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Epilepsy Classification Framework Utilizing Joint Time-Frequency Signal Analysis and Processing

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Abstract
Time Frequency Signal Analysis and Processing (TFSAP) have been proposed in order to analyse the signal in both the time and the frequency domains. Electroencephalography (EEG) as a time-varying frequency signal is an interesting field in which Time Frequency Distribution (TFD) could be used in order to visualize the simultaneous distributions of signal energy in different physiological and pathological brain states. Particularly, epileptic signals due to their great features of seizure activity are introduced as the most attractive research field among researchers. This study outlines an investigation on two main pathologic brain states including, pre-ictal activity and seizure activity compared to normal activity. Pseudo-Wigner -Ville and Choi-William distributions are used in order to visualize the energy content of signals in these states. Different segments of brain electrical activity are analyzed using these distributions. Finally, Renyi's entropy as an important characteristic which offer insight towards the EEG signal processing has been extracted from TFDs. The results obtained indicate that Renyi's entropy is a high-quality discriminative feature especially in alpha and delta sub-bands of the EEG signal.

Keywords: Time-frequency analysis; Signal processing; Epilepsy; Renyi's entropy

Introduction

Epilepsy has affected 1% of the population of the world and is characterized by intermittent abnormal firing of neurons in the brain [1]. Epileptic seizures are the result of this electrical disturbance and are distinguishable from the normal activity with regard to frequency and morphological pattern [1]. Because of the multifaceted nature of epilepsy, detection and identification of epileptic activity during the event or after it is an essential task in the diagnosis procedure. In this way electroencephalography plays an important clinical role for assessment of these changes and detection of seizures. Classification of EEG results, in light of epilepsy, has generated substantial interest, resulting in a voluminous body of literature [2-13]. EEG information used in these methods can be classified into 3 major categories: time domain-based methods, frequency domain-based methods and time–frequency analysis-based approaches [2-13].

In the time domain algorithms, complexity scales, amplitude statistics or entropy measures proved to be more discriminative. Forrest et al. [2] have used the fractal property, Hjorth parameters and the amplitude statistics for distinguishing epileptic activity. Since entropy measures the complexity or the degree of disorder of the EEG signal, this feature has been used by Acharya et al. [3] for discriminating different EEG patterns. Guler et al. [4-5] used chaos measures for classification like Lyapunov Exponents (LE). However, the studies claim that EEG does not meet the theoretical requirements for LE analysis [6].

From the spectral methods in this area one could suggest [7-8] in which spectral features are selected from seizure and non-seizure EEG signals by Gabor functions and Discrete Fourier Transform (DFT). Although in this study, the final performance has been improved by the additional information provided by the/an electrocardiogram (ECG).

Wavelet transform is predominantly effective for representing various aspects of non-stationary signals. Adeli et al. [9] analyse the EEG signals of epileptic patients with absence seizure using wavelet transform and characterize epileptiform discharges in the form of 3-Hz spike and wave complex in these patients. As the decomposition of the original EEG into sub bands alters the original phase space and leads to new phase spaces, mixture of wavelet and Chaos methods proved to have better achievement. Adeli [10] used a Wavelet-Chaos methodology for analysis of EEGs for detection of seizure and epilepsy.

Few researches have been conducted on joint time-frequency domain. The wide range application of time–frequency analysis has been reported in detection of seizure in neonates [11]. Recently, some researchers have presented their work in the TF domain for detection of epileptic adults [12-13]. Tzallas et al. [12] proposed a feature vector formed by splitting the TFD into a lattice and concatenating the total energy in each window with the total EEG energy. However, the features applied in Musselman's work [13] were statistical features extracted from bilinear time–frequency distributions (TFD) of the EEG signal.

