Features Extraction and Classification for Ictal and Interictal EEG Signals using EMD and DCT

Mohammad Zavid Parvez  
School of Computing and Mathematics  
Charles Sturt University  
Bathurst, Australia  
Email: mparvez@csu.edu.au

Manoranjan Paul  
School of Computing and Mathematics  
Charles Sturt University  
Bathurst, Australia  
Email: mpaul@csu.edu.au

Abstract— Electroencephalogram (EEG) is a record of electrical signal to represent the human brain activity. Many researchers are working on human brain as they are fascinated by the idea of secret, thought and feeling from the external and internal stimuli. Feature extraction, analysis, and classification of EEG signals are still challenging issues for researchers due to the variations of the brain signals. Different features are used to identify epilepsy, coma, encephalopathies, and brain death, etc. However, we have observed that extracted features from same kinds of signal transformations are not effective to differentiate the epilepsy periods including \textit{Ictal} (active seizure period) and \textit{Interictal} (interval between seizures) of EEG signals. In this paper we present a new approach for feature extraction using high frequency components from DCT transformation. We also combine the new feature with the bandwidth feature extracted from the empirical mode decomposition (EMD). These features are then used as an input to least squares support vector machine (LS-SVM) to classify Ictal and Interictal period of epileptic EEG signals from different brain locations. Experimental results show that the proposed method outperforms the existing state-of-the-art method for better classification of Ictal and Interictal period of epilepsy for benchmark dataset.

Keywords- EEG, DCT, EMD, LS-SVM, Seizure, and Epilepsy.

I. INTRODUCTION

Brain consists of approximately 100 billion nerve cells, called neurons. It can be considered as an electro-chemical machine, because neurons use chemical reaction to generate electricity. When neuron is excited using external/internal stimuli, it passes electrical signals along its thin biological wire called axon to communicate with other neurons in the brain [1]. Electroencephalogram (EEG) measures the changes of electrical signals in terms of voltage fluctuations of brain within short period of time though multiple electrodes placed on the scalp. EEG signal can discover the information about brain and neurological disorder through the output of the electrodes [2]. Seizure is simply the medical condition or neurological disorder in which too many neurons are excited in the same time and the epilepsy is the another medical condition having spontaneously recurrent seizure. Thus, seizure can be considered as an electrical storm in the brain. During the seizure period the brain cannot perform normal task as a result people may experience abnormal activities in movement, sensation, awareness, or behavior. There are 1% of total population in the worldwide affected by epileptic seizure [3]. The detection of epileptic seizure plays important role for medical diagnosis of epilepsy. The main diagnosis of EEG signal is epileptic seizure detection to investigate brain disorder. Moreover, the analysis of EEG signal has many other applications such as video quality assessment [4], emotion recognition [5], and alcohol consumption measurement [6], etc.

Feature extraction is a key factor of proper classification of EEG signal. Several techniques, including wavelet transform [3][7][8] and Fourier transform [9], have been developed for detection of epileptic seizure. Dastidar et al. [7] used the wavelet transform to extract feature for different bands (delta,
theta, alpha, and beta) and neural network as a classifier. Ocak [8] proposed fourth-level wavelet packet decomposition for various frequency bands to differentiate normal and epileptic EEG signals. Liang et al. [10] used combination of complexity analysis and spectrum analysis features to perform classification of seizure and non-seizure EEG data. Pachori [11] used mean frequency metric of intrinsic mode functions (IMFs) as a feature to differentiate seizure and non-seizure EEG signals for small Epilepsy data set consists of five subsets, each containing 100 single-channel EEG signals with 23.6 seconds [15]. Among them two subsets (i.e., non-seizure dataset) are taken from healthy volunteers, two subsets (i.e., Interictal) are taken from seizure free intervals and one subset (i.e., Ictal) is taken during seizure period from five patients captured by 32 electrodes [15]. Panda et al. [3] produced different features, such as energy, entropy and standard deviation from wavelet transformation to classify Epileptic EEG signals using support vector machine (SVM) [13]. The experimental results show that the classification accuracy is nearly 91.2% using the dataset [15]. Bajaj et al. [12] proposed a technique for classification of seizure and non-seizure EEG signals using the amplitude and frequency modulation bandwidth derived by empirical mode decomposition (EMD) on the dataset [15]. They used least squares SVM (LS-SVM) [14] as a classification technique. The experimental results show that the best accuracy result among the tests for LS-SVM classifier, with radial basis function (RBF) kernel using amplitude and frequency modulation parameters, is 98.5%.

