Volume 3, Issue 2April 2014

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Bio Medical Application of Clustering Techniques forEpilepsy Detection

[1]Lokesh Kumar, [2] Dr.Geetika Srivastava

[1,2]Department of Electronics & Communication Engineering, Amity University,Lucknow Campus, Uttar Pradesh

E-mail: [1]lokeshkmr870@gmail.com., [2]gsrivastava2@lko.amity.edu

ABSTRACT

Signal processing has varied range of applications ranging from our daily life activities to advanced research in different domain. Signal processing is widely involved in communication, artificial intelligence, advance robotics to the advance bio medical applications like ECG, EEG processing etc. In this paper we have studied EEG signal as a part of signal processing for diagnostic understanding of epilepsy. Epilepsy is one of the most common neurological disorder with a widespread0.6-0.8% of the India's population[1-2]. Two-third of the patients achieves sufficient seizure control from medicine and some other 8-10% benefit from respective surgery. For the remaining 25% of patient no sufficient treatment is currently available[3-7].A fixed cluster size approach for epilepsy feature extraction and propose explaining the concepts of the classification of EEG. The experiment result showed that fixed cluster epileptic data algorithm can produce a better classification rate than the previous reported method by Siluly et al[8]. Which used LS-SVM forthe extracted features to classify EEG signals.

Keywords:*EEG, Epilepsy, Signal Processing, Brain activity, BCI*

I. INTRODUCTION

Electro Encephalography (EEG) is the recording of electrical activity along the scalp. The EEG measures voltage fluctuations from ionic current flowing within the neurons of the brain. In clinical terms, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, say 20-40 minutes recorded from multiple electrodes placed on the scalp. EEG is the most used technique to capture brain signals due to its excellent temporal resolution, noninvasiveness, usability, and low set-up costs. An EEG can show state of a person. (sleep, awake, anaesthetized, emotion ,sadness, happiness as the characteristic patterns of the electrical potentials differ for different states[9].

II. EEG Waveforms Analysis

Most of the brain disorders are diagnosed by visual inspection of EEG signals. The improvedanalysis techniques of EEG signals has lead to improved results in EEG feature extraction and classification for epilepsy[13-14]. The recorded brain electrical activity is defined in terms of specific descriptors or features. EEG analysis focuses on the frequency or wavelength of signal and manner of occurrence of voltage fluctuation (random, serial, continuous), its dependency on reactivity (eye opening, mental task, sensory, bodily gesture, affective state) and symmetry of the signal [10-11].

III. Nature of rhythms of the EEG signals

For assessing abnormalities in clinical EEGs and for understanding functional behavior in cognitive research, the frequency is considered to be most important parameter. With billions of oscillating communities of neurons as its sources, the human EEG potentials are visible as aperiodic unpredictableoscillations with irregular burst of oscillations which are typically categorized in specific bands such as 0.5-4 Hz (delta), 8-13 Hz (alpha) 13-30 Hz (beta) and>30Hz (gamma).[12]

IV. Classification of EEG signal

In pattern recognition feature extraction is widely used in the areasof face recognition, database indexing, image recovery,multimedia computation and other model-based coding ofimage sequences.The use of the classifier is to determine the particular class of a signal. The signal to be classified must be defined by features that could be extracted from the signal for the purpose of classification [13].

The classification techniques generally work in two stages,where features are extracted from raw EEGdata in the first stage and then obtained features areused as the input for the classification process in the second stage. It is important to note that features are compressed parameters that characterize the behavior of the original data[14-15]. In the present study, the fixed clustering techniques (FCT) algorithm is used to extract feature parameters representing EEG signals from the original EEG data.

V. Previous Research

Till date several techniques have been proposed for the classification of EEG signals, and diverse classification techniques have been reported in the last decade[39-40].

EEG signal classification by support vector machine (SVM)can detect whether a subject's planning to perform a task or not[17]. In EEG classification SVMVarious different Kernels were utilized to find the best kernel function but it's the more time taking process and inefficient to classify the EEG signal. A wavelet-based neural network (WNN)classifier for recognizing EEG signals is proposed by Guler et.al [17].The Discrete Wavelet Transform (DWT) with the Multi Resolution Analysis (MRA) is applied to decompose the EEG

Volume 3, Issue 2April 2014

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

signal at resolution components of EEG signal[19][20]. For detection of Siluly et.al have processed SVM technique[14].

VI. Proposed Methodology

In this paper we propose a new algorithm of the Clustering. Fixed cluster size approach is used for classifying the EEG signals cluster.Earlier of clustering techniques (CT) method was based on variable cluster size the variable cluster size resulted in variation of results with number of samplesLeast Square Support Vector Machine (LS-SVM)[21-24].

This approach is conducted in three steps: acquisition EEG signal, determination different of clusters and feature parameters extraction from each cluster.

