Epileptic Seizure Detection by Analyzing EEG Signals using Different Transformation Techniques

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ABSTRACT

Feature extraction and classification are still challenging tasks to detect ictal (i.e., seizure period) and interictal (i.e., period between seizures) EEG signals for the treatment and precaution of the epileptic seizure patient due to different stimuli and brain locations. Existing seizure and non-seizure feature extraction and classification techniques are not good enough for the classification of ictal and interictal EEG signals considering for their non-abruptness phenomena, inconsistency in different brain locations, type (general/partial) of seizures, and hospital settings. In this paper we present generic seizure detection approaches for feature extraction of ictal and interictal signals using various established transformations and decompositions. We extract a number of statistical features using novel ways from high frequency coefficients of the transformed/decomposed signals. The least square support vector machine is applied on the features for classifications. Results demonstrate that the proposed methods outperform the existing state-of-the-art methods in terms of classification accuracy, sensitivity, and specificity with greater consistence for the large size benchmark dataset in different brain locations.

1. Introduction

The human brain processes sensory information received by external/internal stimuli. Human brain is an organic electrochemical computer as neurons exploit chemical reaction to generate electricity [1]. Electroencephalogram (EEG) is a graphical record of ongoing electrical activity, which measures the changes of the electrical activity in term of voltage fluctuations of the brain through multiple electrodes placed on the brain [2]. In the clinical contexts, the main diagnosis of EEG is to discover abnormalities of brain activities referred to the epileptic seizure. A seizure occurs when the neurons generate uncoordinated electrical discharges that spread throughout the brain and epilepsy is a recurrent seizure disorder caused by abnormal electrical discharges from brain cells, often in the cerebral cortex [3]. Another clinical use of EEG is in diagnosis of coma, brain death, encephalopathies, and sleep disorder, etc. Moreover, EEG can be used in many applications such as emotion recognition [4], video quality assessment [5], alcoholic consumption measurement [6], sleep stage detection [7], change the brainwaves by smoking [8], and mobile phone usages [9], etc.

People may experience abnormal activities in sensation, movement, awareness, and behavior during seizure as a result they cannot perform normal task. Ictal and interictal both are medical condition of seizure where ictal represents the period of seizure and interictal represents the intermediate period between two seizures. Note that interictal is significantly different from normal non-seizure (mainly for healthy people) signal in terms of signal characteristics. A prediction of seizures (i.e., ictal) from interictal could aware a patient to put away from the next seizure and also can make sure better treatment and precaution. A number of existing EEG features extraction and classification techniques [11]-[17] are able to classify seizure and non-seizure EEG signals for a small size dataset almost perfectly. However, those methods are struggling to provide acceptable classification accuracy for ictal (i.e., seizure period) and interictal (i.e., period between seizures) EEG signals due to the non-abruptness and inconsistence phenomena [10] of the signals in different brain locations. Moreover, it is more challenging to get acceptable label of accuracy by a particular method if we do not have any domain knowledge of the available EEG signals due to different types of seizures (i.e., generalized or partial), patients, hospital setting, brain location, and artifact. Note that ictal signals are considered the EEG signals during the seizure period when a patient shows abnormal activities whereas interictal signals are considered as non-ictal signals between two seizure periods of an epileptic patient. Thus, we can consider the characteristics of interictal signal as a middle stage of non-seizure and ictal signals (although a patient may show normal brain activities similar to the non-seizure signals during the interictal period).

Existing methods [11]-[18] used small epilepsy dataset [19] (for detailed information of the dataset, see Section 3.1). The small dataset with duration 23.6 second has seizure (i.e., ictal) and non-seizure signals which can be distinguished by their visual phenomena such as magnitude of amplitude and changing rate of frequency (see in Figure 1 (a)). For the non-seizure signal the amplitude is low and the frequency is high while the nature of seizure signal is totally opposite (see Figure 1(a)). Figure 1(b)
and (c) show the ictal and interictal EEG signals from a large dataset [22]. The figure demonstrates the non-abrupt phenomena (i.e., not easily distinguishable between ictal and interictal based on amplitude and frequency) of the ictal and interictal signal for both cases of Frontal and Temporal lobes compared to the dataset in [19]. Moreover, EEG signals from different locations exhibit different phenomenal activities for an ictal and interictal period. Thus, classification of ictal and interictal EEG signals are challenging compared to that of seizure (i.e., ictal) and non-seizure EEG signals. It also demonstrates that the characteristics of EEG signals are varied from dataset to dataset.

