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EEG Signal classification by using Empirical Mode Decomposition and LVQ

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ABSTRACT

An Electroencephalogram (EEG) is a test used to find problems related to electrical activity of the brain. An EEG tracks and records brain wave patterns. An EEG can be used to help detect potential problems associated with this activity. In this paper we propose a new prototype for feature extraction method couple with a Kohonen's neural network based classifier for classification of EEG signal. EEG signal is decomposed into intrinsic mode function (IMFs) by Emperical mode decomposition algorithm. Using these seven IMFs, six statistical parameter are calculated and forty two features are extracted for classification of EEG signal. This is the input feature vector of the Learning vector quantization classifier. Learning Vector Quantization (LVQ) method which classifies the EEG signal into binary categories: Set A normal human beings with eyes open with Set-B being the data of regular human being in eyes closed condition, Set -C which was taken from the hippocampal formation of the opposite hemisphere of the brain, Set-D were recorded from within the epileptogenic zone and Set-E is the data of an Epileptic Human in regular condition respectively. The EEG signals are available in the Bonn data-base. The classification accuracy are obtained between A-B is 86.21%, A-C is 82.14% , A-D is 77.8% and A-E is 98.85% respectively.

Keywords: EMD, LVQ and EEG Signal

I. INTRODUCTION

Desirable or unexpected response to a particular stimulus can be tracked back to the neurological activity of the human brain. One important and common medical tool to assess the neurological pattern and response the human brain is the EEG (electroencephalogram) signal. In order to extract information out of it, EEG signal can be considered as a stationary or non-stationary signal. Though considering the variable pattern of the signal it is evaluated as a non-stationary signal. The signal as a whole can be bit tedious to study, instead using certain techniques, features can be extracted out of it so that it can be characterised easily. This report focuses on datasets of EEG signals derived from the human brain ranging from one that is functioning normally and responding accordingly to one suffering from neurological disorder and its corresponding response.

Classification of EEG signal is divided into three stages: one is data acquisition of EEG signals, second is feature extraction and third is classification. EEG signal were decomposed into time-frequency representations using discrete wavelet transform (DWT) [1, 2]. Mixture of Expert (ME) and Optimum Path Forest (OMD) classifier to classify the signals into normal and epileptic. A classification accuracy of as high as 94.5% and

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89.2% were obtained respectively. The author of Boualem Boashash and Samir Ouelha [3] used Sequential Forward Feature Selection (SFFS) technique for feature extraction and time frequency distribution (TFD) based machine learning technique as a classifier. By this method, a total accuracy of 86.61% can be achieved. N. Kannathal, Min Lim Choo, U. Rajendra Acharya and P. K. Sadasivan utilized entropy estimator to distinguish between EEG of normal subjects and epileptic patient. Results were tested using ANFIS classifier which showed that an accuracy of about 90% [4]. Time Frequency Image (TFI) of the signal by using Smoothed Pseudo Wigner- Ville Distribution (SPWVD) based time-frequency representation (TFR) was done by Varun Bajaj and Ram Bilas Pachori [5]. The feature extracted were then given as input to multiclass least squares support vector machines (MC-LS-SVM) along with radial basis function (RBF), Mexican hat wavelet and Morlet Wavelet kernel functions used for classification of sleep stages which gave an accuracy of 92.93%.
In this paper, authors classified the EEG signal by using EMD and LVQ.

II. THE ACQUISITION OF EEG SIGNALS

All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. After 12bit analog -to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. The time series have the spectral bandwidth is 0.5 Hz to 85 Hz. Five sets (denoted A–E) each containing 100 single-channel EEG signals of 23.6s duration, were selected due to muscle activity or eye movements. Sets A and B consisted of signals taken from surface EEG recordings that were carried out on regular volunteers in regular condition using a standardized electrode placement scheme. Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C comprises of EEG data derived from sneezing regular volunteers. Set D- E originated from the EEG data from volunteers suffering from epilepsy under sneezing (D) and normal condition (E) respectively.