Ninefeature parameters are used to classify the signals[25]. Each EEG channel data is considered as a population which is divided into N groups with a specific time duration, called Clusters. The Cluster size is chosen to be20(t=0.2 sec with fs=1000Hz). - In this study, EEG signals were classified over ten set of two subjects each, one epileptic and one healthy. The recording time period is fixed of both subjects (healthy and epileptic).

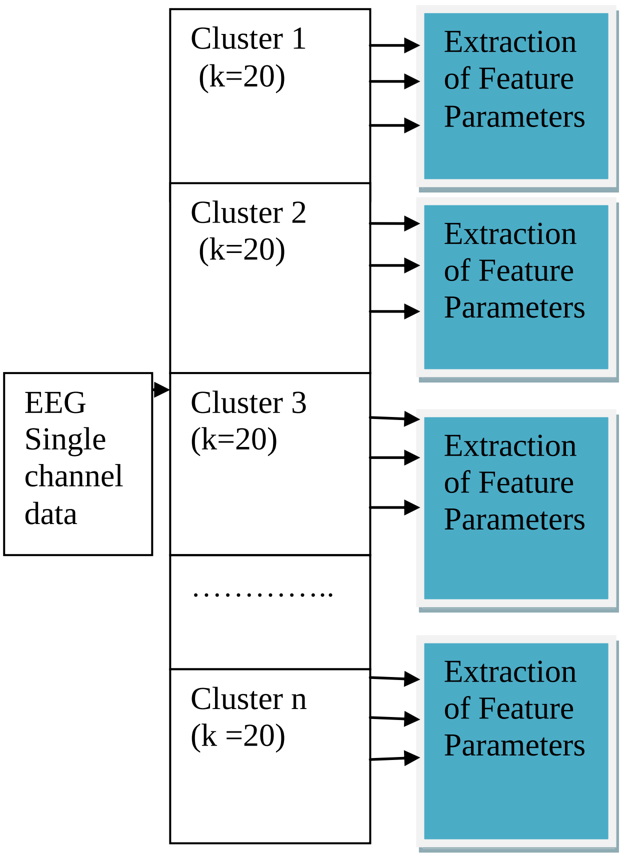


Fig.1 Fixed cluster size feature extraction.

Feature extraction plays an important role in pulling out special patterns from the original data for reliable classification. The feature extraction stage must reduce the original data to a lower dimension that contains most of the useful information being included in the original vector[26-28]. It is therefore, necessary to find out the key features that represent the whole dataset, depending on the characteristics of a dataset.The nine feature parameters are extracted from each cluster data as they are the most representative values to describe the original signals[31].

The nine feature parameters of each cluster of EEG channel data are used as the valuable parameters forthe representation of the characteristics of the original EEG signals[29-30].

I Minimum-Minimum value of cluster
Min=min(K*i*),where i=1……….20

II.Maximum-Maximum value of cluster
Max=max(K*i*) where i=1……….20

III.Mean- Mean of the absolute values of each channel signal.

$$Fi = \frac{1}{n}\sum_{j=1}^{N} |Sij|^2$$

IV.Median-). Median value of cluster **(k)**is**(k/2)**

V.Mode-Mode value of cluster **(k)**that is common value of a single cluster.

VI.First quartile-First quartile of cluster **(k)**that is placing value of cluster **(k/4).**

VII. Third quartile-Third-quartile **is** placing value of cluster **(k/3).**

VIII.Inter-quartile range -Inter-quartileplacing value of cluster **(k/2).**

IX.Standard deviation- Standard deviation of each channel signal.

$$Fi=\sqrt{(\frac{1}{N-1}\sum_{j=1}^{N} S^{2}ij)}$$

(a). Average sample of each channel signal.

$$Fi = \sum_{j=1}^{N} |Sij|^2$$

(b). Sampling frequency (Fs) =1000Hz
(c). Fixed cluster size of epileptic signal (k=20)

VII. EEG Data

Healthy subject and epileptic EEG subject are used separately to test the performance of the proposed method. In epileptic EEG database the data set IV for Brain Computer Interface (BCI) [32-38] contain EEG recording from two subjects during two kind of tasks which are the epilepsy and healthyhuman. The recording was made using Brain Amp amplifier and a 128 channel. Ag/Agcl electrode cap from ECI

EEG Hardware	Brain Amp Amplifier
Kind of electrode	Ag/Agcl
Hardware reference	Electrodes,Neurofeedback
Sampling Rate	1000 Hz
Hardware filter	Hum notch filter

Software filter	Band pass filter
Other Hardware	None
Patient state during reading	Relax sitting on chair

