



MSBE Analysis with Power Metric for Automated Identification of Epileptic Seizure

Hemlata Pal, Abhay Kumar

Abstract: *Objective-This study explores a novel application of multi scale bubble entropy analysis with power metric analysis to achieve efficient epileptic seizure prediction performance. Method-This paper aims to develop a reliable seizure detection technique that incorporates AM FM model for decomposition of EEG into different sub bands. The initially first feature set is formed by acquiring the absolute and relative power components at each electrode. Second feature set is constructed by multi scale bubble entropy analysis from each sub band. These two major feature vectors are fuse into an integrated feature space to perform classification task using ANN. Result-Experimental results show that this method presents: 1) Consistent increase in complexity measures, 2) Increase in stability & discrimination of power. These finding suggest that extracted features can be used for treatment of epilepsy. Significance- This method provides greater stability, so this technique could be used to detect wider range of seizures.*

Keywords: *Epilepsy, EEG, Multi scale bubble entropy, Relative power, Seizure detection*

I. INTRODUCTION

Epilepsy is a serious neurological disorder and it is associated with spontaneous debilitating seizures. EEG recording is required for definitive diagnosis of epilepsy. Monitoring of human brain activity is performed by EEG. EEG technology uses sensors and mounting electrodes to provide electrical metrics of brain. EEG modality has great potential in helping us to understand the concurrent neural activities of brain. EEG is the electrical brain potential and it represents the summation of electrical activities of millions of neurons. Existing approaches for detection of epileptic seizures can be broadly classified on the basis of linear feature extraction and nonlinear feature extraction. There have been several methods for prediction of seizures using linear features such as amplitude, frequency, relative power and energy [3], [6], [7], [11], [13] which provides basic information, but they usually exhibit common drawback of inconsistent performance. In another category of approaches that exploits nonlinear characteristics of EEG, such as HOS, correlation and entropy [1], [8], [11]. Entropy has been extensively used for

computation of features from EEG for automated diagnosis of epilepsy [2], [4], [5], [10], [12]. Several research groups have also worked on method which involves features computation of entropy at multiple scales [20], [15]. This entropy analysis performed feature extraction using sample entropy at multiple scales and is able to provide more detailed information of EEG signal. Some of these entropy measures can have some limitations such as scale factor (r) and embedding dimension (n) to discriminate EEG signal of different complexity. Another recently developed approach termed as bubble entropy analysis [22], computes bubble entropy based on permutation entropy. This method is almost free of the parameter that means it removes the requirement of scale factor and minimizes the importance of embedding dimension for analysis of EEG signal. It provides remarkable stability at original time scale.

In this paper, we make effort to explore the utility of multi scale bubble entropy analysis with power metric suitable for epilepsy detection by employing integrated feature set.

- 1) At first, AM FM model is used to decompose an EEG signal according to its frequency content and identify absolute power and relative power quantities at each electrode.
- 2) Second, multi scale bubble entropy analysis is performed to achieve remarkable stability and discriminating capability.
- 3) Application of an integrated feature vectors to produce intelligent classification working program.

In the rest of the paper, we first present the methodology. In section III experimental results are discussed. This section is followed by the conclusion.

II. PROPOSED METHODOLOGY

A. AM FM model

The frequency band that contains information relative to seizure detection task lies in the frequency spectral range of 0-40Hz. This spectral frequency range is divided into five different sub bands namely, delta, theta, alpha, beta and gamma sub bands. In our method, AM-FM model is used for decomposition of EEG signal into these sub bands. EEG signals are multi component signal that can be considered as superposition of mono component signal. Each EEG epoch can be represented by AM-FM model and being characterized by amplitude parameter and phase parameter. Therefore multichannel EEG signal could be formulated as summation of mono component EEG epochs of $E_y(n)$ and it can be defined as follows:

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$$E(n) = \sum_{y=1}^n A_y(n) \cos \Psi_y(n) + N_y \quad (1)$$

Where $A_y(n)$ is the instantaneous amplitude component, $\Psi_y(n)$ represent the instantaneous phase component and N_y is the additive noise and error.

B. Feature extraction

It is well documented that absolute power and relative power of EEG signal in different band are correlated with affective state of human brain. Therefore we consider the power metric first for feature computation and then entropy analysis is performed for complexity measurement.