Birvinskas et al [17] used DCT (discrete cosine transformation) to reduce the EEG signals and then extracted features from the reduced signals to classify EEG signals. They achieved good classification accuracy by keeping low frequency DCT coefficient for feature extractions. Worrell et al [33] claimed that the seizure onset frequencies are in the gamma frequency i.e., high frequency band (typically between 30 to 100 Hz). They explicitly mentioned that seizure onset frequencies are on the range of frequency $74.3 \pm 13.7$ and $23.7 \pm 6.2$ Hz for Frontal and Temporal lobes respectively. They also observed that dominant spectral peaks are observed in the high frequency spectral components for the Frontal lobe and in the lower gamma frequency for the Temporal lobe during the seizure period. Other literature such as Panda et al. [11], Ocak et al. [13], and Ghosh-Dastidar et al. [12] used other frequency bands such as delta, theta, alpha, and beta with gamma band to extract features for EEG signal classification. From the above findings and the characteristics of the different datasets, we find that the frequency range of seizure onset can be varied based on the brain location, seizure type (general/partial), patient, and hospital setting (e.g., capturing machine quality, artifacts, etc.). However, we observe that the signal has larger spikes i.e., high amplitude in the ictal (i.e., seizure) period compared to the interictal period.

To verify our hypothesis we perform an experiment to find the gamma frequency of signals which provides the maximum amplitude using ictal and interictal signals in different brain locations. The results for 200 EEG signals from ictal and interictal are shown in Figure 2. The figure reveals that relatively high gamma frequencies i.e., high frequencies in the signals provide the maximum amplitude of ictal compared to the interictal signals for both Frontal and Temporal lobes from different patients. We use the maximum amplitude criteria for the gamma band selection in this analysis as our observation and Worrell et al.’s observation indicate that dominant spectral peaks for the seizure onset are in the high frequency (i.e., gamma band). Thus, the features extracted from gamma frequencies i.e., the high frequencies should provide better classification accuracy between the ictal and interictal irrespective of the brain location, patients, type of seizure, and hospital setting.

Figure 1: Ictal and interictal EEG signals from different datasets and different brain locations: (a) Seizure and non-seizure EEG signals from the small dataset [19], the first row and remaining four rows indicated the seizure and non-seizure signals respectively [19], (b) ictal (patient one, 7th datablock, channel one) and interictal (patient one, 95th datablock, channel one) of Frontal lobe signals [22] and (c) ictal (patient 12, 15th datablock, channel one) and interictal (patient 12, 35th datablock, channel one) of Temporal lobe signals [22].
Based on the above mentioned observation, in this paper we proposed generic seizure detection techniques which use different established transformations and decompositions to get different statistical features from the high frequencies component of the signals to classify the ictal and interictal signals using the least square support vector machine (LS-SVM) [23]. Although we use a number of established transformation and decompositions, we use weighted high frequency coefficients to extract the features. In the experiment we investigate the strength of each transformation and decomposition for the capability of classification accuracy as well as the combined strength through different feature extraction. We use a large dataset [22] consists of raw ictal and interictal signals (no explicit artifact removal technique is applied) from different brain locations, different seizures, and patients to verify the performance of the proposed methods against two state-of-the-art methods. The experimental results demonstrate that the proposed generic methods outperform the existing methods in terms of accuracy (i.e., overall), sensitivity (i.e., ictal or positive), and specificity (i.e., interictal or negative) with greater consistency for the challenging ictal and interictal EEG signals classification.

The contributions and novelties of the proposed methods are in the capacity to (i) classify challenging ictal and interictal signals irrespective of brain location, patient, type of seizure, and hospital setting with a certain range of artifact tolerance, (ii) identify that high frequency component of EEG signals have the distinguishing features to classify ictal and interictal EEG signals, (iii) formulate a weighing vector for high frequency coefficients to provide individual importance of different coefficients, (iv) provide the rationality and way of extracting high frequency components from each transformation/decomposition technique, (v) to analysis EEG signals for seizure detection, best of our knowledge we are the first to use two dimensional SVD, (vi) identify the distinguishing features (provided pictorial comparison) for ictal and interictal signals for classification, and (vii) provide comprehensive result analysis using receiver operating characteristics (ROC) curve, Whisker-box, graphical view of classification outcome, and classification performance in terms of sensitivity, specificity, and accuracy.

