TIME-FREQUENCY IMAGE DESCRIPTORS–BASED FEATURES FOR EEG EPILEPTIC SEIZURE ACTIVITIES DETECTION AND CLASSIFICATION

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ABSTRACT

This paper presents new class of time-frequency (T-F) features for automatic detection and classification of epileptic seizure activities in EEG signals. Most previous methods were based only on signal features derived from the instantaneous frequency and energies of EEG signals in different spectral sub-bands. The proposed features based on image descriptors are extracted from the T-F representation of EEG signals and are considered and processed as an image using T-F image processing techniques. The proposed features include shape and texture-based descriptors and are able to describe visually the normal and seizure activity patterns observed in T-F images. The results obtained on real EEG data show that T-F image descriptor-based features achieve an overall classification accuracy of up to 98% for 100 EEG segments using one-against-one SVM classifier. The results suggest that the proposed method outperforms those methods, which employ signal features only or combined signal-image features by about 3% for 100 EEG signals.

Index Terms— Time-frequency image, time-frequency feature extraction, Electroencephalogram (EEG), epileptic seizure detection, EEG classification.

1. INTRODUCTION: CONTEXT, PROBLEMATIC AND RELATED WORK

Electroencephalogram (EEG) signal which contains information about the brain's electrical activity, has become the most used signal for detecting epileptic seizures due to abnormal excessive or synchronous neuronal activity in the brain [1]. A manual detection of seizures is achieved by visually scanning EEG recordings and is high computationally intensity task especially with long recordings [2]. Skilled medical interpreters are required to interpret the observed seizure activities and to determine the appropriate diagnostics (i.e. neurophysiologist). It is therefore desired to develop an automated system -which can help the neurophysiologists- for detecting and classifying EEG seizure activities. A typical scheme for EEG seizure detection and classification system includes the following steps: (1) analyze EEG signal in either time, frequency, time-scale or joint T-F domain, (2) extract and select the relevant features which characterize the seizure activity patterns and (3) classify the extracted features to assign EEG signal to its corresponding class (i.e. seizure, non-seizure or normal) [3]. Various methods based on the above mentioned schemes have been proposed in the literature. These methods extract EEG features in the time domain [4, 5, 6, 7], frequency domain [5, 6, 8], or T-F domain [3, 9, 10], as well as time-scale domain [11, 12]. The relevant proposed features extracted from EEG signals in the time domain are based on amplitude information (e.g. average EEG amplitude, derivatives of the EEG signal's amplitude, zero-crossing rate, coefficient of variation, average EEG duration) and entropy information (e.g. Shannon entropy, Fisher information, approximate entropy) [4, 5, 6, 7]. In the frequency domain, the proposed features are extracted from the spectrum of EEG signal where the most relevant ones are based on power spectrum such as mean frequency, average power in the main energy zone, normalized spectral entropy, normalized power, frequency subband powers, and intensity weighted bandwidth [5, 6, 8]. In the time-scale domain, the features are extracted from a multiscale representation (e.g. wavelets and X-lets) of EEG signal and include the statistical moments of details coefficients of EEG signal and their relative energies [11, 12]. In the T-F domain, the features are extracted from the T-F representation of EEG signal and are capable to characterize the non-stationary nature and multi-component characteristics of EEG signals such as the Instantaneous Frequency (IF) and sub-band energies [3, 9, 10]. Recently, a novel class of T-F features was proposed in [13], and is based on the translation and calibration of the relevant time-domain and frequency-domain features.

In this work, we propose new image descriptor-based features to describe visually the normal and seizure activity patterns in the T-F domain. The proposed features are extracted from the T-F representation of EEG signals and processed as an image, by applying T-F image processing techniques. These features are used to define a new feature vector which can be used to characterize and hence classify EEG epileptic seizure activities.