Absolute power-In the first step, absolute power is extracted from each of 19 electrodes, in order to be used as features leading to a total of 84 features. F_{AP} is defined as:

$$[F_{AP} = F_{A\delta 1}, F_{A\theta 1}, F_{A\alpha 1}, F_{A\beta 1} \dots F_{A\delta 19}, F_{A\theta 19}, F_{A\alpha 19}, F_{A\beta 19}] \quad (2)$$

Relative power- The relative spectral power (P_R) of EEG signal at each electrode is defined as:

$$P_R = 10 \log_{10}(P_{ij}/P_i) \quad (3)$$

$$i \in \{ \delta, \theta, \alpha, \beta \}$$

$$j \in \{ 1, 2, 3, \dots, 19 \}$$

Where P_i is the pooled spectral power and P_{ij} is the average spectral power in different frequency sub band ($\delta, \theta, \alpha, \beta, \gamma$). Relative power is determined from nineteen region of brain for computation of second feature set (F_{RP}). (F_{RP}) can be represented as:

$$[F_{RP} = F_{R\delta 1}, F_{R\theta 1}, F_{R\alpha 1}, F_{R\beta 1} \dots F_{R\delta 19}, F_{R\theta 19}, F_{R\alpha 19}, F_{R\beta 19}] \quad (4)$$

C. Bubble entropy

Bubble entropy is defined as entropy which is almost free of parameters. Bubble entropy provides higher stability because of two key features: 1) Elimination of necessity of scale factor (r). 2) Minimize the importance of embedding dimension (m). Bubble entropy is basically based on combination of conditional permutation entropy and renyi's entropy. Initially, it is computed from permutation entropy, but they usually exhibit common drawback of unconditional and non descriptive performance. Permutation entropy is given as:

$$E_{pe} = - \sum_{k=1}^i p(jk) \log(p(jk)) \quad (5)$$

J_k is time series of vectors which is constructed using sorting process from EEG.

To make the output performance to be more descriptive, renyi's entropy is also used. Renyi's entropy is defined as:

$$E_R = - \log \sum_{k=1}^i p(k)^2 \quad (6)$$

Therefore a combination of permutation and renyi's entropy is used which provides both conditional and descriptive metric. Conditional renyi's permutation entropy is given as:

$$E_{CRPeN} = (E_R^{n+1} - E_R^n) / \log(n+1) \quad (7)$$

Where the factor $[1/ \log(n+1)]$ is used for normalization purpose and n is the embedding dimension.

Bubble entropy analysis utilize bubble sort algorithm and count the number of swaps necessary to sort vectors in ascending order and then computes CRPeN entropy from EEG signal at multiple scales.

$$E_B = (E_{swaps}^{n+1} - E_{swaps}^n) / \log(n+1 / n-1) \quad (8)$$

Multi scale bubble entropy analysis is performed for construction of third feature set. (F_{MSBE}) can be given as:

$$[F_{MSBE} = F_{BE\delta}, F_{BE\theta}, F_{BE\alpha}, F_{BE\beta}, F_{BE\gamma}] \quad (9)$$

Finally, all three parameter set are used to construct final feature vector (F_T). F_T is defined as:

$$[F_T = F_{AP} + F_{RP} + F_{MSBE}] \quad (10)$$

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Database

In this paper, we have used EEG database provided by university of Bonn, Germany. This database contains normal EEG signal from healthy subjects as well as ictal EEG signal acquired from epileptic patient. EEG signals are sampled at 173.61Hz and having 12 bit A/D resolution. The signals utilize 128 channel amplifier systems for recording.

B. Results

We begin this subsection analyzing the power metric for epileptic seizure activity from EEG signal. The fig 1 shows the 3D view of brain with corresponding EEG at each electrode. The values for absolute power feature of four sub band for nineteen regions can be appreciated in graph in fig 2 and fig3. It can be seen from figure; in general, the features vectors attain higher values for epochs corresponding to seizure activity and lower values for non seizure EEG. The higher values of features are observed for seizure activity in most of electrode especially in theta and alpha band. The relative power graphs obtained for different sub band are presented in fig. 3 and fig 4. The increasing values of features are observed for seizure pattern, 16 out of 19 features experiencing it and in alpha sub band significant increase are observed. Thereafter the features of multi scale bubble entropy are summarized in table I. The complexity measures decreases for epileptic seizure pattern, so we attain lower values of bubble entropy for seizure activity and higher values for non seizure EEG.