III. OVER VIEW OF EMD

It is a fundamental part of Hilbert–Huang transform (HHT) which was proposed by Huang et al [7]. The basis of EMD is to decompose a signal into so-called Intrinsic Mode Functions (IMFs). IMFs helps refining the non-stationary signal into a more smooth and continuous signal following a repetitive approach. This approach involves deriving the 1^{st} IMF, deducing an envelope enclosing the extremas of the function, take the average, subtract it from the waveform of the main signal to obtain the next IMF and continue until the conditions satisfies and no more component can be derived any further.

EMD follows a repetitive or iterative technique for signal decomposition known as Sifting.

It can be summarized as:

Considering the signal to be: s (t)

1) Identify local maxima and minima of distorted signal s(*t*)
2) Interpolate respective minima and maxima to obtain two envelopes

$e_m(t)$ and $e_l(t)$.

3) Compute the average(mean) as:

$m1(t) = (e_m(t) + e_l(t))/2$

4) Extract the detail as:

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c1 (t) = s(t) –m1(t)

5) Check whether c1(t) is an IMF or not
6) If not step 1-4 are repeated until the new c1(t) obtained satisfies the conditions of an IMF. An appropriate stopping criterion can be used for avoiding 'over-improving' c_1(t) as that can lead to significant loss of information.
7) Compute the residue:

r_1 (t) = s(t) – c_1(t),

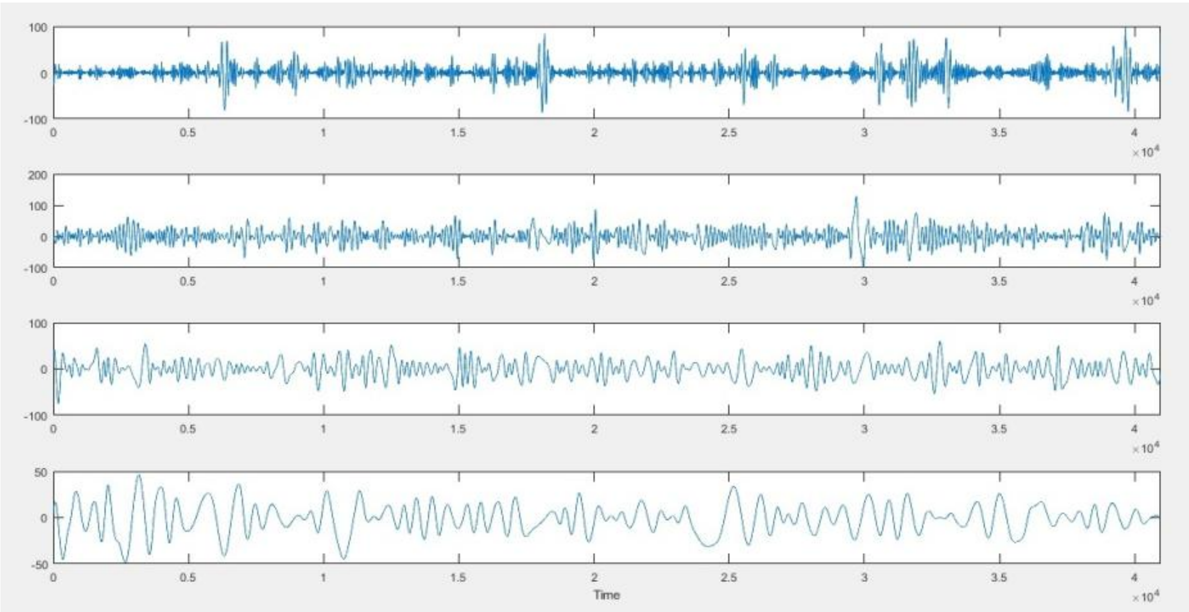
If the residue, r_1 (t), is above a threshold value of error tolerance, then repeat steps 1-6 on r_1(t), to obtain the next IMF and a new residue.

The first IMF obtained, consists of the highest frequency components present in the original signal. The subsequent IMFs obtained, contain progressively lower frequency components of the signal.