2. Existing Methods for Seizure Detection

Existing feature extraction and classification methods based on wavelet [11]-[13] and Fourier transformation [14] were employed for the detection of seizure in EEG signals. Panda et al. [11] computed various features like energy, entropy, and standard deviation (STD) using discrete wavelet transformation (DWT) and used support vector machine (SVM) as a classifier. Dastidar et al. [12] applied wavelet transformation to decompose the EEG signals into different range of frequencies and then extracted three features, such as STD, correlation dimension, and the largest Lyapunov exponent (quantifying the non-linear chaotic dynamics of the signals) and applied different methods for classification. Ocak [13] proposed fourth level wavelet packet decomposition method to decompose the normal and epileptic EEG epochs to various frequency-bands and then used genetic algorithm to find optimal feature subsets which maximize the classification performance. Polat et al. [14] extracted feature using fast Fourier transform (FFT) and then classified using decision making classifier. The techniques [11] [12] [14] have used small dataset [19] (for detailed information of the dataset, see Section 2.1). Sample examples of the dataset are shown in Figure 1. (a) The classification accuracies were 91.20% [11], 96.70% [12], and 98.72% [14], respectively. Ocak’s [13] experimental dataset was the same pattern with the dataset in [19] and the classification accuracy was 98%.

Other feature extraction and classification methods [15]-[18] based on empirical mode decomposition (EMD), principle component analysis (PCA), and genetic algorithm (GA) have been proposed. Liang et al. [15] extracted EEG features where the approximate entropy (ApEn) analysis was evaluated for its ability to analyse multiclass EEGs, and the performance of ApEn analysis was enhanced by incorporating the power of EEG subbands or autoregressive models. PCA and GA were compared for their ability to select features by applying various linear and nonlinear methods for classification. The maximum accuracy was 98.67%. Pachori [16] decomposed EEG signals into intrinsic mode function (IMF) using EMD and then computed mean frequency for each IMF by Fourier-Bessel expansion [20] to differentiate seizure and non-seizure EEG signals. Zhang et al. [21] proposed an approach for the pattern recognition of four complicated hand activities, such as grasping a football, a small bar, a cylinder, and a hard paper, based on EEG signal, in which each piece of raw data sequence for EEG signal is decomposed by wavelet transform. After forming a matrix and then they applied singular value decomposition (SVD) on the matrix to find the singular value feature vectors. These features are used as input to artificial neural network to discriminate four hand activities and they got 89.00% classification accuracy.

Recently, Bajaj et al. [18] extracted amplitude modulation and frequency modulation bandwidth as features from IMF using EMD. Among the existing contemporary techniques, Bajaj et al.’s technique is the latest and the best in terms of performance. They used LS-SVM [23] technique for the classification of seizure and non-seizure EEG signals using the small dataset [19]. They obtained 98.0 to 99.5% accuracy using radial basis function.
We have observed that the existing methods [11]-[18] exhibit almost perfect classification accuracy for the small dataset of seizure and non-seizure EEG signals. However, their performance is below the expected results using the large dataset [22] for ictal and interictal EEG signal classifications. For example, when we applied Bajaj et al.’s [18] feature extraction and classification method to differentiate ictal and interictal EEG signals for the first IMF in the large dataset from Epilepsy Center of the University Hospital of Freiburg [22], the classification accuracy is 77.90% for Frontal lobe and 80.20% for Temporal lobe which is far below the accuracy 98.50% obtained using the small dataset [19] of seizure and non-seizure EEG signals.

The paper is organized as follows: the detailed of the proposed four methods with dataset, feature extractions, classification techniques, and computational time are described in section 3; the detail experimental results are explained in section 4 while section 5 concludes the paper.

3. Proposed Methods

In this paper, we propose four methods based on the various new features extracted from DCT, DCT-DWT, SVD, and IMF. We use the transformation and decompositions to separate high frequency components and then apply innovative ways to extract different statistical features. When we extract features from the high frequency component (i.e., IMF and detail signals respective) using EMD and DWT, we take total length of the high frequency components and we do not use any weighting for them as all the coefficients represent the high frequency components. As the SVD and DCT provide coefficients of all frequencies, we need to select a subset of the coefficients which can represent high frequency components. We investigate the strength of each transformation and decomposition for the capability of classification accuracy as well as the combined strength through different feature extractions. The dataset, individual method, their corresponding rationality, and detailed methodology of feature extractions are described in the following sub-sections.

3.1. Dataset

Small Dataset [19]: The existing seizure and non-seizure feature extraction and classification schemes [11]-[18] except [13] used small dataset [19]. The dataset consists of five subsets, each subset contains 100 single-channels recoding, and each recoding has 23.6 seconds in duration captured by the international 10–20 electrode placement scheme i.e., 32 electrodes [14]. Among them two subsets are taken from healthy volunteers, two subsets are taken from seizure free intervals and another subset is also taken during seizure period [18] (see sample examples in Figure 1 (a)). Ocak [13] used different dataset with the same pattern of small dataset where 300 were normal and 100 were epileptic patients.