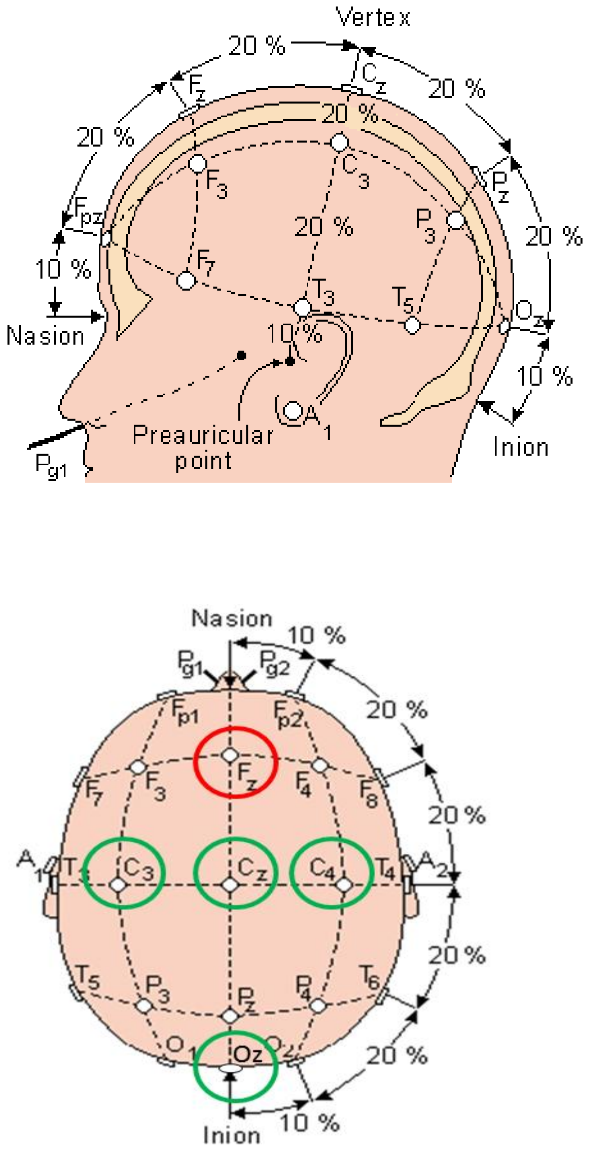
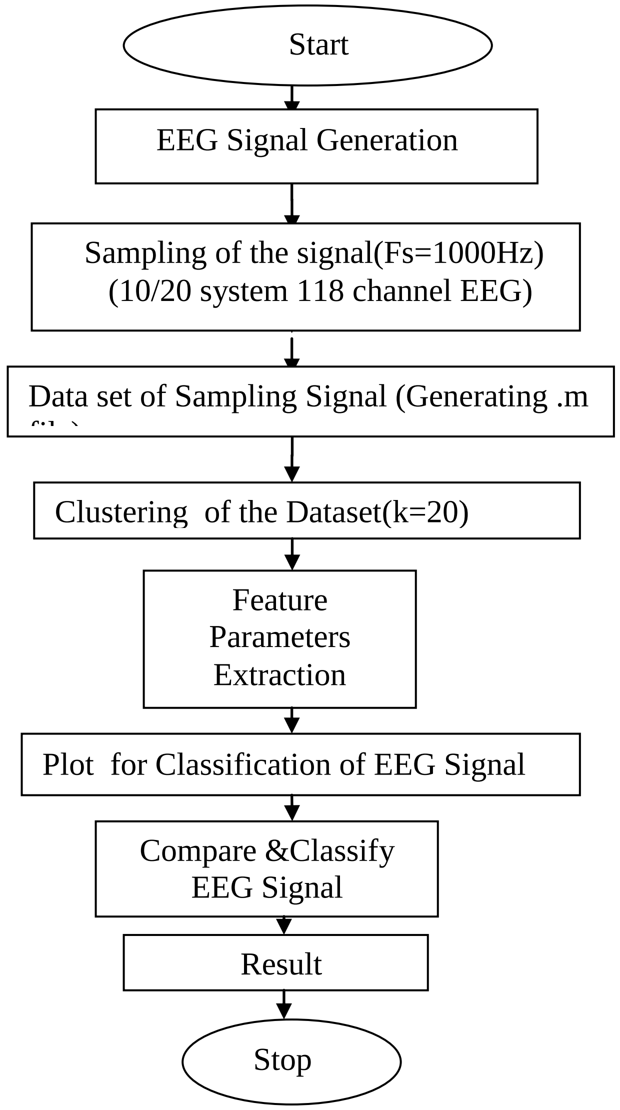


Fig. 2 Channel placement detail

118 EEG channel were measured. Analysis have been done for each data Here we are taking some fixed channel data which are more important for classification of signal. Selection of channel are shown in figure (2).

