IV. RESULT

The epilepsy signal has been implemented using mablab. Fig.3 and 4 shows simulation result for epileptic seizure signal using histogram in time interval 60-63 and 136-

139.The performance of proposed system in table(1) shows the sensitivity and specificity in different subject. Hence,we train the monitoring stage with high sensitivity. This reduces its FN and delay of detection. The analysis stage is trained for a very high efficacy to reject any FP that passed through the monitoring stage. The efficacy of the system is calculated as the average of the sensitivity and specificity. The specificity, sensitivity and the ADR were calculated as per following

$$\text{Sensitivity} = \frac{TP}{TP+FN} * 100\% \quad (5)$$

$$\text{Specificity} = \frac{TN}{TN+FP} * 100\% \quad (6)$$

$$ADR = \frac{\text{Sensitivity} + \text{Specificity}}{2} * 100\% \quad (7)$$

Table 1. Performance of proposed System

Signal	Sensitivity	Specificity	ADR
Subject-1	92 %	96%	94%
Subject-2	88%	94%	91%
Subject-3	84%	93%	88.5%
Subject-4	76%	91%	83.5%
Subject-5	90%	95%	92.5%

V. CONCLUSION

We conclude that using power gating and aggressive voltage scaling (near-VT), energy optimality is achieved, thereby significantly increasing the battery life of the implant. These dual stage algorithm is used for energy consumption. The analysis stage operates for 10 s before restoring to monitoring operation. Recently there is a great need of developing power efficient methods to predict and prevent the onset of seizures in epileptic patients. The proposed model of histogram feature seizure detection would provide not only power efficiency but also classification accuracy in presence of noise in the sample. Considering all these factors, development of an algorithm for the automated processing of rat EEG was less complicated than an equivalent algorithm for humans, and very high accuracies were achieved through our proposed algorithms. The average energy consumed by the system is dependent on the number of seizures and the duration of baseline. The majority number of signal determines the seizure signal.

REFERENCES

[1] D. Labar, J. Murphy, and E. Tecoma, “Vagus nerve stimulation for medication-resistant generalized epilepsy,” Neurology, vol. 52 pp. 1510–1512, Apr. 1999.

[2] S. Raghunathan, M. P. Ward, K. Roy, and P. P. Irazoqui, “A low-power implantable event-based seizure detection algorithm,” in Proc. 4th Int.IEEE EMBS Conf. Neural Eng., May 2009, pp. 151–154.

[3] H. Adeli, Z. Zhou, and N. Dadmehr, “Analysis of EEG records in an epileptic patient using wavelet transform,” J. Neurosci. Methods,vol. 123, no. 1, pp. 69–87, 2003
.

[4] H. Markandeya, G. Karakonstantis, S. Raghunathan, P. P. Irazoqui, and K. Roy, “Low-power DWT-based quasi-averaging algorithm and architecture for epileptic seizure detection,” in Proc. 16th ACM/IEEE ISLPED, Aug. 2010, pp. 301–306.

[5] S. Raghunathan, S. K. Gupta, H. S. Markandeya, K. Roy, and P. P. Irazoqui, “A hardware-algorithm co-design approach to optimize seizure detection algorithms for implantable applications,” J. Neurosci. Methods, vol. 193, no. 1, pp. 106–117, 2010.

[6] M. T. Salam, M. Sawan, and D. K. Nguyen, “A novel low-power-implantable epileptic seizure-onset detector,” IEEE Trans. Biomed. Circuits Syst., vol. 5, no. 6, pp. 568–578, Dec. 2011.

[7] H. Markandeya, S. Raghunathan, P. P. Irazoqui, and K. Roy, “A lowpower „near-threshold‟ epileptic seizure detection processor with multiple algorithm programmability,” in Proc. ACM/IEEE Int. Symp. Low Power Electron. Des., Feb. 2012, pp. 285–290.

[8] G. Karakonstantis and K. Roy, “An optimal algorithm for low power multiplier-less FIR filter design using Chebychev criterion,” in Proc.IEEE ICASSP, vol. 2. Feb. 2007, pp. 49–52.

[9] J. H. Choi, N. Banerjee, and K. Roy, "Variation-aware low-power synthesis methodology for fixed-point FIR filters," in Proc. IEEE TVLSI,2010.

[7] A. Berdakh et al," Epileptic Seizures Detection using Continuous Time Wavelet Based Artificial Neural Networks",
SixthInternational Conference on Information Technology, 2009.

[8] J. Aziz et al., "Towards real time in-implant epileptic seizure prediction", Proc. 28th IEEE EMBS Annual InternationalConference, 2006, pp. 5476-5479.

[9] C. Souani et al," VLSI design of 1-D DWT architecture with parallel filters", Integration, the VLSI journal, 2000, Vol 29, Issue 2, pp.
181-207.

[10] G. Karakonstantis et al., "An optimal algorithm for low power multiplier-less FIR filter design using Chebychev criterion",
IEEEICASSP, 2007, Vol 2, pp. II-49-II-52.

[11] White A.M., Williams P.A., Ferraro D.J., Clark S., Kadam S.D., Dudek F.E. et al., 2006, Efficient unsupervised algorithms for the detection of seizures in continuous EEG recordings from rats after brain injury, *J. of Neuroscience Methods*, 152, 255–266.

[12] Kaiser J. F., 1990 "On a simple algorithm to calculate the `energy' of a signal," *International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 1,* 381-384.

[13] Zaveri H. P., W. J. Williams W. J., and Sackellares J. C., Energy Based Detection of Seizures, 1993, *15th Annual International Conference on Engineering and Medicine in Biology*, 363-364.

[14]Hjorth B., An on-line transformation of EEG scalp potentials into orthogonal source derivations, 1975, *Electroencephalography and Clinical Neurophysiology*, 39,526–530.

[15]Pfurtscheller G., Lopes da Silva F.H., 1999, Event-related EEG/MEG
synchronization and desynchronization: basic principles, *Clinical Neurophysiology*, 110, 1842

AUTHOR'S PROFILE

Dr.R.Ganesan received his B.E. in Instrumentation & Control Engineering from Arulmigu Kalasalingam College Of Engineering and M.E. (Instrume-ntation) from Madras Institute of Tech- nology in the year 1991 and 1999 respectively. He has completed his Ph.D. from Anna University, Chennai, India in 2010. He is presently working as Professor and head in the department of M.E-VLSI Design at Sethu Institute of Technology, India. He has published more than 25 research papers in the National & International Journals/ Conferences. His research interests are VLSI design, Image Processing, Neural Networks and Genetic algorithms

K. MONISHA received her B.E. Electronics and Communication Engineering from K.L.N College of Engineering in the year 2010 and M.E. VLSI DESIGN from Sethu Institute of Technology in the year 2012. She is presently working as an Assistant Professor in the department of ECE at Sethu Institute of Technology, India. Her research interests include Low Power VLSI and Analog VLSI.

R.MONISHA received her B.E. degree in Electronics and instrumentation Engineering fromsethu institute of technology,virudhunagar, Anna University, Chennai, India, in 2013. Pursuing M.E. degree in VLSI Design from Sethu Institute of Technology, Anna University, Chennai, India. Her research interest includes transducer engineering and Low power VLSI design.