2. T-F APPROACH FOR EEG EPILEPTIC SEIZURE DETECTION AND CLASSIFICATION

In order to develop EEG seizure detection methods in the T-F domain, it is necessary to select a suitable T-F distribution (TFD [14]) to represent EEG signals. The most common are quadratic TFDs (QTFDs) such as Wigner-Ville distribution (WVD), Smoothed WVD (SWVD), Spectrogram (SPEC), Choi-Williams distribution (CWD), B distribution (BD) and Modified-B distribution (MBD) [14, 15].

2.1. Quadratic time-frequency distribution

The general formula for QTFD of a given analytic signal $z[n]$ associated with the real discrete time signal $x[n], n = 0, 1, \ldots, N-1$ is given by [15]:

$$\rho[n,k] = 2 \underset{n \to k}{\mathrm{DFT}} \left\{ G[n,m] \underset{n}{*} (z[n+m] z^*[n-m]) \right\} \quad (1)$$

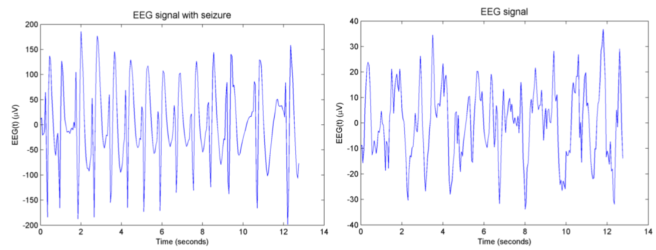
where DFT is the Discrete Fourier Transform, $G(t,\tau)$ is the time-lag kernel of the TFD and $\underset{n}{*}$ stands for convolution in time. For an N-point signal $x[n]$, $\rho[n,k]$ is represented by an $N \times M$ matrix ρ with $n = t.f_s$ and $k = \frac{2M}{f_s} f$ where t and f are the continuous time and frequency variables, respectively; and f_s is the sampling frequency rate of the signal. M is the number of FFT points used in calculating the TFD ($M \geqslant N$) . Table 1 gives examples of most popular QTFDs with their corresponding time-lag kernel G. All these QTFDs can be considered as filtered versions of the WVD and different kernels in (1) allow to define different distributions in the class, that are most specifically adapted to particular classes of signals.

QTFD	$G[n,m]$
WVD	$\delta[n]$
SWVD	$\delta[n]w[m]$
CWD	$\frac{\sqrt{\pi\sigma}}{2\lvert m\rvert} \exp(\frac{-\pi^2 \sigma n^2}{4m^2}) ** [\mathrm{sinc} n \ \mathrm{sinc} m]$
BD	$\left(\frac{\lvert 2m\rvert}{\cosh^2 n}\right)^{\beta} * \mathrm{sinc} m$
MBD	$\frac{\cosh^{-2\beta} n}{\sum_n \cosh^{-2\beta} n}$
SPEC	$w[n+m]w[n-m]$

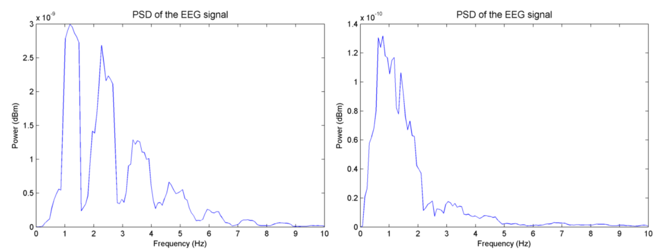
Table 1. Time-lag kernels of the most popular QTFDs. *The parameters β and σ are positive reals and w represents the window function.*

2.2. T-F signal analysis for EEG seizure detection

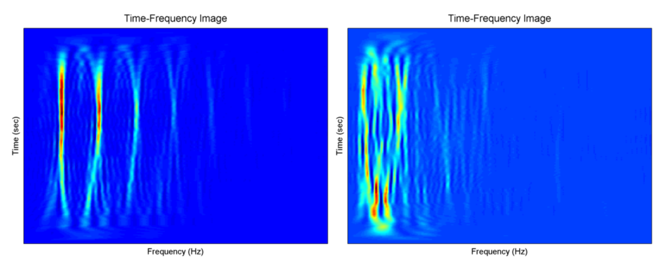
As EEG signals are non-stationary, they are best represented by a TFD, which is intended to describe how the energy of the signal is distributed over the 2-dimensional T-F space [15]. The TFD shows the start and stop times of signal components and their frequency range, as well as the component variation in frequency with time, described by the IF. The IF can be estimated using a peak detector in the T-F domain that selects the frequency with the maximum value in the T-F representation as a function of time. Figure 1 shows an example of seizure and non-seizure EEG signals in the time, frequency and joint T-F domains, in order to illustrate the difference between them and show how the TFD plot can provide more information about the IF, non-stationary nature and multi-component characteristics of the signals than the time or the frequency representations [3, 10, 15].