In this work, discrimination of epileptic activity has been discussed by means of Time Frequency Signal Analysis and Processing (TFSAP). TFSAP in contrast with the traditional time or frequency analysis considers the properties of the signal in both the time and the frequency domains [14]. Actually, TFDs could represent how the energy of the signal is distributed over the two-dimensional time-frequency space [14]. Hence, TFDs could be used in order to visualize the energy content of an EEG as a non- stationary time-varying frequency signal in different physiological and pathological brain states [15]. As mentioned before decomposition of signal may lead to a new phase space. So, by means of multiresolution wavelet analysis, the original EEG signal is decomposed into 5 sub-band (Delta (0 –4 Hz), Theta (4 –8 Hz), Alpha (8 –15 Hz), Beta (15–30 Hz) and Gama (30–60 Hz) [10]. Afterwards, Renyi's entropy as a time-frequency measure is compared in these sub-bands. This methodology seeks to extract time-frequency features in EEG and its sub-bands in order to show in a statistically meaningful way, how differences among time-frequency properties may occur in certain sub-bands. The aim of this study was to compare joint time-frequency properties of brain electrical activity from different physiological and pathological brain states, using TFDs.

Material and Method

A. Dataset

The EEG time series made available online by Dr. Ralph Andrzejak of the Epilepsy Centre at the University of Bonn, Germany [16] are utilized for evaluating the algorithm. This dataset contains five subsets of EEG signals (denoted A–E) each containing 100 single channel EEG segments. These segments were selected and cut out from continuous multichannel EEG recordings of patients from their archive after visual inspection for artefacts, e.g., due to muscle activity or eye movements [15].

Sets A and B have been acquired using surface EEG recordings of five healthy subjects. Volunteers were asked to be relaxed with eye- open (A) and eye- close (B), respectively. Sets C, D, and E are originated from countinuous EEG recordings of five patients with presurgical diagnosis. Segments in set C were recorded from the hippocampal formation of the opposite hemisphere of the brain while those in D from within the epileptogenic zone. Sets C and D contained only activity measured during seizure free intervals and set E only contained seizure activity [15].

The sampling rate of the data was 173.61 Hz with 12 bit resolution. In this study, four data sets (A, B, D and E) were used.

B. Pre-processing

In order to enhance signal to noise ratio (SNR) and remove power-line noise along with out-of-band noise, the EEG time series were low-pass filtered using a low-pass FIR filter between 0 to 60 Hz [10]. Matlab software was used for implementation of the algorithm. and all codes were written in matlab. Since the EEG signal is a real signal and for TFDs, the analytic signal is needed, the Fourier Transform of the signal is taken. Afterwards, inverse Fourier Transform is performed on the positive portion of the signal's spectrum [11]. Using 4-level wavelet decomposition the following sub-bands are obtained: Gamma (30-60 Hz), Beta (15-30 Hz), Alpha (8-15Hz), Theta (4-8 Hz), and Delta (0-4 Hz) [10].

C. Time Frequency Analysis

Time-frequency analysis techniques are highly effective for signal processing especially in non-stationary signals with time-varying frequency components. For this study, The Cohen's class distributions are used which satisfy time and frequency covariance property [14]. In fact, these properties guarantee that, if the signal is delayed in time and modulated, its time-frequency distribution is translated of the same quantities in the time-frequency space. It has been shown that this distribution possesses the following general expression [14]:

$$C_x(t,\nu;f) = \iiint_{\infty}^{\infty} e^{j2\pi\xi(s-t)} f(\xi,\tau)x(s+\tau/2)x^*(s-\tau/2)e^{\ j2\pi\nu\tau} d\xi ds d\tau \tag{1}$$

where x is the selected signal and f is the kernel function for eliminating cross-term artifacts [14]. Different kernel functions have been designed to overcome this obstacle. In the next sections two different TFDs have been discussed.