If n orthogonal IMFs are obtained in this iterative manner, the original signal may be reconstructed as:

$$s(t) = \sum_{n} c_i(t) + r(t)$$

In this paper the proposed EMD technique has been applied upon five datasets in order to find out IMFs and from this extract features. For a comparable distinction and assessment, several statistical parameters have been derived out of these datasets namely: mean, median, mode, maximum, minimum, standard deviation. Using EMD technique 7 IMFs were derived out for each of the datasets. Forty two features are extracted. Set- A, set-B, set-C, set-D and set-E signals and its six IMF and residual as shown in Fig.1 (a, b, c, d, e)



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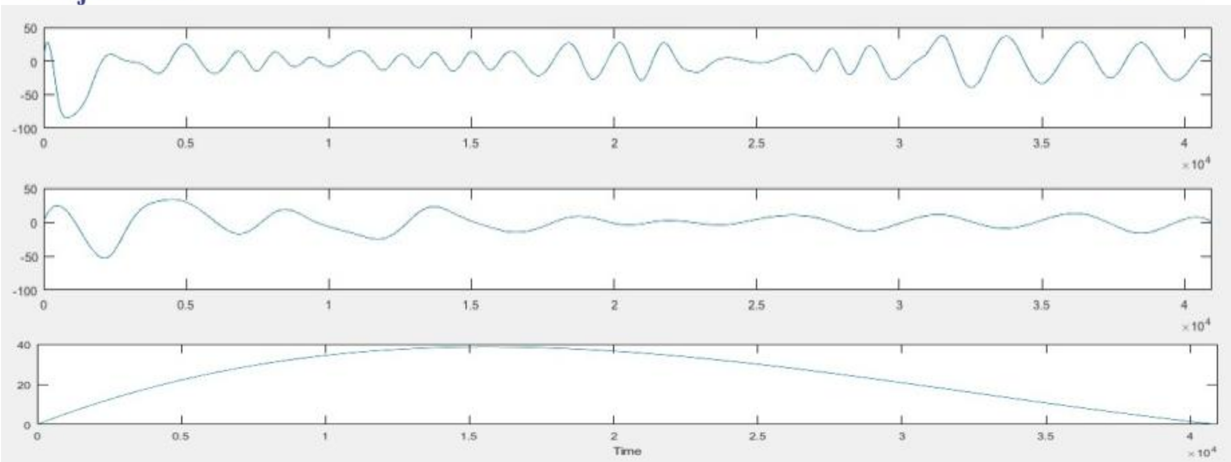

Fig.1.a: Normal EEG with eyes open condition (6 IMFs, 1 residue)