(a)



(b)



(c)

Fig. 1. Example of EEG signal with seizure (1^{st} col.) and non-seizure (2^{nd} col.) activity in time (a), frequency (b), and joint T-F domains (c).

2.3. T-F approach for EEG classification

A T-F approach for automatic classification of EEG seizure activities includes the following steps: (1) finding the optimal TFD that best represents EEG signals, (2) extracting features that characterize the seizure activity pattern from this TFD, and finally, (3) allocating the vector containing the extracted T-F features to the relevant class (i.e. seizure or non-seizure), using a multi-class classifier. The success of such approach depends mainly on the quality of the T-F features extracted from the TFDs of EEG signals. These features need to have the ability to characterize the seizure activity patterns, and also to discriminate between different classes (i.e. seizure with degree of severity: mild, moderate or severe).

3. PROPOSED METHOD: T-F IMAGE DESCRIPTORS-BASED FEATURE EXTRACTION

This paper proposes new T-F features to describe visually normal and seizure patterns in the TFD. These features based on image descriptors are extracted from the T-F representation of EEG signals and are processed as an image using T-F image processing techniques. The idea of the proposed feature extraction is to detect and exploit all EEG information that appears in the T-F image in order to characterize normal and seizure activities (e.g. all components, high amplitude, normal or seizure patterns). In this way, we present a set of image descriptors based on shape and texture as new T-F features for detecting and classifying EEG seizure activities.

3.1. Shape-based features

By analyzing T-F images of the example shown in Figure 1(d), we observe that the high amplitudes can be exploited to characterize the normal and seizure patterns. Color-based image segmentation approach using k-means clustering was adapted in our methodology to detect and extract the high amplitude regions [16], and then to compute their statistical and geometrical features. This approach aims to segment amplitudes in an automated fashion using k-means clustering. In the proposed technique, the T-F image is segmented in 3 regions: low, medium and high-amplitudes; where only the high-amplitude regions are exploited to define and compute the shape-based features. Figure 2(b) shows the segmented high-amplitude regions detected of the TF image shown in Figure 2(a) using the proposed method, their binary image in Figure 2(c) and their convex hull image (the smallest convex shape that contains the high-amplitudes) in Figure 2(d).

We denote the TF image, binary-segmented and binary convex hull images by $\mathcal{I}$, $\mathcal{I}_s$ and $\mathcal{I}_{ch}$, respectively. The moments of $\mathcal{I}_s$ and $\mathcal{I}_{ch}$ are used to compute some shape features from the segmented regions, such as perimeter and compactness. Five morphometric features based on the geometric shape of the segmented regions in $\mathcal{I}_{ch}$ and $\mathcal{I}_s$, can then be defined as:

- Area, Perimeter and Compactness of the segmented region in $\mathcal{I}_{ch}$:
  $F_1 = \sum_n \sum_k \mathcal{I}_{ch}[n,k]$
  $F_2 = (m_{30} + m_{12})^2 + (m_{03} + m_{21})^2$
  where m_{pq} is the moment of order (p,q) defined as
  $m_{pq} = \sum_n \sum_k n^p k^q \mathcal{I}_{ch}[n,k]$
  $F_3 = (F_2)^2 / F_1$