D. Wigner-Ville Distribution

Wigner-Ville distribution (WVD) which is particularly interesting because of its simplicity is defined as equation (2):

$$W_x(t,f) = \int_{\infty}^{\infty} x(t+\tau/2)x^*(t-\tau/2)e^{\ j2\pi f\tau} d\tau \tag{2}$$

where * is the complex conjugate operator. Since the Wigner-Ville Distribution function is not a linear transform, the cross-term artifacts will occur in multi component signals or in non-linear FM signals [14]. These interference terms are troublesome since they may overlap with signals and thus make it difficult to visualize the WVD's image. These interferences could be eliminated or reduced by windowed version of WVD. Actually, this windowing procedure is equivalent to frequency smoothing of WVD and called Pseudo- WVD (PWVD) [14]. For a given signal x, its PWVD is defined as:

$$PW_x(t,\nu) = \int_{\infty}^{\infty} h(\tau)x(t+\tau/2)x^*(t-\tau/2)e^{\ j2\pi\nu\tau} d\tau \tag{3}$$

where $h(\tau)$ is a regular window.

E. Choi-Williams Distribution

Choi-Williams Distribution (CWD), proposed by Choi and William [17], is one of the Cohen's class distributions which uses a gaussian kernel function to reduce cross – term interferences. That is why CWD is also known as the Reduced Interference Distributions (RID). In this distribution the kernel function depends only on the product of the variables τ and ξ in doppler-lag domain. The Equation (4) represents a kernel function for Choi-Williams distribution:

$$f(\xi,\tau) = \exp\left[\frac{(\pi\xi\tau)^2}{2\sigma^2}\right] \tag{4}$$

where σ is a real parameter which controls the cross-term reduction. Since, interference components occur far from the origin, this parameter is designed to be close to unity around the origin and exponentially decrease in regions far from the origin [11]. For further noise attenuation, one could use smoothing windows to the kernel in both time and lag directions [11]. The best choice for smoothing window might be a Hamming window with N point. N is the number of points of window considered for the sake of better resolution.

E. Renyi's Entropy

Renyi's entropy introduced in time-frequency analysis by Williams et al. [18] is interesting information which varies by the existence of the different EEG waveforms and events in their corresponding frequency. It is the generalized form of Shannon entropy which admits negative values in the distribution [14]. The Renyi's entropy, applied on the TFD is given by Equation (5).

$$R_\alpha = \frac{1}{1-\alpha}\log_2\left(\sum_n \sum_k \rho_x^\alpha(n,k)\right) \tag{5}$$

where ϱ is the histogram of the time–frequency coefficients and α is the order of Renyi's information.From the limit case if α meet 1,the entropy converges to Shannon entropy. If the components are less separated in the time-frequency plane, the information measure will be affected by the overlapping of the components or by the interference terms [14]. In this work, Renyi's entropy order of 3 is used for CWD.

The mentioned TFDs were applied to A, B, D and E categories of the dataset which correspond to normal brain activity with eye-open, eye-close, pre-ictal and seizure activities, respectively. Signals from each category were first pre-processed in order to remove noise and eliminate artefacts. Then, pre-processed signals were converted into analytic form. After applying multi-resolution wavelet analysis using Coifman wavelet, each EEG signal along with its five sub bands go through TF analysis process.

PWVD and CWD as two candidates for evaluation of our algorithm have some parameters to be chosen. Because there is no exact value to optimize the parameters against, these parameters were chosen to make sure that time-frequency components of the signal were represented clearly with minimum rate of cross-term interferences. As discussed in [11], for PWVD a hamming window with 105 points had the best results. Kernel width in CWD was set at 5 that could filter cross-terms without any over-smoothing. Finally, for smoothing windows of CWD again hamming windows of 15 and 151 points were used in time domain and lag domains, respectively. It was shown that a Hamming window of 15 points in time domain represents a good trade-off between resolution and cross-term elimination and for the lag smoothing window this parameter was set to 151 points [11]. For evaluation of the distributions four subsets, namely, normal (sets A and B), pre-ictal (set D) and seizure or ictal activities (set E) of single channel EEG signals had been used.

Results

A. Normal Activity (eye-open vs. eye-close)

Characteristically, the normal signal is a constant amplitude signal with no abnormal pattern. It can be said that in the normal signal there is no particular or regular patterns. Figure 1 shows PWVD of this kind of signals. The color legend for the heat maps show the energy level of the signal at a specific frequency. It is noteworthy that the energy of the signal in both (a) and (b) is mostly concentrated below 5 Hz without any high frequency component or any regular pattern. The CWD of normal EEG is presented in Figure 2. Hence, CWD visualize the signal's energy better than PWVD and calculation of Renyi's entropy is done using this transformation.