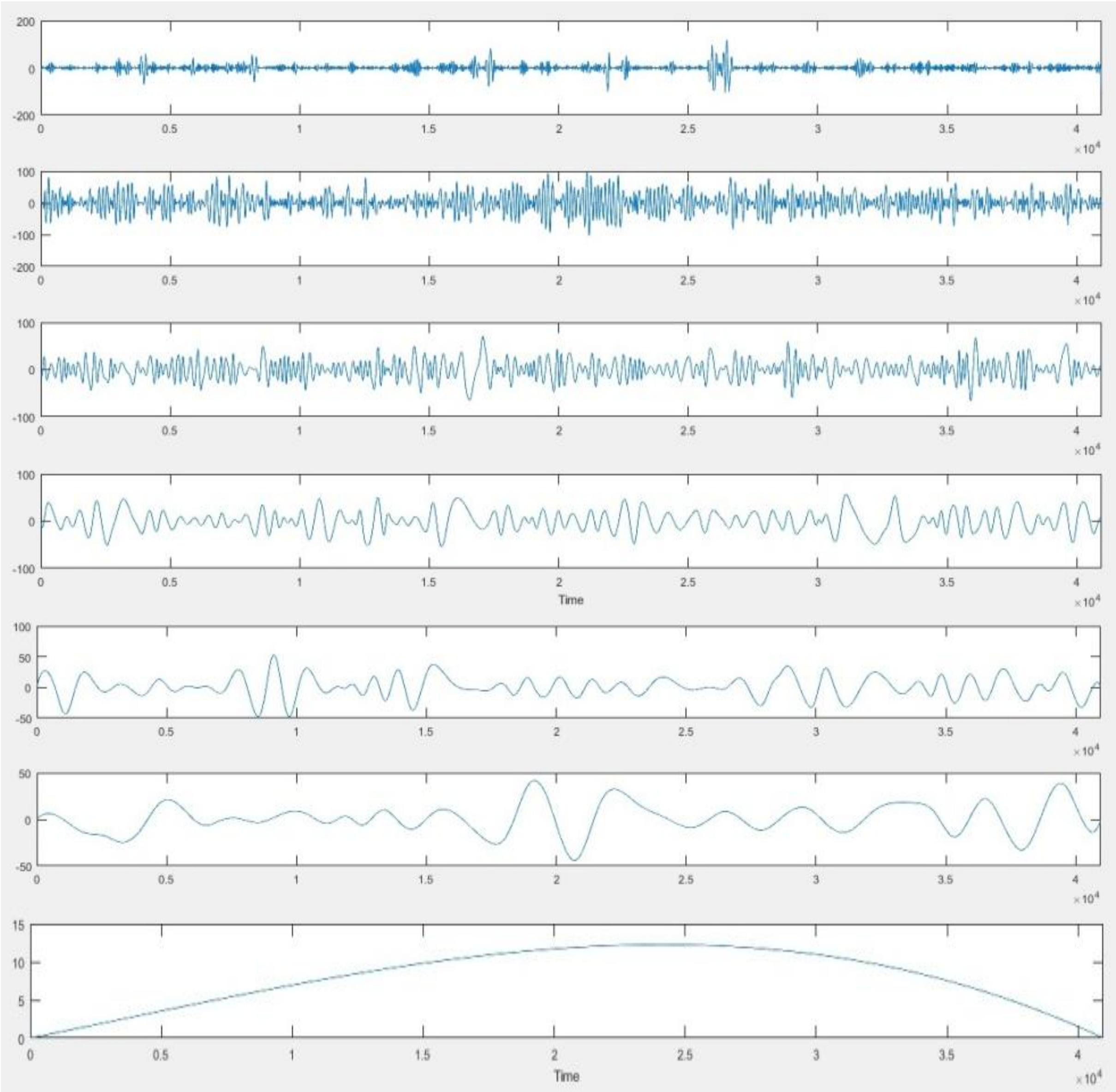

Fig.1.b: EEG with eyes closed condition (6 IMFs, 1 residue)