Large Dataset [22]: Seizure and brain discharges are much more complicated than what can be seen in the scalp. Thus, in the paper we have used intracranial EEG dataset using grid, strip and depth electrodes rather than scalp EEG. The dataset used in the paper was recorded at Epilepsy centre of the University Hospital of Freiburg, Germany [22]. The database contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data obtained by Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and 16 bit analogue-to-digital converter. According to the dataset [22], epileptic EEG signals can be classified into (i) ictal (i.e., seizure), (ii) preictal (a certain period before seizure onset), (iii) interictal (period between seizures), (iv) non-seizure (period without any seizure activity after a certain time of interictal). Normally, duration of ictal is varied from few seconds to 2 minutes. The ictal records contain epileptic seizures with at least 50 minutes of preictal data preceding each seizure. The median time period between the last seizure and the interictal data set is 5 hours and 18 minutes, and the median time period between the interictal data set and the first following seizure is 9 hours and 36 minutes[29]. As suggested in the dataset, we have treated preictal and ictal period as an ictal signals in our experiments. We do not consider any non-seizure signals into the interictal period as we carefully select the same duration of interictal signal (with the ictal signal) from the above duration of interictal signal.

3.2. Feature Extraction using DCT

DCT is a transformation method for converting a time series signal into basic frequency in such a way that the DCT coefficients are arranged from low frequency to high frequency components. Low frequency components represent the coarse signals and high frequency components represent the detail signals. DCT is widely used in the image processing and video coding areas to compress image signals based on their frequencies [34]. As the ictal and interictal EEG signals have different amplitude and frequency (not visually separable), thus...
the most distinguishable features should be located in the high frequency components of DCT coefficients see in Figure 3(a). As the EEG signal is non-linear and non-stationary in nature, thus, for real time processing of EEG signals, DCT may not be correct to directly correspond to the frequency analysis, however, if we segment the EEG signals in time window and apply DCT on them to find DCT coefficients; we can avoid non-linear and non-stationary nature of the signals. In our experiment, we apply DCT on the benchmark dataset [22] and take the higher frequency component (i.e., the last quartile (Q4) i.e., last 25% of DCT coefficient). Then, we extract statistical features such as entropy and energy of the weighted higher frequency coefficients to classify ictal and interictal signals.

The extraction of the statistical features from the Q4 is not straightforward. We use heuristics to provide different weight to the different coefficients and investigate the classification accuracy. Although we try different type of weighting approximations, the experimental results show that exponential weight performs well. The weight \( w_i \) for the \( i \)-th position coefficient is selected as \( w_i = \beta e^{-\beta x_i} \), where \( x_i - x_j = \frac{1}{\text{Number of Selected Coefficients}} \). We also try different \( \beta \) and test for the classification results. We find that \( \beta = 2 \) provides the best results for the dataset. The Figure 4 shows an example of weights. According to the proposed weight, we provide more weight to the relatively low frequency coefficients and less weight to the relatively high frequency coefficients within the higher frequency area of the overall signal as sometimes the high frequency coefficients in the tail would be very small.

![Weight against coefficients](https://via.placeholder.com/150)

Figure 4 Weight for different coefficients of selected high frequency coefficients.

We define weighted entropy and energy as follows:

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

where \( n \) is the length of signal, \( X_i(t) \) is the higher frequency DCT coefficients and \( Y_i(t) \) is the normalized value of \( X(t) \).

The representation of ictal and interictal data for different higher frequency DCT coefficients and their entropy and energy are given in Figure 3 (a). It can be observed that the changing rate of frequencies is higher for interictal signal than ictal signal from Temporal lobe. It is also interesting to observe that the amplitude of the higher frequency DCT coefficients for ictal signals is larger compared to that of interictal signals. Note that although the original ictal and interictal EEG signals are not visually separable, the high frequency DCT coefficients of ictal and interictal signals are visually separable. The third row of Figure 3 (a) also demonstrates that the weighted energy and entropy extracted from the higher frequency DCT components have different values for ictal and interictal signals. Thus, weighted entropy and energy would be effective features for ictal and interictal signals classification.

3.3. Feature Extraction using DCT-DWT

DWT is a transformation and widely used in the image and signal processing research to decompose the image/signals into different frequency and bands. DWT can be specified by low pass (LP) and high pass (HP) filters named as standard quadrature mirror filters [28]. The cut-off frequency of these filters is one-fourth of the sampling frequency. The bandwidth of the filter outputs are half the bandwidth of the original signal, which generates downsampled output signals without losing any information according to the Nyquist theorem [13]. The downsampled signals from LP and HP filters refer to first-level approximation and details of the original signal respectively[24].