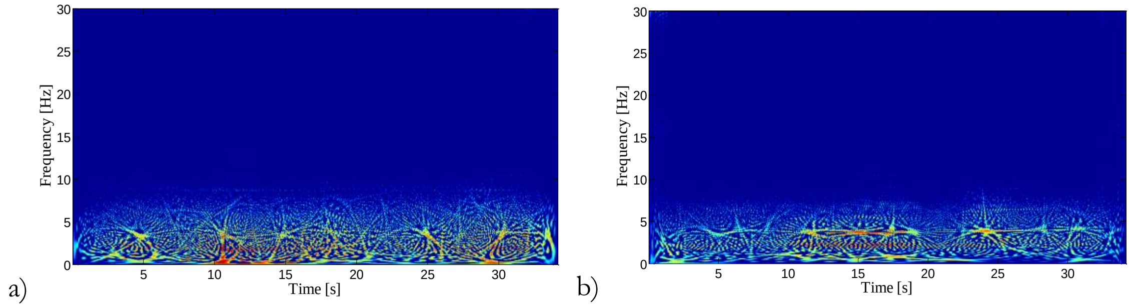

Figure 1. PWVD of normal EEG signals. **(a)** Eye-open**, (b)** Eye-close

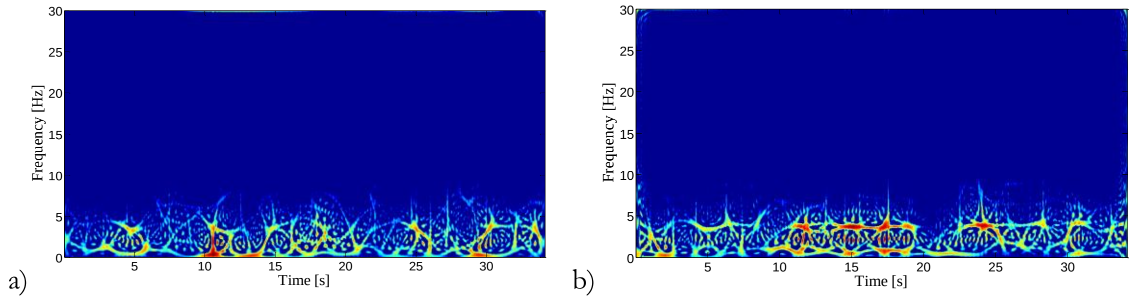

Figure 2. CWD of normal EEG signals. **(a)** Eye-open**, (b)** Eye-close

The closing of eyes represents the imposing of such a constraint in dynamics resulting in the well-known physiological alpha rhythm.This could be approved by Renyi's entropy measure which is lower in signals of set (A).

B. Pre-ictal Activity

The pre-ictal EEG data in set D was recorded intracranially from the same five epilepsy patients during seizure free intervals. All EEG segments in this subset were recorded from within the epileptogenic zone when there is no seizure.

Figure 3 depicts results of applying PWVD and CWD on the exemplary pre-ictal activity segment. Even though energy of the signal in both PWVD and CWD is totally concentrated below 5 Hz, the indications of periodic regular pattern are presented. This regular pattern which is almost similar to the seizure activity pattern (discussed in the next section) suggests that the pathological epileptic process imposes certain constraints on neuronal dynamics. Even in the absence of seizure activity these constraints appear to be reflected by periodic patterns in the EEGs from epileptogenic zones in the brain.