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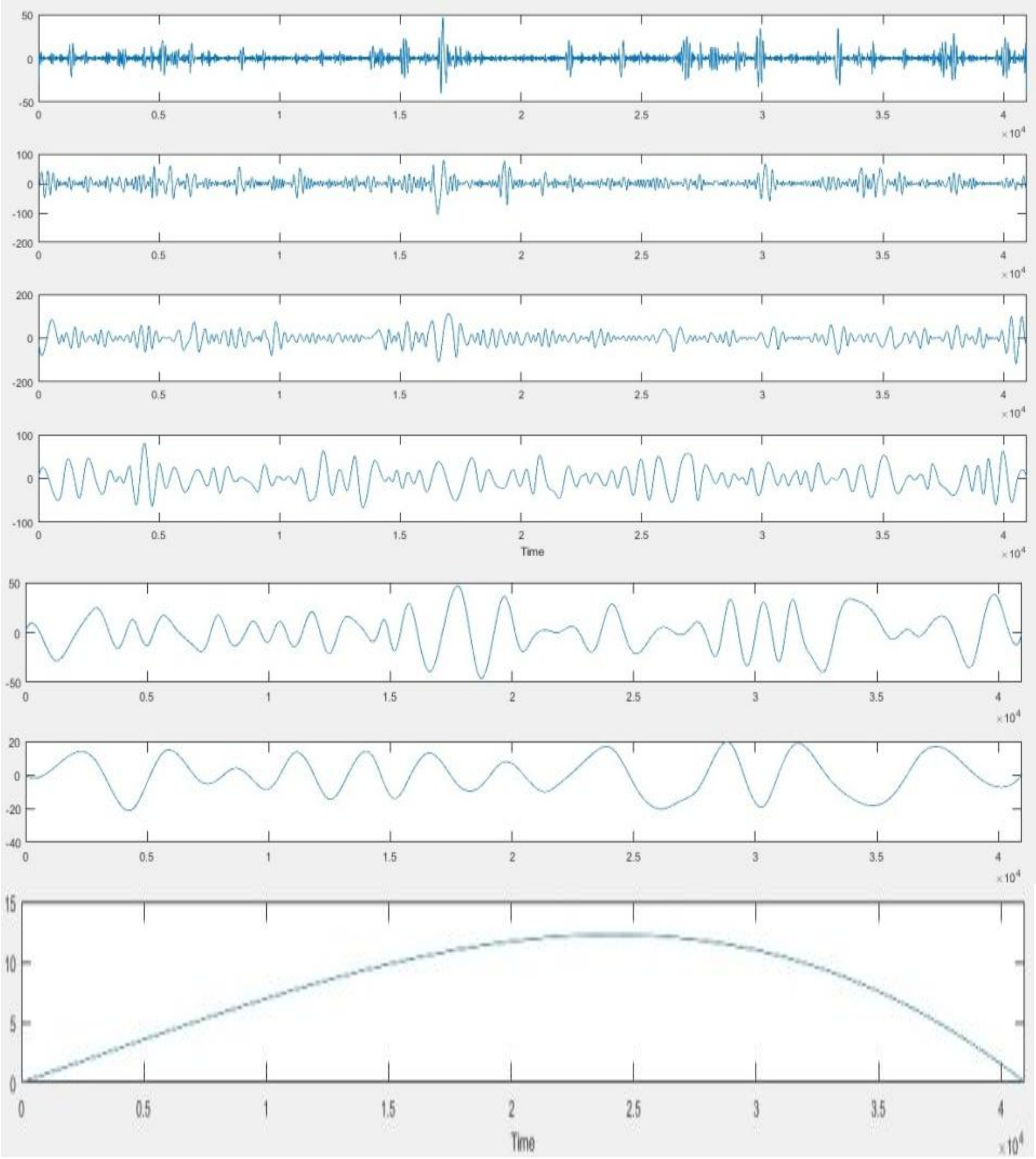

Fig.1.c: EEG measured during seizure free intervals from the hippocampal formation of the opposite hemi-sphere of the brain (6 IMFs, 1 residue)