The large dataset comprising Ictal and Interictal signals from Temporal Lobe location of human brain is shown in Fig 2. For clear visualization we have shown only a small portion of time (i.e., 4000 samples) of EEG signal from the dataset [16]. From the data we can easily observe that Interictal signal has more variations compared to Ictal signal. Thus, any transformation, which has the ability to decorrelate data, can be applied on the Ictal and Interictal signals to differentiate them. For this, we apply DCT (Discrete Cosine transformation) on 4000 samples of the Ictal and Interictal signals and the results are shown in Fig 3. For clearer visualization only first 200 DCT coefficients are shown in the first row and first 200 DCT coefficients from last quarter of coefficients are shown in the second row. First row in Fig 3 shows that DCT coefficients of Ictal signals are different from Interictal signal where large magnitude coefficients are concentrated in the low frequency areas (i.e., beginning part of the signal) for the Ictal signals compared to that of Interictal signals. On the other hand, the second row shows that the magnitude of high frequency coefficients is larger for Interictal signal compared to that of Ictal signal. Since the variance of a signal is reflected into the
high frequency DCT coefficients, our hypothesis is that the characteristic (i.e., magnitude differences) of high frequency DCT coefficient can be a good feature to distinguish Ictal signal from Interictal signals. If we use recorded data for a time window (e.g., 4000 samples) and apply DCT coefficient characteristic, we can avoid the effect of non-stationary and non-linear characteristics of EEG signal analysis.

In this paper, we proposed a classification technique using two features namely entropy and energy from the high frequency DCT coefficients from Ictal and Interictal signals and then classify Ictal and Interictal signals using LS-SVM using entropy and energy. We used energy and entropy features for classification since those features can exploit magnitude of high frequency components of the DCT coefficients. The last row of Fig 3 clearly demonstrates that the value of entropy in Ictal signal for 200 signals (the last quarter of DCT coefficients are only considered for each signal) is higher compared to that of Interictal signal. We also proposed another technique by combining DCT feature and EMD features for better classification. Our experimental results show that these two features have better classification accuracy compared to the state-of-art method proposed by Bajaj et al. [12] for the benchmark dataset [16] for different locations of human brain.

II. PROPOSED METHOD

We proposed two techniques in our experiment. In the first technique we extracted entropy and energy features from DCT. In the second technique, we used entropy from DCT transformation and bandwidth parameter from EMD. In this experiment, it has been used the dataset [16] of six patients from Ictal and Interictal data of temporal lobe. Details procedure of feature extractions and classifications are provided in the following sub-sections.

A. Dataset

The data were recorded at Epilepsy centre of the University Hospital of Freiburg, Germany [16]. The data obtained by Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and 16 bit analogue-to-digital converter. There was line noise 50 Hz and notch filter used to remove line noise. Data recording temporarily paused after each block due to technical reasons and pause time 1-3 seconds. For each of the patients, there are datasets called Ictal and Interical. Firstly, system containing epileptic seizures file with 50 pre-ictal data. Later on, it was containing 24h of EEG recording without seizure activity. The Ictal periods were determined based on identification of typical seizure patterns of experienced epileptologists. In our experiment, we used Ictal and Interical dataset of Temporal Lobe along six patients with 10 minutes duration. The representation of the dataset is in Fig 2.

B. Feature Extraction using EMD

Empirical mode decomposition can successively separate the intrinsic oscillatory modes of signals into a finite number of IMFs. The IMFs of EEG signals are ordered from highest frequency component to the lowest frequency components. The algorithm includes the following steps: i) calculated the IMF for each iteration using EMD on EEG signals, ii) calculated two features namely instantaneous frequency and amplitude using Hilbert transform applied on IMFs for each iteration and iii) combined those two features to generate bandwidth parameter. The process of EMD briefly descrit in [12]. Representation of IMFs of Ictal and Interical dataset for iteration is shown in Fig 4 and Fig 5 respectively. After generating the final IMF, the decomposition of original signal, $x(t)$ can be written [12] as:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t)$$

(1)

where $n$ is the number of IMFs, $c_i$ is the $i^{th}$ IMF and $r_n$ is the final residue. Seven IMFs are given in Fig 4 and Fig 5.