DWT is sometimes more effective compared to DCT to separate signals into low and high frequency components when the signal is longer. Thus, we also investigate the effectiveness of the DWT to extract some other statistical features (such as STD) to classify ictal and interictal signals. In our second approach, we apply single-level one dimensional DWT on the EEG signal to find the high frequency components from the signal. Then, we calculate the STD from the detail frequency (i.e., high frequency) components of the DWT coefficients and use as a feature. We use the whole high frequency component for feature extraction as DWT separates the signals into low and high frequency components. Another feature is extracted using the STD of the weighted high frequency DCT coefficients (similar to Figure 4). Two STD features from DCT and DWT higher frequency components are then used for the classification purpose. Note that we use different primary functions of the wavelet transformation including Daubechies (db) series. We find that db16 is the best for our experiment.

In the experiment we take only the high frequency DWT components. The first two rows in Figure 3 (b) show the higher change of frequency and lower amplitude for interictal signal compared to ictal signal from Temporal lobe. The third row of Figure 3 (b) represents the STDs generated from the high frequency DCT coefficients (weighted) and DWT for ictal, which are higher than that of interictal signal. Thus, the STDs extracted from the high frequency DCT (weighted) and DWT coefficients can be good features for classification.

3.4. Feature Extraction using SVD

SVD decomposes two dimensional signals into three matrixes in such a way that the middle matrix (i.e., singular value) has unique properties to separate signals. The middle matrix, containing the square root of eigenvalues and diagonalized, contains much less non-zero coefficients compared with the coefficient matrices of other transformations [35]. The values of diagonal matrix are with descending order from top-left to bottom-right. As the original ictal and interictal signals are almost the same nature, we do not expect a significant different values of other two matrixes after SVD, however, we expect some distinguishable values on the extreme part (i.e., bottom-right) of diagonal matrix. Thus, any feature extracted from the bottom-right singular values could be used to classify ictal and interictal signals. Best of our knowledge we are the first to use
two dimensional SVD to analyze EEG signals for seizure detection.

To extract the features using SVD, we reshape the EEG signals into a two dimensional matrix. The column vector of EEG signal is rearranged to square matrix for the computation of singular value components using SVD. From the singular values, we take the weighted Q4 (weight is similar to Figure 4 but the number of selected coefficients are different) of the non-zero diagonal values to calculate the STDs and energy and treat as the two features to classify ictal and interictal signals. The SVD allows transforming any given matrix \( A \in \mathbb{C}^{m \times n} \) to diagonal form using unitary matrices, i.e. \( A = U \Sigma V^H \), where \( U^{nn} \) is a matrix, \( U^{m \times m} \) and \( V^{n \times n} \) are orthogonal matrix, and \( \Sigma^{m \times n} \) matrix with non-negative diagonal entries.

The columns of \( U \) are called left singular vectors and the rows of \( V^H \) are called right singular vectors. If \( A \) is a rectangular \( m \times n \) matrix of rank \( K \) than \( U \) will be \( m \times m \) and \( \Sigma \) will be:

\[
\Sigma = \begin{bmatrix}
\lambda_1 & 0 & \cdots & 0 \\
0 & \lambda_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \lambda_n \\
\end{bmatrix}
\]

where \( \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0 \).

The data distribution of non-zero singular value of the ictal and interictal signals from the Frontal lobe is shown in Figure 5 (a). The top part of the figure clearly shows that the Q4 singular values of interictal signals are larger than that of the ictal signals. The bottom part of Figure 5 (a) shows the STD and energy extracted from the weighted Q4 of non-zero singular values from ictal and interictal signals respectively. The figure exposes that the STDs extracted from the ictal and interictal signals have distinguishable values, thus, they can be used for ictal and interictal signal classification.

3.5. Feature Extraction of IMF using EMD

The main strength of EMD is its ability to analyze nonlinear and non-stationary signals like EEG signals. When we apply EMD on a signal, the signal is decomposed into a finite number of signals into IMFs, which are ordered from higher frequency component to lower frequency component. The number of IMFs in a signal depends on the local characteristics of the signal rather than pre-defined number of IMFs. This feature makes each IMF crucial to identify some characteristics of the original signal. Since the IMFs are the representations of different frequencies/amplitudes of the original signal and the distinguishing features between ictal and interictal EEG signals lie on the frequency/amplitude, our hypothesis is that any feature extracted from IMFs will be an effective feature to classify ictal and interictal successfully. We also observe that the ictal and interictal signals are deferred in higher order frequency components, thus our other hypothesis is that features extracted from the first few IMFs should be enough to classify ictal and interictal signals successfully. Through the decomposition we keep only few mode functions of the original signals for the final feature extraction, however, we are able to keep the important mode functions for the classification purpose. Experimental results reveal that our both hypothesis are correct as extracted features from the first IMF successfully classify ictal and interictal signals (see Section 4). Thus, IMFs can be used in classification applications where the original signals are nonlinear and non-stationary and distinguishing features exist on the different frequencies/amplitudes.

Each IMF satisfies two following conditions: (i) the number of extrema and the number of zero crossing are identical or differ at most by one and (ii) the mean value between the upper and the lower envelope is equal to zero at any time.