VIII. Flow chart of classification of single channel EEG data



ITEE Journal
Information Technology & Electrical Engineering
ISSN: - 2306-708X

Cluster Max value of different channel for healthy subject

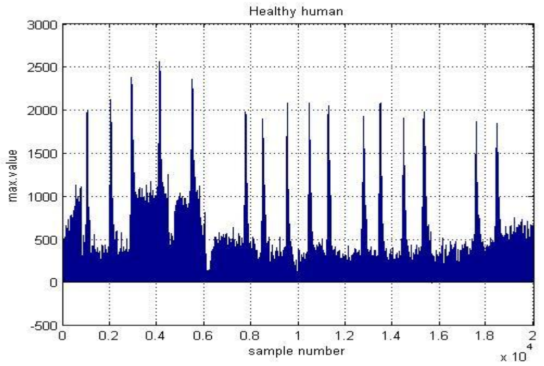


Fig.2 for channel C2

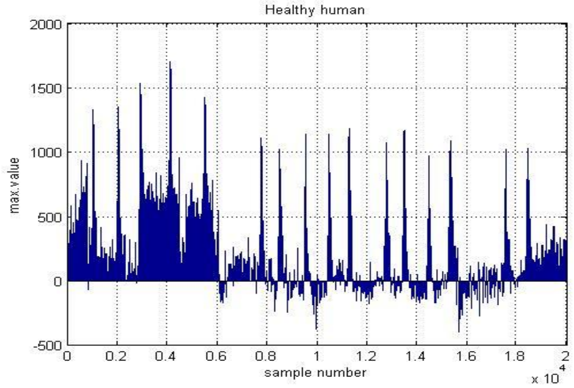


Fig.3 for channel C3

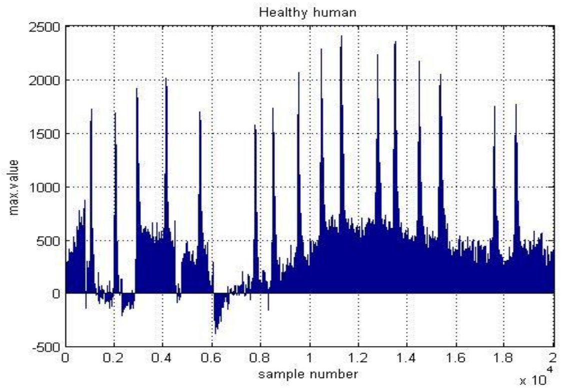


Fig.4 for channel FZ

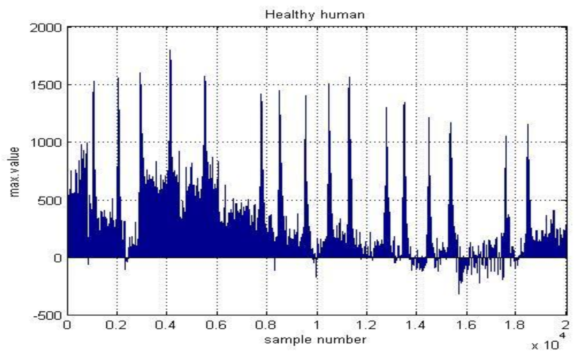


Fig.5 for channel OZ

For Cluster max value of different channel forEpileptic Subject

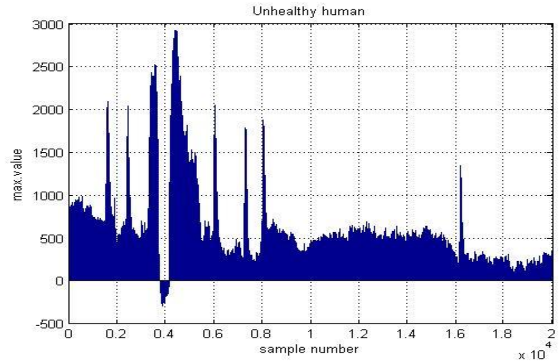


Fig.6 for channel C2

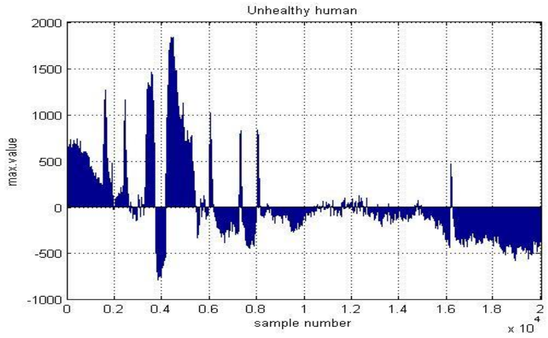


Fig.7 for channel C3

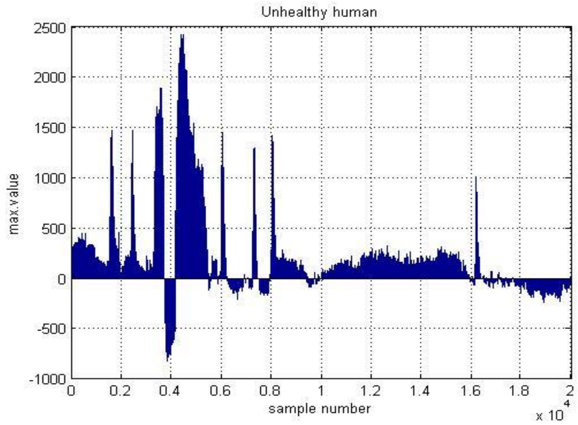


Fig.8 for channel FZ

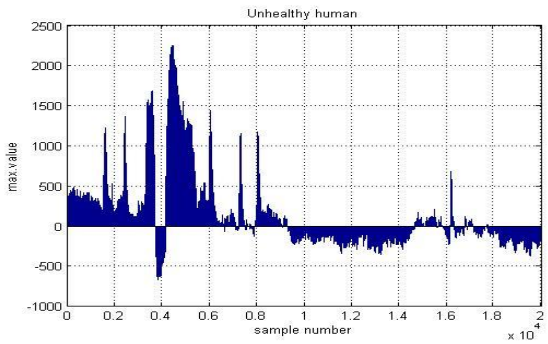


Fig.9 for channel OZ

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Result-Cluster min value of different channel for healthy subject