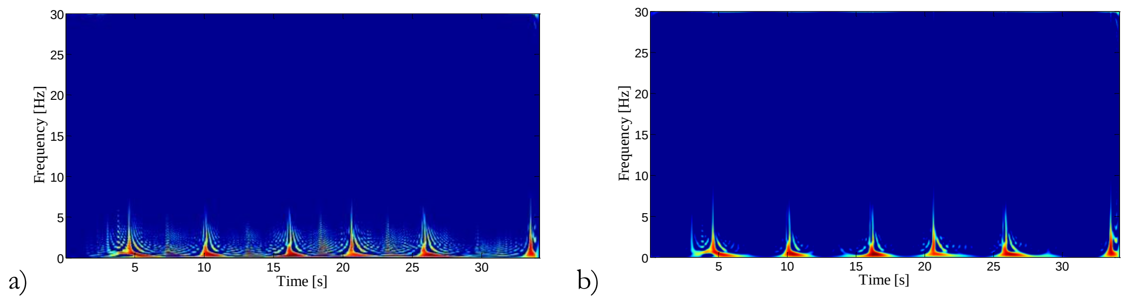

Figure 3. TFDs of pre-ictal activity EEG signal: (a) PWVD, (b) CWD

C. Seizure Activity

Epileptic activity can create clear abnormalities on a standard EEG. These abnormalities might be defined as repetitive waves with any shape or amplitude, and often evolve with changes in frequency or shape. TFDs of this kind of signals are shown in Figure 4. In this Figure, part (a) is the PWVD of signal with seizure activity and part b shows the CWD of the same signal. It is clear that apart from whether seizure evolve in the duration of signal studied or not, these distributions consist of lines which appear to be parallel in the frequency direction.

This regular pattern could be the indication of harmonics of the dominant frequency. However, CWD provides better time and frequency resolution. From the energy point of view, the results represent that most of the energy of the signal lie above 5 Hz with dominant spikes along with frequencies of about 10 Hz.

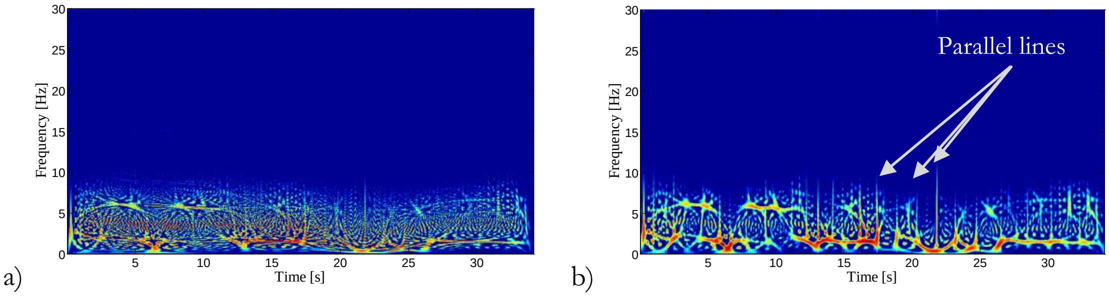

Figure 4. TFDs of seizure activity in EEG signal: (a) PWVD, (b) CWD

Evaluation of discrepancies in Renyi's Entropy between the three groups and their sub bands was performed using ANOVAs test. One-way ANOVA is used for comparing the means of these categories of data. The test returns the p-value under the null hypothesis that all samples in the data are drawn from populations with the same mean. P-value near zero suggests that at least one sample mean is significantly different than the other sample means. Common significance levels are 0.05 or 0.01. It is observed from Figure.5 that this parameter yields a sufficient measure for quantification of the differences in the three groups. It is noteworthy that the p-value of the test for 3 groups is much less than 0.05.

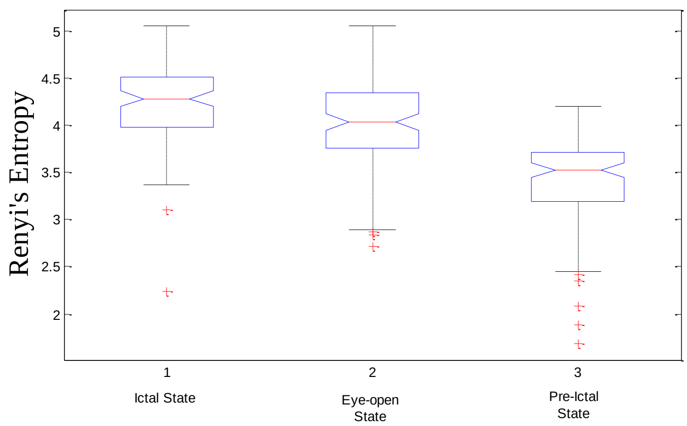

Figure 5. Renyi's entropy range in (a) Seizure activity, (b) Pre-ictal activity and (c) eyes-open normal activity