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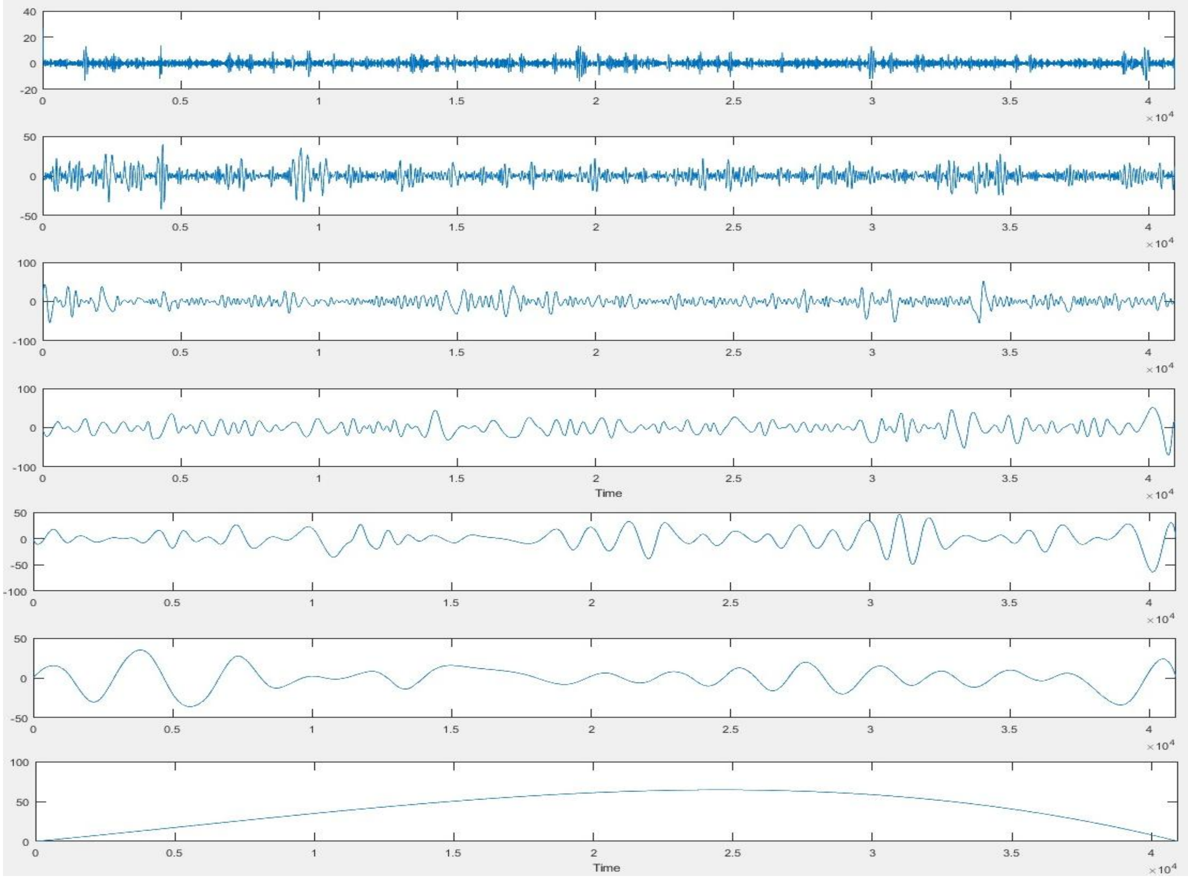

Fig.1.d: EEG measured during seizure free intervals from within the epileptogenic zone (6 IMFs, 1 residue)