Hilbert transformation is then applied on IMFs to generate analytic IMFs. The analytic signal amplitude $A(t)$ is defined in [12] as :

$$A(t) = \sqrt{c_i^2(t) + c_i^2(t)}$$

(2)
Where \( c(t) \) is the IMF and \( c_i(t) \) refer to Hilbert transform of IMF. The instantaneous frequency \( \omega(t) \) is defined as:

\[
\omega(t) = \frac{d\phi(t)}{dt}
\]

(3)

where \( \phi(t) \) is instantaneous phase. Then calculate the centre frequency which can be defined as:

\[
\langle \omega \rangle = \frac{1}{E} \int \omega |Z(\omega)|^2 d\omega
\]

(4)

where \( E \) is the energy of analytic signal and \( Z(\omega) \) is the Fourier transform of analytic signal. The amplitude and frequency modulation bandwidth are defined respectively [12] as:

\[
B_{am}^2 = \frac{1}{E} \int |\phi(t)|^2 dt
\]

(5)

\[
B_{fm}^2 = \frac{1}{E} \int \langle \omega \rangle |\dot{\phi}(t)| dt.
\]

(6)

The technique in [12] used two features \( B_{am} \) and \( B_{fm} \) for classification and provided around 98.5% accuracy for small dataset [15]. When we applied this technique on large dataset [16], it only provides 79% accuracy (details are in Section III).

C. Feature Extraction using DCT

In our experiment, we applied DCT on benchmark dataset [16] and taken last 25% of DCT coefficient (i.e., higher frequency components). These frequency components generated statistical feature such as entropy and energy which can distinguish Ictal and Interictal signal as described in the fourth paragraph of Introduction section. We defined entropy and energy of the high frequency coefficients in the similar fashion used in [3] as:

\[
\text{Entropy} = -\sum_{i=1}^{n} X_i^2(t) \ln(X_i^2(t))
\]

(7.1)

\[
\text{Energy} = \sum_{i=1}^{n} |X_i(t)|^2
\]

(7.2)

where \( n \) is the length of signal, \( X_i(t) \) is the higher frequency components of \( x(t) \). The representation of Ictal and Interictal data for different higher frequency components is given in Fig 3. The experimental results reveal that the entropy and energy of higher frequency DCT coefficients are the better features compared to bandwidth features for Ictal and Interictal dataset [16] while we applied on LS-SVM classification technique (details are in Section III). The accuracy is 83.25%.

D. Combined features using DCT and EMD

Bajaj et al. [12] formulated \( B_{am} \) and \( B_{fm} \) features from EMD are good for seizure and non-seizure small dataset, while the entropy and energy from DCT are good for large dataset. To exploit both kinds of features, we combined those features and make new features for better classification. In the combined features we have used entropy from DCT and total bandwidth parameter from EMD. The total bandwidth parameter is defined as:

\[
B = \sqrt{B_{am}^2 + B_{fm}^2}
\]

(8)

E. Classification

The efficiency of the amplitude/frequency bandwidth of analytic IMF and entropy/energy of DCT high frequency components in classifying the Ictal and Interictal signals is assessed using LS-SVM classification technique. SVM [13] is a potential methodology for solving problem in linear and nonlinear classification, function estimation, and kernel based learning methods. It can minimize the operational error and maximize the margin hyperplane, as a result it will maximize the classification performance [13]. LS-SVM [14] is the extended version of SVM and it is closely related to regularization networks and Gaussian process and it has primal-dual interpretations [14]. The equation of LS-SVM can be defined [12] as:

\[
f(x) = \text{sign} \left( \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \right)
\]

(9)

where \( K(x, x_i) \) is a kernel function, \( \alpha_i \) are the Lagrange multipliers [17], \( b \) is the bias term, and \( y_i \) is the training output pairs. RBF kernel is used in our experiments and this function can be defined as [12]:

\[
k(x, x_i) = e^{-\frac{|x-x_i|^2}{2\sigma^2}}.
\]