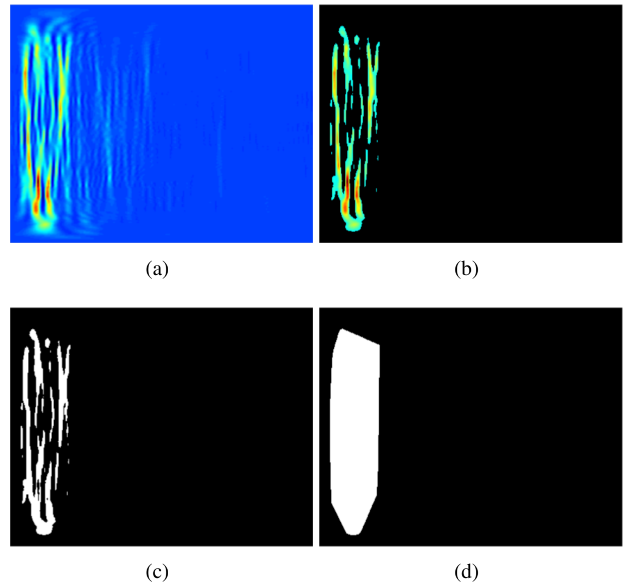


Fig. 2. Example of a TF image of an EEG signal (a) and the segmented high-amplitude region (b) with their corresponding binary (c) and convex hull (d) images.

- Area and Euler number of the segmented regions in $\mathcal{I}_s$:
  $F_4 = \sum_n \sum_k \mathcal{I}_s[n,k]$
  F_5 is the number of the segmented regions computed using the Euler-Poicaré formula [17]

3.2. Texture-based features

Texture-based features are defined to characterize the texture in $\mathcal{I}$. These features are based on the statistical moments, entropy, contrast and energy informations. The first and second order statistics-based features, denoted respectively F_6 and F_7, are computed as follows:

- First-order moments of $\mathcal{I}$: $F_6 = \frac{1}{NK} \sum_n \sum_k \mathcal{I}[n,k]$
- Second-order moments of $\mathcal{I}$:
  $F_7 = \sqrt{\frac{1}{NK} \sum_n \sum_k \left(\mathcal{I}[n,k] - \mathcal{M}_1\right)^2}$

The entropy-, contrast- and energy information-based features are computed from the gray-level co-occurrence matrix (GLCM[1]) $\mathcal{C}$ of $\mathcal{I}$ as follows [18]:

- Entropy : $F_8 = -\sum_n \sum_k \left(\mathcal{I}[n,k] \log_2(\mathcal{C}[n,k])\right)$
- Contrast : $F_9 = -\sum_n \sum_k |n-k|^2 \, \mathcal{C}[n,k]$
- Energy : $F_{10} = -\sum_n \sum_k \left(\mathcal{C}[n,k]\right)^2$

[1]GLCM is a well known method for analyzing texture images which estimates image properties related to second-order statistics. Each entry $[n,k]$ in GLCM, $\mathcal{C}$, corresponds to the number of occurrences of the pair of gray levels n and k which are a distance d apart in original image.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Methodology and evaluation criteria

During the classification step, a EEG signal is assigned to a certain class (i.e. normal or seizure) based on the location of its feature vector. We extracted the proposed features from the TF image of EEG signals and used them to train a two-class SVM classifier. The following statistical parameter was used in order to evaluate the classification performances.

$$\text{Total accuracy (ACC)} = \frac{\mathrm{TP} + \mathrm{TN}}{(\mathrm{TP} + \mathrm{FN}) + (\mathrm{TN} + \mathrm{FP})} \quad (2)$$

where TP, TN, FN, and FP represent the true positive, true negative, false negative, and false positive rates, respectively.

The performance of the proposed features for EEG classification is evaluated using the real EEG database described in [19]. It consists of 5 sets of data referred to as sets A-E where each set contains 100 artifact-free single-channel EEG segments of 23.6 seconds duration acquired from normal subjects and patients with epileptic seizures. Each EEG segment has been recorded at $f_s = 173.6$Hz sampling rate and has 4096 samples ($23.6 \times f_s$). The desired classification is done in two different classes of EEG signals, namely: **N** and **S**. The class **N** includes set A which contains EEG segments without seizure acquired from 5 healthy volunteers and the class **S** includes set E which contains EEG segments with seizure acquired from 5 patients. Each class has 100 segments.