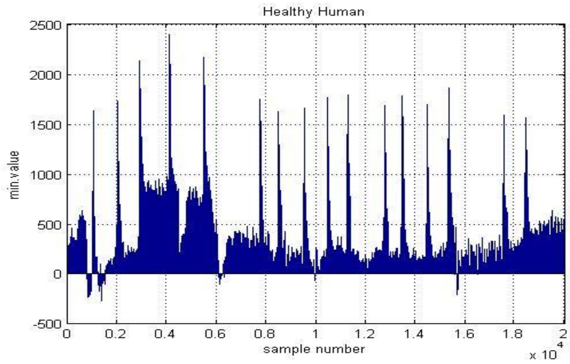


Fig 10 for channel C2

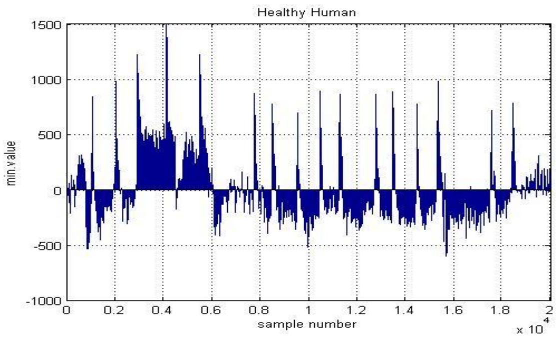


Fig 11 for channel C3

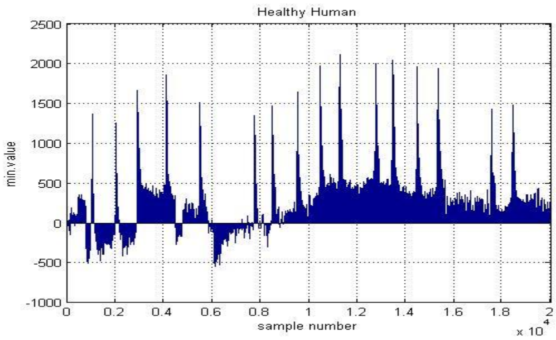


Fig 12 for channel FZ

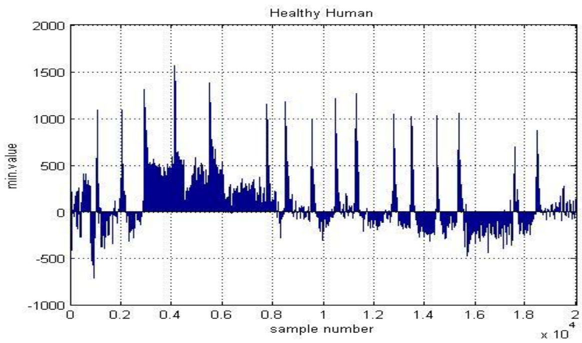


Fig 13 for channel OZ

Result - Cluster min value of different channel for Epileptic Subject

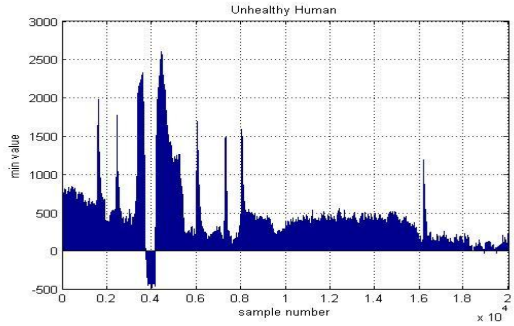


Fig 14 for channel C2

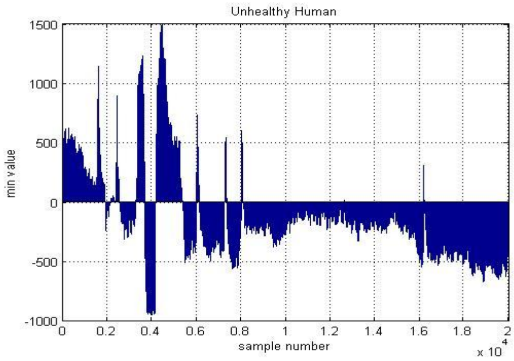


Fig 15 for channel C3

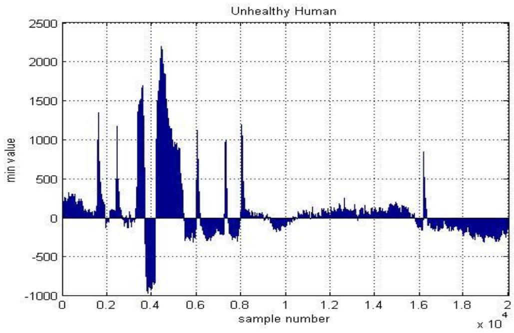


Fig 16 for channel FZ

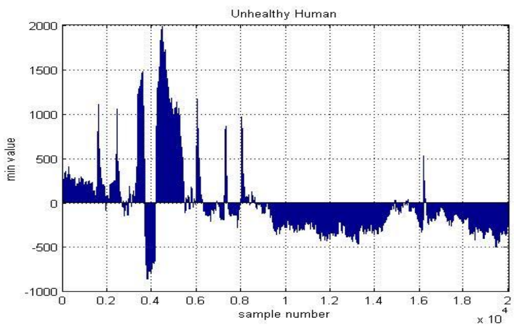


Fig 17 for channel OZ

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Result –Cluster mean value of different channel for healthy subject

