Application of Global Coherence Measure to Characterize Coordinated Neural Activity during Frontal and Temporal Lobe Epilepsy

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Abstract— **Time- and frequency-domain studies of EEG signals are most commonly employed to study the electrical activities of the brain in order to diagnose potential neurological disorders. In this work, we applied the global coherence approach to help estimating the neural synchrony across multiple nodes in the brain, prior and during a seizure. The ratio of the largest eigenvalue to the sum of the eigenvalues of the cross spectral matrix at a certain frequency and time allowed detecting a strong coordinated neural activity in alpha sub-band for the frontal lobe epilepsy. Kruskal Wallis test reveals that global coherence is an efficient tool before the seizure for the temporal lobe epilepsy in a wide range of frequencies from Delta to Beta sub-bands.**

Clinical Relevance— **The work introduces global coherence as a new and efficient feature in prediction of seizure and specifically for the frontal lobe epilepsy.**

I. Introduction

Seizure, a neurological disorder, affects more than 70 million worldwide and there is not yet a concrete treatment for a majority of patients [1, 2]. A seizure activity is generally associated with a sudden and excessive electrical discharge in a part or the entire brain. During the epileptic seizure, the normal activity of the brain is interrupted, which affects an individual's behavior and cognitive function [3]. A reliable automated system that can predict seizure will help caretakers/physicians in monitoring and treating the disorder thus, enhancing the patient's quality of life and safety. Electroencephalogram (EEG) and intracranial electroencephalography (iEEG) have been used to unravel and understand the mechanisms that can help identifying different neurological disorders, such as epilepsy, and studying the functioning and behavior of the brain [4, 5]. The proposed work aims to introduce a novel and efficient measure to help predicting epileptic seizures based on invasive EEG electrode recordings. The results could provide further insight into the brain behaving and underlying mechanisms that are behind various forms of epilepsy.

Intracranial EEG (iEEG) is an electroencephalography recording utilizing invasive techniques or employing invasive intracranial electrodes implanting in the brain during surgery. So, compared to the scalp electrodes, the seizures can be identified typically earlier through the intracranial electrodes [6].

The International League Against Epilepsy (ILAE) divided epileptic seizures into partial or focal and generalized seizures. Focal seizures originate in a limited region of the brain and may spread to other regions. On the other hand, generalized seizures are initiated in bilateral hemispheric areas, which appear to be simultaneously involved [7]. Though there are different forms of seizures, we focused on those that happen "locally", mainly in the frontal and temporal lobes.

Frontal lobe epilepsy is the second-most common form of focal epilepsy after the temporal lobe. Frontal lobe seizures are usually brief and tend to occur during sleep [7-9]. Few researches have been done for patients with frontal epilepsy due to the complexity of this kind of seizure [10]. Since only a small number of papers have been published, then research in frontal lobe epilepsy is still valuable to be considered. Diagnose of the frontal epilepsy is rather hard due to having similar symptoms as sleep disorder or night terror and psychiatric [11].

Many algorithms have been developed including Phase-Amplitude Coupling Measure [12], Phase and Amplitude Lock Values [13], Cross-Frequency Coupling [14] and there is still room to enhance or develop new techniques that can help us to better detect, analyze, and study the seizure and its mechanisms.

To distinguish between the normal and abnormal synchronization of a neural activity, a coherence-based analysis can be proposed. Coherence is a measure that provides synchrony between pairs of brain regions while global coherence offers coordinated neural activity across multiple brain areas. Unlike pairwise coherence, global coherence gives a better understanding of neural synchronization across several brain regions due to rendering a higher coordinate spatial activity [15, 16].

Global coherence can be described based on the eigenvalues of a cross spectral matrix for a range of frequencies and, therefore, spectral analysis should be applied [118]. Global coherence can be defined as the ratio of the largest eigenvalue of the cross spectral matrix to the sum of its eigenvalues at a given frequency [17-19].

To the best of the authors' knowledge, global coherence has not been used to study seizures, evaluate the potential of this measure in prediction of the seizure, as well as to explore the synchronous activities during and before the seizure.

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The paper is structured as follows: section II describes the database employed in this study to acquire the iEEG signal as well as the preprocessing step. Further, this section details the calculation of the coherence. Section III presents and discusses the results. Section IV concludes the work.

II. II. Database and Methodology

A. EEG Database

The EEG dataset employed in this research is from the University Hospital of Freiburg, Germany. The EEG-database consists of two sets of files: “preictal (pre-seizure) data,” i.e. epileptic seizures with at least 50 min preictal data, and “interictal data,” which contains about 24 hours seizure-free EEG-recordings. The EEG-database comprises six iEEG electrodes from 21 patients with a sampling rate of 256 Hz. We studied six patients with ictal origin in the temporal lobe (134 hours) and six with frontal lobe epilepsy origin (200 hours) [20].