4.2. Analysis of results

The T-F feature set $\mathbf{F} = \{F_1, \ldots, F_{10}\}$, was extracted from TF image of TFD of each EEG segment of length 5.9 sec (with $N = 1024$ samples). Only the QTFDs listed in Table 1 are chosen in this simulation. The parameters of the MBD and CWD were respectively chosen as $\beta = 0.01$ and $\sigma = 0.9$ with lag-window length of 127. These values are typical ones for which the TFD has shown good performances in analyzing EEG signals [15]. The window $w[n]$ for the SWVD and SPEC distributions was chosen to be a Hanning window of length $\lfloor N/4 \rfloor$ samples. The simulations were carried out in MATLAB. For the performance evaluation, one-against-one SVM classifier was trained using the features extracted from EEG signals in the database. We have compared the classification results for each QTFD. The database $\{\mathbf{N}, \mathbf{S}\}$ that includes 200 EEG segments was split randomly into two parts; 50% of the data (i.e. 100 segments with 50 segments in each class) were used for training and 50% for testing the classifier. Table 2 shows the confusion matrices representing the classification results using the proposed features extracted from the T-F images generated using different QTFD of the EEG signals; where "Number of signals" indicates the number of EEG segments used for the testing step. For every QTFD the total number of EEG segments correctly classified as well as those misclassified as other classes are shown including the overall classification accuracy. From the Table it can be noticed that the use of the proposed features achieves a better classification result. This is confirmed by the total classification accuracy calculated for each QTFD where the best results are obtained in a range $[94, 98]\%$ for 100 EEG segments. This can be improved by increasing the number of EEG segments in the training-step. For example, experiments were carried out by increasing the training data to 160 signals (i.e. 80% for training and 20% for testing) and the results have led to an overall accuracy in a range $[95, 100]\%$ (see the results between parentheses of Number of signals in Table 2). In addition, our proposed method outperforms the methods in [3], which use only signal features and combined signal-image features where their best total classification accuracy using the same dataset $\{\mathbf{N}, \mathbf{S}\}$ is in a range between $[92, 95]\%$ for 100 EEG segments.

TF image	Number of signals		Classifier outputs		Total accuracy
QTFD	Class	50% (20%)	N	S	ACC (%)
MBD	N	50 (20)	47 (20)	3 (0)	95 (100)
	S	50 (20)	2 (0)	48 (20)	
SPEC	N	50 (20)	47 (20)	3 (0)	94 (95)
	S	50 (20)	3 (2)	47 (18)	
SWVD	N	50 (20)	49 (20)	1 (0)	97 (100)
	S	50 (20)	2 (0)	48 (20)	
CWD	N	50 (20)	49 (20)	1 (0)	94 (97.5)
	S	50 (20)	5 (1)	45 (19)	
WVD	N	50 (20)	50 (19)	0 (1)	98 (95)
	S	50 (20)	2 (1)	48 (19)	
BD	N	50 (20)	49 (20)	1 (0)	96 (97.5)
	S	50 (20)	3 (1)	47 (19)	

Table 2. Confusion matrices of the EEG classification using the proposed features set **F** extracted from the TF images generated from different QTFD, using 2-class SVM classifier with EEG databset $\{\mathbf{N}, \mathbf{S}\}$.

5. CONCLUSION AND FUTURE WORK

In this paper, we demonstrate that it is possible to detect and classify epileptic seizure activities in EEG signals using only image descriptors-based features extracted from the TFD of EEG signal considered as an image. The experimental results on real EEG data, show that the use of T-F image-related features provides a total classification accuracy by up to 98% for 100 EEG signals. Also, the classification performance of our proposed method outperforms the performances of the methods proposed in [3] by 3% for 100 EEG signals. Finally, the results obtained suggest us that it is important to pursue this direction and focus on the extraction of other T-F image-based features allowing to classify EEG seizures with their degree of severity (i.e. mild, moderate or severe).

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