The EMD algorithm can be summarized as follows:

1. Extract the extrema (minima and maxima) of the signal \( x(t) \).
2. Interpolate between minima and maxima to obtain \( \epsilon_{\text{min}}(t) \) and \( \epsilon_{\text{max}}(t) \).
The strength of a signal is distributed in $\omega \omega$. We do not sacrifice any significant information in the first two rows in Table 1. The third row of the figure represents the STD of the first IMF and residual signal. We observe that features extracted from the first two IMFs provide the best classification results. To reduce computational complexity, we consider only the first IMF from the EMD and then calculate STD of IMF to capture the variation of the signal. By ignoring other IMFs, we do not sacrifice any significant classification accuracy. The strength of a signal is distributed in the frequency domain, relative to the strengths of other ambient signals, is central to the design of any filter intended to extract or suppress the signal. To find the strength of the signal, we apply power spectral density (PSD) on the first IMF. Then, determine the STD feature from normalized PSD. The calculation of PSD is as follows:

$$P(w_i) = \frac{1}{N} |D(w_i)|^2$$

where $D(w_i)$ is the discrete Fourier transform of IMF $d_i(t)$. Normalized PSD can be defined as:

$$p_i = P(w_i) / \sum_i P(w_i)$$

In the experiment, we extract two features such as STD of the first IMF and STD of normalized PSD of the first IMF. The first two rows in Figure 5 (b), it can be observed that the first IMF of ictal signal carries the higher amplitude compared to the interictal signal.

The third row of the figure represents the STD of the first IMF and STD of PSD of the same IMF from using ictal and interictal signals. The STDs for both cases of interictal signal are significantly larger than that of ictal signal. Thus, the two new features extracted by EMD method can be good features for classification.

Table 1 shows the summary of all corresponding features use for ictal and interictal classification by each method.

### 3.6. Classifier

We extract a number of features from different transformations/decompositions. To classify ictal and interictal signals, we need to use a classifier. The goal of a classifier is to classify.
find patients states such as ictal (class 1) and interictal (class 2) using machine learning approaches with cross-validation. The challenge is to find the mapping that generalizes from training sets to unseen test sets. For the cross-validation, data are partitioned into training set and test set. In our experiment we use 4-fold cross validation where each dataset was randomly divided into 4 splits, where three of them were used for training and the fourth one used for testing.

To classify the ictal and interictal signals, we extract various features from DCT, DWT, SVD, and IMF of EMD. For classification, we use SVM-based classifier as the SVM is one of the best classifiers in the EEG signal analysis. SVM is a potential methodology for solving problem in linear and nonlinear classification, function estimation, and kernel based learning methods [25]. It can minimize the operational error and maximize the margin hyperplane, as a result it will maximize the classification performance [25]. LS-SVM is the extended version of SVM and it is closely related to regularization networks and Gaussian process, and it also has primal-dual interpretations [23]. The major drawback of SVM is its higher computational burden of the constrained optimization programming. However, LS-SVM can solve this problem [26].

The classifier is a LS-SVM, which learns nonlinear mapping from the training set features \( \{x_i\} = \{x_1, x_2, \ldots, x_N\} \), where \( N \) is the number of training features into the patient’s state, ictal (+1) and interictal (-1). For unbiased classification results [27], we divide the whole 1000 trials into four subsets; in each subset we randomly select 75% samples for the validation training set and the remaining 25% for the validation testing set. Let \( y_i \in \{-1,1\} \) designate the LS-SVM validation test outputs mapping to class 1 or class 2. The equation of LS-SVM can be defined in [18] as:

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

(6)

where \( K(x, x_i) \) is a kernel function, \( a_i \) are the Lagrange multipliers, \( c \) is the bias term, \( x_i \) is the training input, and \( y_i \) is the training output pairs. Linear, RBF and Morlet kernel are used in our experiments and RBF and Morlet functions can be defined in [18] as:

\[
 k(x, x_i) = \exp(-\sigma^2 ||x - x_i||^2) 
\]

(7)

where \( \sigma \) controls the width of the RBF function;

\[
 k(x, x_i) = \frac{d}{k} \cos \left( \frac{\pi}{a} (x_k - x_i^k) / a \right) \exp\left( -\frac{||x - x_i||^2}{2\sigma^2} \right) 
\]

(8)

where \( d \) is the dimension, \( a \) is the flexible coefficient, \( x_i^k \) is the \( k \)-th component of \( i \)-th training data. Matlab codes for LS-SVM classifier are available at http://www.esat.kuleuven.ac.be/sista/lssvmlab/.