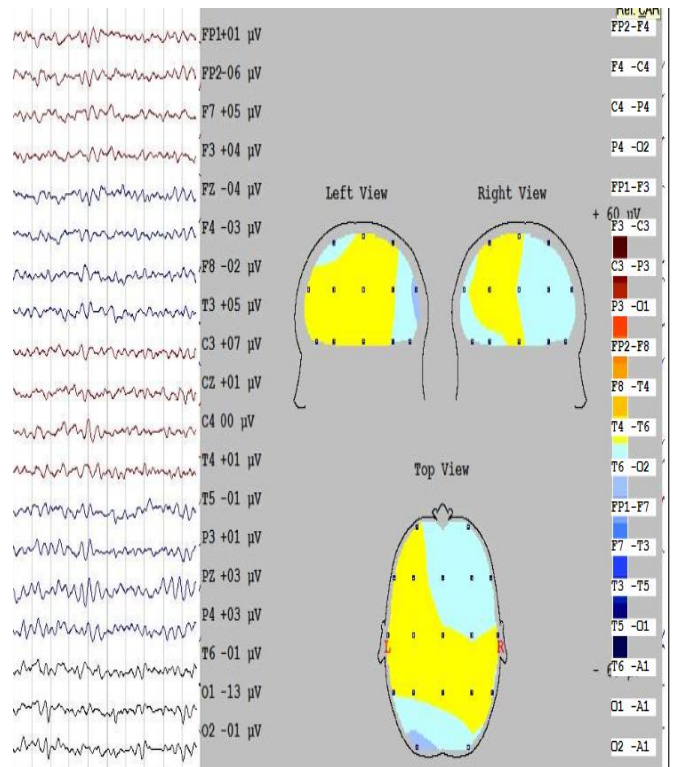


Fig.1. 3D view of brain

Table- I: Bubble entropy parameters for different sub bands

Sub-bands	Bubble entropy parameter		
	Frequency range	Seizure event	Non seizure event
DELTA	0-4 Hz	11.52	14.26
THETA	4-13 Hz	13.17	17.61
ALPHA	8-13 Hz	11.34	15.55
BETA	13-30 Hz	12.32	12.45
GAMMA	F> 30 Hz	11.31	11.38

Classification performance was assessed by measuring standard metrics: Accuracy and Sensitivity.
 TP- Seizure event correctly identified as seizure.
 TN- Non seizure event correctly identified as non seizure.
 FP- Non seizure event incorrectly identified as seizure.
 FN- Seizure event incorrectly identified as non seizure.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

Our result shows that, proposed method provides accuracy of 99.71%, sensitivity of 98.1%. Table II provides brief summarization of studies that presents various techniques for seizure detection using same dataset used in this study and hence results are comparable. Now we are able to answer that when we used these integrated feature vectors of MSBE and power metric, then ANN classifier is able to perform classification task with good accuracy.