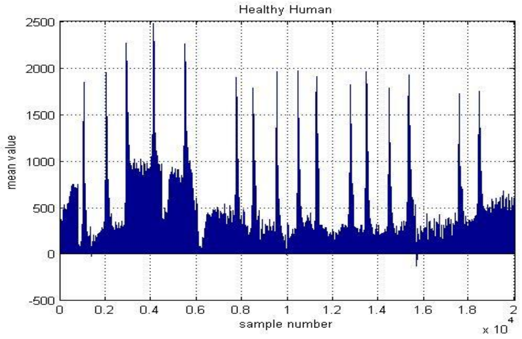


Fig 18 for channel C2

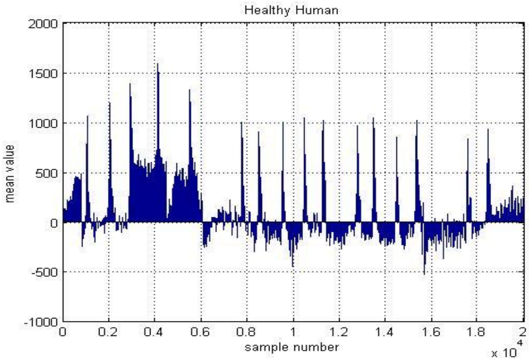


Fig 19 for channel C3

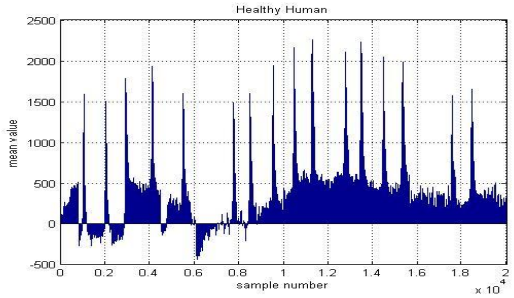


Fig 20 for channel P 3

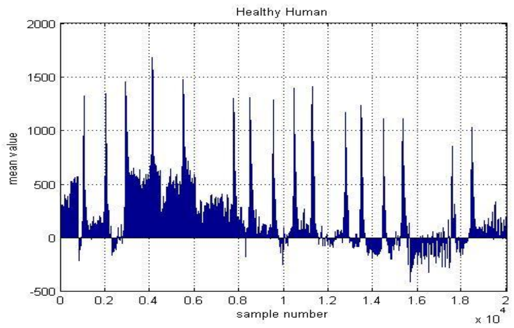


Fig 21 for channel OZ

For Cluster mean value of different channel for Epileptic Subject

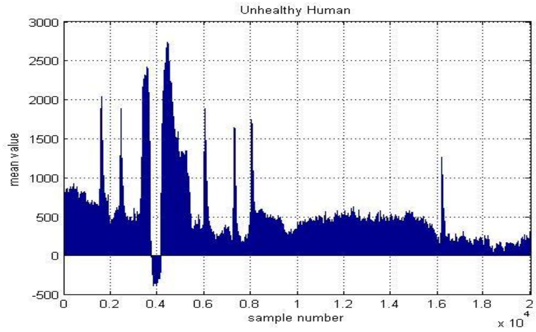


Fig 22 for channel C2

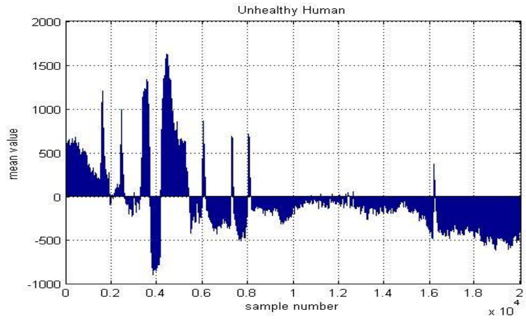


Fig 23 for channel C3

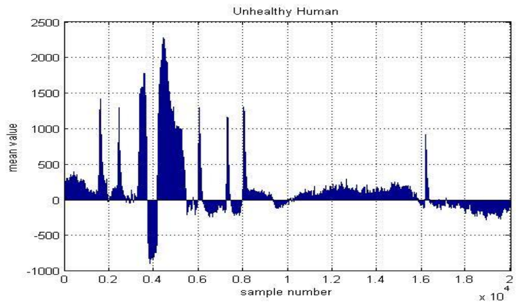


Fig 24 for channel FZ

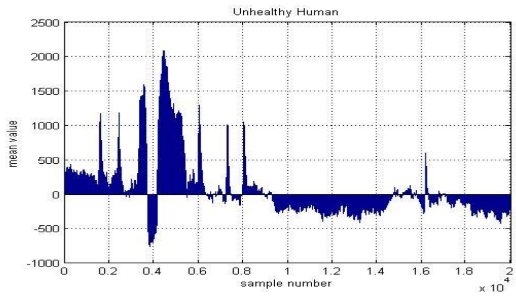


Fig 25 for channel OZ

IX. Result and discussion

In this study, EEG signals were classified over ten set of two subjects each,one epileptic and one healthy.For the specific channel (Fz, C2, C3, C4, &Oz) the average value of cluster feature more in epileptic subjects.. After classification from feature parameters the comparison is done between these two subjects average fluctuation is checked by classifying the data. In this result also indicate that average fluctuation in epileptic higher than the healthy subject. In epileptic signal repeated fluctuation occurred in a particular sample valueIt is well

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

evident from these result that epileptic data set can be easily identified by method of feature extraction using fixed cluster size**.** In above given result we summarized that the difference between the healthy human and epileptic.

REFERENCES:

[1] CharyU.R., Molinari F., Sere S.V., Chattopadhyay S., Ng K. H., Suri J.S., Automated diagnosis of epileptic EEG using entropies, Biomedical Signal Processing and Control, doi: 10.1016 / j.bspc. 2011.07.007, 2011

[2]Pravin Kumar S., Sriraam N., Benakop P.G., Jinaga B.C., Entropies based detection of epileptic seizures with artificial neural network classifiers, Expert Systems with Applications, 37 (2010), 3284–3291

[3] Ubeyli E.D., Combined neural network model employing wavelet coefficients for EEG signals classification, Digital Signal Processing, 19 (2009), 297–308

[4] Aarabi A., Fazel-Rezai R., Aghakhani Y., A fuzzy rule-based system for epileptic seizure detection in intracranial EEG, Clinical Neurophysiology, 120 (2009), 1648–1657