3.7. Computational Time

Feature extractions using IMF through EMD take longer time due to two fold iterations to find all IMFs. In the first iteration EMD decomposes a signal and checks whether the signal makes an IMF and in the second iteration it subtracts the current IMF from the signal and continues for the next IMF. Even if we stop the iteration for the first IMF, the EMD-based technique takes a full first iteration for calculating the IMF. The experimental data reveals that the proposed technique using DCT, DWT, and SVD takes less computational time compared to the EMD-based technique as DCT, DWT, and SVD transformation is faster compared to the EMD decomposition. Thus, the proposed methods (except FIMF_EMD method i.e., First IMF using EMD) take insignificant time compared to the existing method [18].

4. Experimental Results

Sometimes EEG signals have line noise and other kinds of artifacts due to muscle and body movements. Notch filter and independent component analysis (ICA)-based method are recommended to remove the line noise and artifacts respectively for sufficient amount of EEG signals [30]-[32]. However, in this experiment we do not use any explicit noise/ artifacts removal technique to see the tolerance of the proposed method against noise/ artifacts.

We propose fours method and the experimental results of the proposed methods are compared with existing methods [17]-[18]and corresponding features are explained in Table 1. Our ultimate target is to classify ictal and interictal EEG signals using LS-SVM with different kernels such as RBF and Morlet where the value of regularization parameter and kernel parameter are 10 and 6, respectively for both kernels. We also use linear kernel. In this paper, four methods are proposed based on the new features of ictal and interictal EEG signals captured from Frontal and Temporal lobes using DCT, DWT, SVD, and IMF of EMD to see the strength of individual transformation/decomposition techniques for seizure detection. Then we also test the classification accuracy by combining all features. In our experiment, we use 200 signals from ictal and 800 signals from interictal EEG signals. After training and testing of all features, we calculate average value from the four subsets to compute sensitivity, specificity, and accuracy [18]. The sensitivity, specificity, and accuracy are defined as:

\[
 \text{Sensitivity} = \frac{(TP)}{(TP + FN)} \times 100
\]

(9)

\[
 \text{Specificity} = \frac{(TN)}{(TN + FP)} \times 100
\]

(10)

\[
 \text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100
\]

(11)

where TP and TN represents the total number of detected true positive events and true negative events respectively. The FP and FN represent false positive and false negative respectively.

The technique in [18] claims that the second IMF provides better classification results while they use frequency and amplitude modulation bandwidth features for the dataset [19]. We conduct experiments using first four IMFs; however, we provide results using only the first IMF in Table 2 as it carries the best result compared to other IMFs. For the RBF kernel function, the proposed methods outperform the state-of-the-art method consistently and the average sensitivity using the proposed methods, such as Quatile four weighted high frequency component using SVD (Q4WHF_SVD), Quatile four weighted high frequency component using DCT (Q4WHF_DCT), First IMF using EMD (FIMF_EMD), and Quatile four weighted high frequency component using DCT and high frequency from DWT (Q4WHF_DCT–HF_DWT) are 83.33%, 99.12%, 96.47%, and 87.13% for RBF kernel, respectively, whereas, the average sensitivity using the state-of-art-methods [17] and [18] are 6.35% and 48.04%. Using Morlet kernel, the average sensitivity of the proposed methods is higher compared to the existing methods [17] and [18]. Moreover, we justify our result applying linear kernel. Table 2 also shows that the most of the cases the proposed methods with linear kernel provide better results compared to the proposed methods with Morlet and RBF kernels in terms of sensitivity. Table 2 also reveals that the proposed Q4WHF_DCT method is the best among all proposed methods in terms of sensitivity. It is also interesting to note that the accuracy of the proposed Q4WHF_DCT–HF_DWT method is reasonably consistent in terms of three criteria for RBF and Morlet kernel.
According to the LS-SVM, the performance of the proposed methods always outperform the existing methods [17][18] in terms of sensitivity (i.e., seizure i.e., ictal detection rate), however, some cases the existing methods [17][18] outperform one or more proposed methods in terms of specificity (interictal detection rate). For seizure detection, specificity is more important compared to the specificity detection as the cost of false detecting ictal is heavier compared to interictal. In overall classification the proposed methods are also better compared to the existing methods. We combine all features to classify ictal and interictal EEG signals. However, combine is not good because LS-SVM may not properly combine all available features to make a good prediction model. The average specificity of the proposed methods is 91.36% (average result of all kernel and lobe), whereas the specificity of the state-of-the-arts methods are 54.61% [18] and 7.99% [17], respectively.