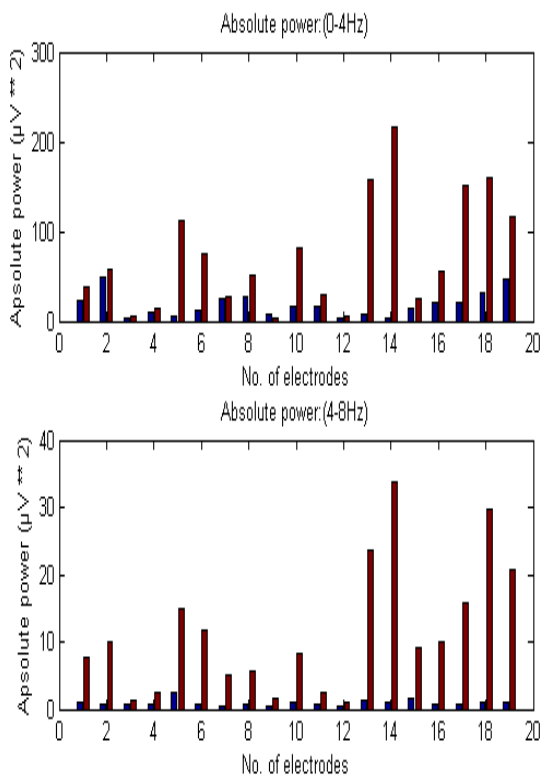


Fig. 2. Absolute power of delta and theta band

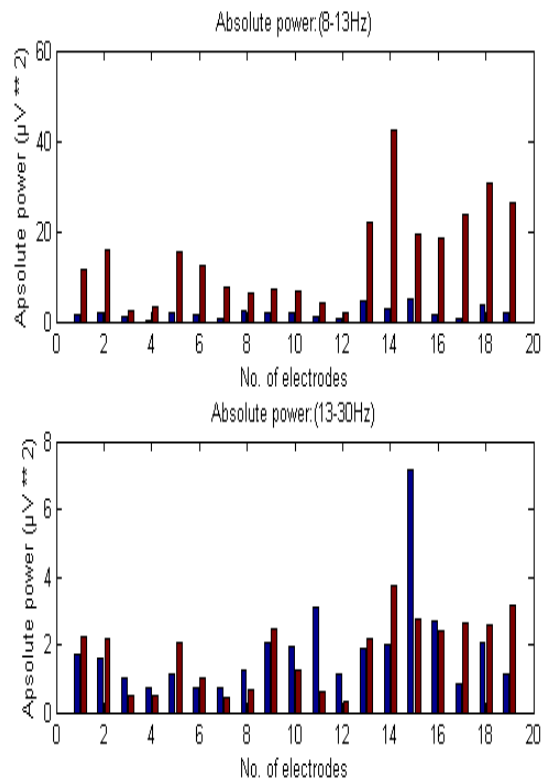


Fig. 3. Absolute power of alpha and beta band

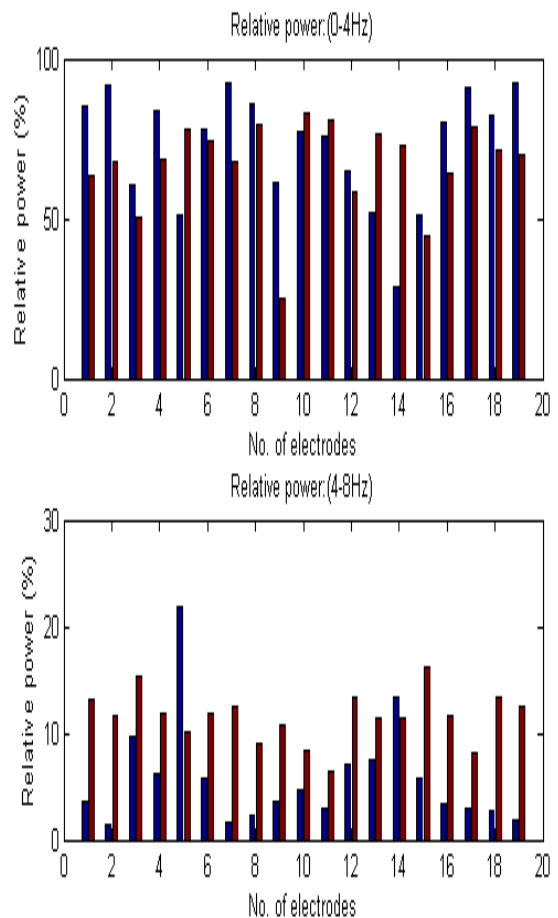


Fig. 4. Relative power of delta and theta band

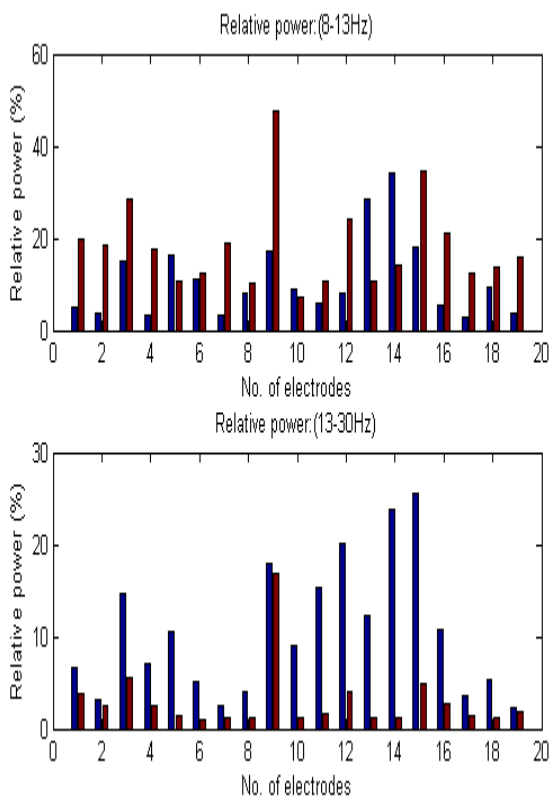


Fig. 5. Relative power of alpha and beta band

Table- II: Performance comparison with the previous works for classification of normal, pre seizure and seizure data

Authors	Method	Accuracy
K. C. Chua et al. (2009)	Higher order spectra analysis	93.1
Ocak et. Al. (2009)	ApEn and DWT	96
Guo et al. (2010a)	Line length	97.77
Guo et al. (2010b)	ApEn	98.27
Z. Shanksri (2011)	Energy	85.9
Orhan et al. (2011)	K mean clustering	99.6
Martis et al. 2012	Hilbert transform	95.3
Samiee et al. (2015)	Discrete STFT	98.1
Peker et al. (2016)	Complex value analysis	99.15
Ashwani et al. 2017	Histogram analysis	99.3
Bhattavharyya et al. 2017	Multi scale entropy analysis	99.4
Proposed method	MSBE analysis Power metric	99.71

IV. CONCLUSION

This study proposes a reliable method of automatic seizure detection that offers different level of complexity measures and remarkable stable performance. We have developed a novel method to identify and classify epileptic seizure pattern which is based on the multi scale bubble entropy analysis with the power metric analysis. It is able to fuse two major feature vectors into an integrated feature space (MSBE & power) to perform classification task with good accuracy and higher stability. The clinical significance of this novel

technique arises from its integrated feature vectors which include high accuracy of 99.71% and sensitivity of 98.1%.

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