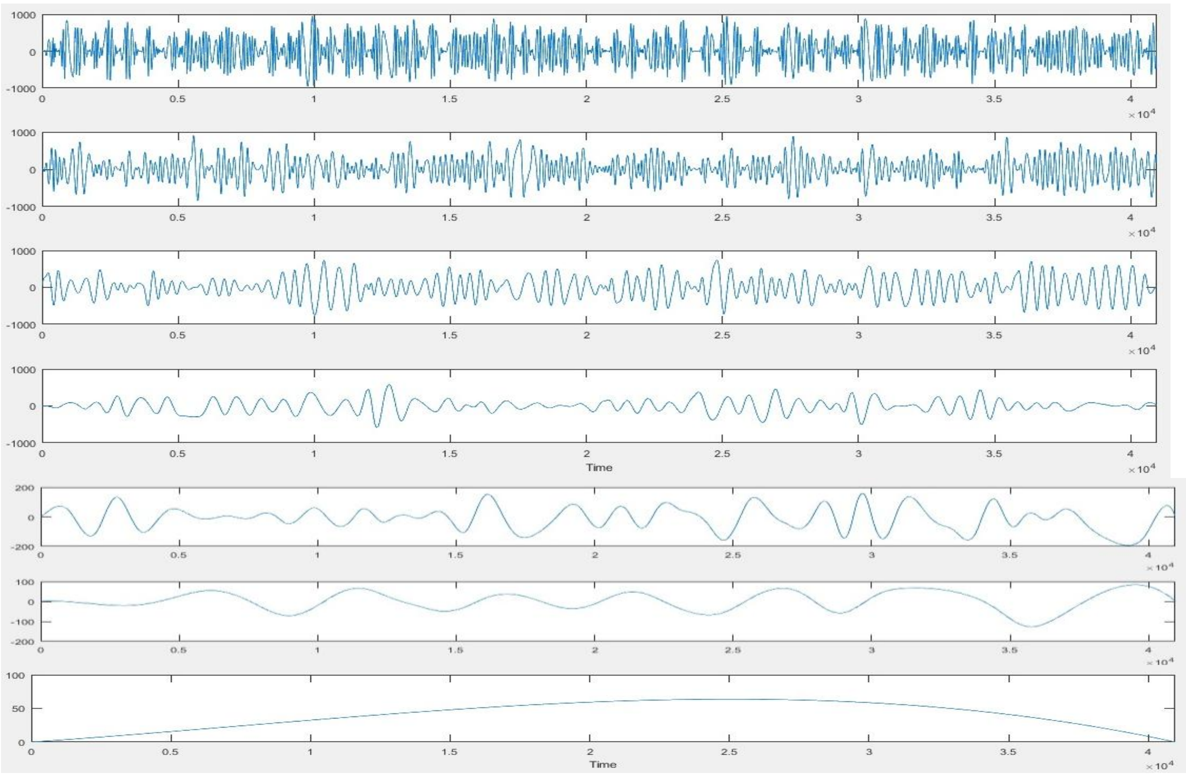

Fig.1.e:Epileptic human under normal condition (6 IMFs, 1 residue)

Furthermore for classification of these extracted features, an algorithm known as LVQ (Learning Vector Quantization) is imposed upon them to classify the EEG signal.

IV. LVQ

Learning Vector Algorithm is a feed forward neural network (ANN) based on winner take all hebbian learning. It was introduced by T Kohenen [8] as a simple and efficient algorithm. It is a supervised version of vector quantization that can be used when we have labeled input data. It improves the quality of classifier decision regions by repositioning the voroini vectors by using the class information.

This classification method is much more efficient because the number of vectors that should be stored or compared with is significantly reduced. In this paper authors used LVQ1 and LVQ2.1 algorithms. Learning vector quantization (LVQ) is used for pattern classification.

The architecture of Kohonen's Neural network that implements LVQ operations is shown in Fig. 2. It consists of three layers; named input, hidden called competitive, and output called linear layers. The weights of the input-competitive links represent the codebook vectors. They are M-dimensional vector, as the input vectors that are positioned in the input data space to identify cluster regions.

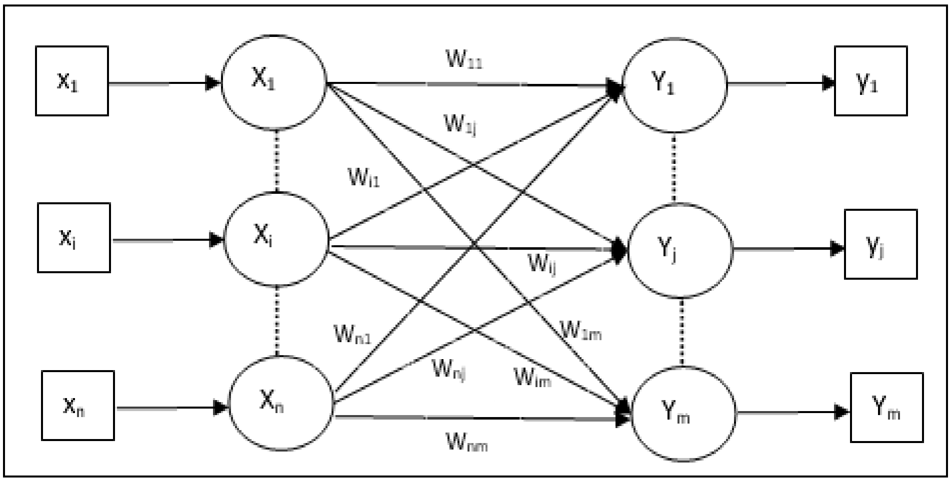

Fig.2: Architecture of LVQ

V. CONCLUSION

The primary focus of the paper dealt with application of above discussed techniques and methodologies for drawing out a comparison and proper classification of the neural response of the human brain functioning under normal condition and the one showing symptoms of some sort of neurological disorder. The disorder under study in this report one was Epilepsy. It is also the fourth most common neurological disorder in the world. In future this method can be applied to Multi Classification system.

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