The performance of the LS-SVM is evaluated by (ROC) plot is shown in Figure 7(a) ROC illustrates the performance of a binary classifier system where it is created by plotting the fraction of true positives from the positives i.e., true positive rate (TPR) vs. the fraction of false positives from negatives i.e., false positive rate (FPR) with various threshold settings. TPR is known as sensitivity, and FPR is one minus the specificity or true negative rate. Figure 7(a) demonstrates that the proposed four methods are carrying good classification results than that of the state-of-the-art method [18] using dataset from Frontal lobe of the third subset of training and testing EEG signals.

Figure 7(b) shows the distribution of normalized feature values (i.e., energy & entropy in the Q4WHF_DCT method, STD in the Q4WHF_DCT–HF_DWT method, STD & energy in the Q4WHF_SVD method, and STD in the FIMF EMD method) of ictal and interictal from the Frontal lobe dataset [22]. The figure shows that the range of feature values for ictal is different from that of the interictal signals. This phenomenon is the other evidence why we use those features to classify ictal and interictal EEG signals in the proposed methods.

First column of Figure 8 represents classification comparison using the proposed methods (i.e., FIMF EMD and Q4WHF_DCT–HF_DWT) and the state-of-the-art method [18]. Figure 8(b) and (c) show the LS-SVM classification results using the proposed FIMF EMD and Q4WHF_DCT–HF_DWT against the state-of-the-art method (i.e., EMD Figure 8(a)). We generate first column of Figure 8 from Frontal lobe for the second subset of training and testing and obtain the classification accuracy 91.20% for the Q4WHF_DCT–HF_DWT method.

Table 2: Sensitivity, specificity, and accuracy for different features of ictal and interictal EEG signals from Frontal and Temporal lobe.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Brain Location</th>
<th>Existing Method</th>
<th>Proposed Method</th>
</tr>
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<tbody>
<tr>
<td>RBF</td>
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<td>SEN</td>
<td>29.41</td>
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<td></td>
<td></td>
<td>SPE</td>
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<td></td>
<td></td>
<td>ACC</td>
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<td></td>
<td>SPE</td>
<td>80.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ACC</td>
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</tr>
<tr>
<td></td>
<td>Average</td>
<td>SEN</td>
<td>48.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPE</td>
<td>80.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ACC</td>
<td>79.05</td>
</tr>
<tr>
<td>Morlet</td>
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<td>33.82</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPE</td>
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<tr>
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<td></td>
<td>ACC</td>
<td>77.80</td>
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<tr>
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<td>SEN</td>
<td>84.62</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPE</td>
<td>83.54</td>
</tr>
<tr>
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<td></td>
<td>ACC</td>
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<td></td>
<td></td>
<td>SPE</td>
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<td></td>
<td>ACC</td>
<td>80.70</td>
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<tr>
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<tr>
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</table>
87.20% for the FIMF_EMD method, and 80.80% for the EMD method. It can be concluded from these figures that the proposed method based on the DCT-DWT and the IMF outperform the state-of-the-art method (i.e., EMD). The same classification comparisons are also provided in second column of Figure 8 using the state-of-the-art method based on the EMD and the proposed method based on the SVD and DCT respectively. We consider Temporal lobe for the fourth subset of training and testing; obtain classification accuracy 91.20% for Q4WHF_SVD, 89.60% for Q4WHF_DCT, and 85.20% for EMD [18]. Thus, it is concluded that the proposed methods based on the DCT and SVD also outperform the EMD method [18].

5. Conclusion

Unlike seizure and non-seizure EEG signals, classification of ictal and interictal EEG signal is a challenging task due to non abrupt phenomena (i.e., visually non-separable) between ictal and interictal EEG signals. Moreover, the features of ictal and interictal signals are not consistence in different brain locations, patient, types of seizure, and hospital setting during epileptic period of a patient. Thus, the classification performance for ictal and interictal EEG signals using the existing features extraction and classification techniques is not at expected level. Our initial observation indicates that high frequency components of EEG signals have distinguished characteristics. To improve the accuracy, in this paper we propose novel feature extractions strategies from the high frequency components based on a number of established transformation and decompositions. The average sensitivity (which is the measure for seizure) of the proposed methods is 91.36% (average result of all kernel and lobe) whereas the sensitivity of the state-of-the-arts methods are 54.61% [18] and 7.99% [17], respectively. The experimental results show that the proposed methods outperform the state-of-the-art methods in terms of accuracy, sensitivity, and specificity for the ictal and interictal EEG signals with greater consistence from the large benchmark dataset in two different brain locations.

References


Figure 8 First column represents the classification of ictal and interictal EEG signals from Frontal lobe for the second subset of training and testing using (a) the state-of-the-art method against (b) the proposed IMF and (c) the DCT-DWT method. Second column represents the classification of ictal and interictal EEG signals from Temporal lobe for the fourth subset of training and testing using (d) the state-of-the-art method against (e) the proposed SVD and (f) the DCT methods.


[22] Large dataset, 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.

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