[5]Adeli H., Zhou Z., Dadmehr N., Analysis of EEG records in anepileptic patient using wavelet transform, Journal ofNeuroscience Methods, 123 (2003), 69–87

[6] Subasi A., Automatic recognition of alertness level from EEGby using neural network and wavelet coefficients, ExpertSystems with Applications, 28 (2005), 701–711

[7]Abdullah H, Maddage N C, Cosic I and Cvetkovic D (2010) 'Cross-correlation of EEG frequency bands and heart rate variability for sleep apnoea classification', Med Bio Eng Computer 48 1261-1269

[8] Siuly, Y. Li and P. Wen, EEG signal classification based on simple random sampling technique with least square support vector machines, International journal of Biomedical Engineering and Technology (2010), forthcoming.

[9]Adeli, H., Zhou, Z. and Dadmehr, N. (2003) 'Analysis of EEG Records in an Epileptic Patient Using Wavelet Transform', J. Neurosci. Methods, Vol. 123, no. 1, pp. 69-87. .M. Kostyunina and M. Kulikov. Frequency characteristics of eeg spectra in the emotions.

[10].Agarwal, R., Gotman, J., Flanagan, D. and Rosenblatt, B. (1998) 'Automatic EEG analysis uring long-term monitoring in the ICU'.

[11].Akay, M. (1998) Time Frequency and Wavelets in Biomedical Signal Processing, New York: Institute of Electrical and Electronics Engineers, Inc.

[12]Abdulkadir, S. (2009) 'Multiclass least-square support vector machines for analog modulation classification', Expert System with Applications, Vol. 36, pp. 6681–6685.

[13].Allison. B.Z., Wolpaw, E.W., and Wolpaw, J.R. (2007) 'Brain computer interface systems: progress and prospects. In. E.Poll (Ed.).

[14]Siuly, Li, Y. and Wen, P. (2009) 'Classification of EEG signals using Sampling Techniques and Least Square Support Vector Machines', *RSKT 2009*, LNCS 5589 pp. 375-382.

[15] M. Makinac, Support vector machine approach for classification of cancerous prostate regions, World Academy of Science, Engineering and Technology (2005) .

[16] M. Makinac, Support vector machine approach for classification of cancerous prostate regions, World Academy of Science, Engineering and Technology (2005) 7.

[17] I. Guler and E.D. Ubeyli, Multiclass support vector machines for EEG-signal classification, IEEE Transactions on Information Technology in Biomedicine 11(2) (March 2007) 117-126.