Renyi's entropy of epileptic signals is more than normal signal's entropy and confirms that these signals are more complicated and more disposed to have diversity, uncertainty, or randomness. Since CWD provides better time and frequency resolution the value of Renyi's entropy is calculated using CWD. This value for pre-ictal signals is lower than normal and epileptic activity which is shown in Figure 5. As indicated in Table 1 the entropy values in case of the alpha and delta subband for all groups differ significantly with? their P values being much less than 0.001. From the results in Table 1 it is clear that Renyi's entropy might be a high-quality discriminative feature especially in alpha and delta sub-bands of the signal.

Table 1. P-values of Renyi's entropy extracted from band limited EEG signals and their sub-bands in each group

Signal	Normal vs. seizure	Pre-ictal vs. normal	Seizure vs. pre-ictal
Band limited EEG	0.02	<0.001	<0.001
Gama sub-band	<0.001	0.6	<0.001
Beta sub-band	<0.001	<0.001	0.5
Alpha sub-band	<0.001	<0.001	<0.001
Theta sub-band	0.87	<0.001	<0.001
Delta sub-band	<0.001	<0.001	<0.001

Discussion

In this paper, the ability of TFDs to discriminate EEG signals from different physiological and pathological brain states was explored. For this purpose, two different distributions from Cohen's class were selected for visualizing the energy content of brain electrical activity. Parameters of these distributions were chosen to attain a trade-off between time and frequency resolution and make sure that time-frequency components of the signal were represented by the distributions clearly with minimum rate of cross-terms. CWD provides better resolution because of its exponential kernel. Finally, three special categories of our dataset were evaluated using these transformations including normal, pre-ictal and ictal activities.

Despite the assumed random nature of normal surface EEG signals, the presence of some episodic patterns, as found for set A, suggested that mental activity might represent the imposing of rhythmic harmonics resulting in the physiological alpha rhythm. However, as reported in [15], noticeable differences between the conditions of eye- close and eye- open could not be obtained by TFDs.

As shown in Figure 3 pre-ictal activity has clear indications of rhythmic activity similar to seizure activity. In addition, a number of studies in which a successful connection between the anticipation of seizures by analysis of EEGs recorded from patients and epileptogenic zone during seizure free intervals has been demonstrated [15, 19] and it is supported by the results of the presented analysis. Epileptic activity evolves with changes in frequency of harmonics. As illustrated in Figure 4, distributions consist of lines that appear to be parallel in the frequency direction. Looking at the TFDs of the categories, it is interesting to note that the presence of a pattern in the TFD could help to indicate certain markers specifically in terms of seizure detection. Also, TFDs from epileptogenic zones might be useful. Renyi's entropy provided a powerful numerical measure of the randomness of a signal in each category. As shown in Table 1, Renyi's entropy is a high-quality discriminative feature especially in alpha and delta sub-bands of the signal.

In our opinion, the classification of epileptic signals is one of the most important applicable fields of computer science in the medicine scope. In this field, so many algorithms have tried to detect, classify, or identify epileptic patterns in EEG signals. One of the most important algorithms is joint time-frequency analysis. In this study, discrimination of epileptic activity has been discussed by means of TFSAP that considers the properties of the signal in both the time and the frequency domains. Two well-known distributions from Cohen's class were selected for visualizing the energy content of brain electrical activity. By utilizing multiresolution analysis results show that Renyi's entropy with respect to CWD is a high-quality discriminative feature especially in specific sub-bands of the signal. The novelty in our work is that we use Renyi's entropy calculated from Choi-Wiliams Distribution and show that this measure significantly differs statistically between three data sets (A, D and E).

Conflict of Interest

The authors declare that they have no conflict of interest.

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