(10)

III. EXPERIMENTAL RESULTS

The EMD based method [12] decomposed the Ictal and Interictal signal into narrow band components which are represented as an IMF. Amplitude and frequency modulation bandwidths are generated from IMF that leads to compute Bandwidth parameter. Fig 2 shows the original signals and Fig 4 and Fig 5 show the IMFs of those signals. It can be observed that the order of IMFs represented from higher frequency to lower frequency component in Fig 4 and Fig 5 respectively. The method in [12] is considered as the state-of-the-art method because it is the latest and high accurate method in our knowledge. Thus, we have compared our results with the method. In the proposed DCT based method, we have applied the DCT in the large size dataset [16] and taken the higher frequency components to generate entropy and energy. Entropy and energy can distinguish Ictal and Interictal information according to the nature of amplitude. In another proposed method, we have used entropy and total bandwidth parameter features from DCT and EMD respectively.

For all techniques, we have classified the Ictal and Interictal data for Temporal Lobe signals using LS-SVM classifier with RBF kernel. In our experiment, we have used 200 signals from Ictal data and 800 signals from Interictal data of 10 minutes recording. We have combined the Ictal and Interictal dataset.
randomly. Then, for testing and training we have divided the whole dataset into 60% and 40% where 60% dataset is used for training and other 40% dataset is used for training.

It can be observed that DCT and combined features give us better classification accuracy for Temporal Lobe data. To verify the effectiveness of the proposed technique in other location of the brain, we have also applied the proposed techniques in the dataset of Frontal Lobe. Interestingly, we have observed that accuracy level of DCT is 70% and better accuracy i.e., 79% for combined features. The pictorial scenario of classification results are shown in Fig 10 and Fig 11 respectively. The combined features improve marginally for Temporal Lobe dataset; however, it improves significantly for Frontal lobe dataset. Thus, features from different transformations provide better results for different brain locations of EEG signal classifications.

Firstly we have applied EMD method [12] by training and testing of extracted features such as amplitude and frequency modulation bandwidth and achieved the classification accuracy 79% and the pictorial scenario of classification is shown in Fig 6. Secondly we have applied DCT and taken the higher frequency components and calculated energy and entropy as features. As a result, we have obtained 83.25% accuracy and the pictorial scenario of classification is shown in Fig 7. Finally we have taken two features from EMD and DCT such as total bandwidth parameter (8) and entropy (7.1) and achieved 83.5% accuracy. The pictorial scenario of classification is shown in Fig 8.

Fig 9 shows the distribution of Ictal and Interictal dataset for different features. This figure shows that the data distribution is higher for Ictal data based on energy and entropy compared to Interictal data. On the other hand, the Interictal data distribution is higher for amplitude modulation, frequency modulation, and bandwidth parameter compared to Ictal data.

IV. CONCLUSIONS

We proposed a new approach based on energy and entropy features from high frequency DCT coefficients to classify Ictal and Interictal EEG signals using LS-SVM classifier. The magnitude of high frequency DCT coefficients for Ictal and Interictal signals are different, thus, entropy and energy extracted from high frequency DCT coefficients are the good features to distinguish Ictal and Interictal signals. We also proposed another method by using two features namely bandwidth of analytic IMFs (i.e., total bandwidth defined in...
(8)) and entropy from EMD and DCT respectively for better classification. The experimental results show that the proposed DCT-based method outperforms the EMD-based method for Temporal Lobe method. The experimental results also show that the combined method outperforms the DCT-based method for different location EEG signals such as Temporal and Frontal Lobe areas.

In future we like to apply the proposed techniques for EEG signals from other locations of brain. We also investigate other features extracted from different transformations/decompositions techniques for better accuracy. It would be interesting to investigate EEG signals for different applications such as subjective quality assessments, alcoholic effect assessment, and emotion recognition.

Fig 10: Classification of Ictal and Interictal EEG signals from Frontal lobe for testing set using DCT method along LS-SVM classifier with RBF kernel.

REFERENCES


[16] EEG Data set from Epilepsy Center of the University Hospital of Freiburg, http://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database, Visited Date: June 10, 2012.