[18] Siuly, Y. Li and P. Wen, EEG signal classification based on simple random sampling technique with least square support vector machines, International journal of Biomedical Engineering and Technology (2010), forthcoming.

[19] A.E. Silver, M.P. Lungren, M.E. Johnson, S.W. O‟Driscoll, K.N. An and R.E. Hughes, Using support vector machines to optimally classify rotator cuff strength data and quantify post-operative strength in rotator cuff tear patients, Journal of Biomechanics 39 (2006) 973-979.

[20] J. Fan, C. Shao, Y. Ouyang, J. Wang, S. Li and Z. Wang, Automatic seizure detection based on support vector machine with genetic algorithms, SEAL 2006, LNCS 4247, pp. 845-852.

[21] E.D. Ubeyli, Least square support vector machine employing model-based methods coefficients for analysis of EEG signals, Expert System with Applications 37 (2010) 233-239.

[22]P. Lang, M. Bradley, and B. Cuthbert. International affective picture system (iaps): Affective ratings of pictures and instruction manual. Technical Report A-6, University of Florida, Gainesville, FL, 2005.

[23] N.F. Guler, E.D. Ubeyli and I. Guler, Recurrent neural networks employing Lyapunov exponents for EEG signals classification, Expert System with Applications 29 (2005) 506-514.

[24] A. Subasi, EEG signal classification using wavelet feature extraction and a 39
mixture of expert model, Expert System with Applications 32 (2007) 1084-1093.

[25] E.D. Ubeyli, Wavelet/mixture of experts network structure for EEG signals classification, Expert System With Applications 34 (2008) 1954-1962.

[26].T. Musha, Y. Terasaki, H. A. Haque, and G. A. Ivamitsky. Feature extraction from EEGs associated with emotions. Artificial Life and Robotics, 1(1):15–19, March 1997.

[27].R. W. Picard and J. Healey. Affective wearables. In ISWC,

[28].R.W. Picard, E. Vyzas, and J. Healey. Toward machine emotional intelligence: Analysis of affective physiological state. IEEE Transactions on Pattern Analysis and Machine Intelligence.

[29]Siuly, Li, Y. and Wen, P. (2010) 'Analysis and classification of EEG signals using a hybrid clustering technique', *Proceedings of the 2010 IEEE/ICME InternationalConference on Complex Medical Engineering (CME2010)*, pp. 34–39.

[30] D. Hanbay, An expert system based on least square support vector machines for diagnosis of the valvular heart disease, Expert System with Applications 36 (2009) 4232-4238.

[31] EEG time series (epileptic data) (2005, Nov.) [Online],http://www.meb.uni-bonn.de/epileptologie/science/physik/eegdata.html

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

[32] S. Chiappa and J.R. Millán, Data Set V<mental imagery, multi-class>.[online] (2005).
http://ida.first.fraunhofer.de/projects/bci/competition_iii/desc_V.html
[33] BCI competition III, http://www.bbci.de/competition/iii
[34] S. Abdulkadir, Multiclass least-square support vector machines for analog modulation classification, Expert System with Applications 36 (2009) 6681–6685.
[35] K. Polat and S. Gunes, Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform, Applied Mathematics and Computation 187 (2007) 1017-1026.
[36] Sample size calculator, http://www.surveysystem.com/sscalc.htm
[37] R.G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David and C.E. Elger, Indication of non linear deterministic and finite-dimensional structures in time series 40
of brain electrical activity: dependence on recording region and brain state, Physical Review E 64 (2001) 061907.
[38] J.R. Millán, On the need for online learning in brain-computer interfaces, Proc. 2004 Int. Joint Conf. Neural networks, Vol. 4, pp.2877-2882.
[39] Abdulkadir, S. (2009) 'Multiclass least-square support vector machines for analogmodulation classification', *Expert System with Applications*, Vol. 36, pp. 6681–6685.
[40] Abdullah H, Maddage N C, Cosic I and Cvetkovic D (2010) 'Cross-correlation ofEEG frequency bands and heart rate variability for sleep apnoea classification', *MedBioEng Computer* 48 1261-1269
[40] Adeli, H., Zhou, Z. and Dadmehr, N. (2003) 'Analysis of EEG Records in an
Epileptic Patient Using Wavelet Transform', *J. Neurosci.Methods*, Vol. 123, no.
1, pp. 69-87.

AUTHOR PROFILES:

1. **Lokesh Kumar** received the degree in Electronics & Communication Engineering from Uttar Pradesh Technical University Lucknow, in 2012. He is currently pursuing M.Tech.(EC.E) as well as research from Amity University Uttar Pradesh,Lucknow campus.
2. **Dr.Geetika SrivastavaM.tech,Ph.D(low power VLSI)** has more than 10 years teaching and research experience and published many reputed international journal papers.Qualified UGC NET in electronics Science & presently working as ASET Prof.in Amity School of Engineering &Technology,Amity University Lucknow Uttar Pradesh.