In Fig. 1, one-hour data from a patient with frontal and temporal lobes is depicted. As we can see, epilepsy from the frontal lobe (which takes about 7 seconds) is shorter than the temporal one (which takes about 91 seconds). In addition, the morphology of the signal over a given period of time for each type of epilepsy is completely different. In fact, we can observe some hints in the preictal stage of the temporal one that are not in the other one.

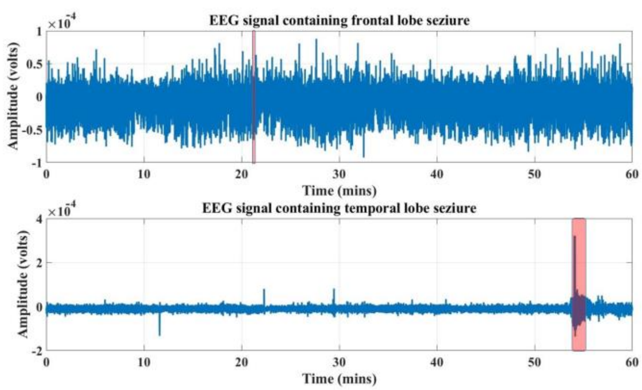

Figure 1. An overview of an EEG signal containing seizure for a patient suffering from frontal and temporal lobe epilepsy (the seizure period is highlighted in red).

B. Proposed Method

In order to explore global coherence on iEEG data, we used the multitaper FFT, a nonparametric technique, to determine the cross spectral matrix and, then, the global coherence, which can be defined by the eigenvalues of the cross spectral matrix, calculated per each frequency over time.

Applying techniques like the periodogram offers inaccurate (biased) and noisy (variable) estimation of the power spectrum and spectrogram with a high-resolution spectra. Other possible approaches to improve the EEG spectral estimation can be refereed to averaging these spectra across time like the Welch’s method. Whereas this approach generates high-resolution and low-variance spectra, the temporal resolution is significantly weakened because of applying an extra smoothing over time [21].

Therefore, one needs to look for a trade-off between frequency and temporal resolution. Interestingly, a modern approach, the multitaper spectral estimation, can generate a clear, precise, and high-resolution spectral estimation, without taking an average over frequency or time [21]. Also, it involves a fast algorithm to estimate the global coherence [19].

Prior to applying the multitaper FFT, the power line interference at 50 Hz was eliminated with a second-order Butterworth filter then multitaper parameters were set using a DPSS (Discrete Prolate Spheroidal Sequence) window length of 2 s with 50% overlap, time-bandwidth product TW of 3.5, and a number of Slepian tapers L=2×TW-1=6. To improve the performance of the spectral estimation we filled the cross-spectral matrix by considering a 30 s segment window. For a given 6 channels, we have then a 6×6 matrix

$$C_k^f(i,j) = <\tilde{X}_{i,k}(f)\tilde{X}^*_{j,k}(f)> = \frac{1}{Q}\sum_{q=1}^{Q} X_{i,k}^{(q)}(f)X_{j,k}^{(q)*}(f) \quad i,j = 1,\dots,M \quad (1)$$

where $\tilde{X}_{i,k}(f)$ is the spectrum estimate of the i^{th} channel (of M channels) at time interval k (of K time intervals), $X_{i,k}^{(q)}(f)$ is the q^{th} tapered Fourier transform (of Q Slepian tapers), which can be defined by

$$X_{i,k}^{(q)}(f) = \int_{-\infty}^{+\infty} X_{i,k}(t) \times q(t) \times e^{-2\pi i t f}\, dt \quad (2)$$

where q(t) is the q^{th}Slepian taper. For calculating eigenvalues from cross spectral matrix, you can use SVD decomposition [15, 19] and decompose C_k^finto eigenvalue and eigenvector components

$$C_k^f = L_k^f D_k^f {L_k^f}^H \quad (3)$$

where L_k^f is the eigenvector matrix and D_k^f the orthogonal eigenvalue matrix at time interval k and frequency f. Its i^{th} element $\lambda_{i,k}^f$ can be expressed as

$$\lambda_{i,k}^f = D_k^f(i,i) \quad i = 1,\dots,M \quad (4)$$

From that, the Global Coherence measure at time interval k and frequency f would be:

$$g_k^f = \frac{\lambda_{1,k}^f}{\sum_{i=1}^{M}\lambda_{i,k}^f} \quad (5)$$

where $\lambda_{m,k}^f$ is the m^{th} largest eigenvalue ($\lambda_{1,k}^f > \lambda_{2,k}^f > \cdots . > \lambda_{M,k}^f$) [16].

This measure varies from 0 to 1, a low value (0) dealing with a random reading from all the channels, while a large value (1) indicates that all the channels are completely coherent. Then, higher the global coherence value, higher coordinated activity is suggested [15].

III. Results and Discussion

An EEG signal consists of various frequency sub-bands namely, Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), as well as low-Gamma (30-70 Hz) and high-gamma bands (>70 Hz) [22-24].

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We illustrated the global coherence for both preictal and interictal over various frequencies in Figs. 2 and 3. Fig. 2 shows the global coherence of preictal (two consecutive hours) and interictal (One hour) portions for a frontal lobe epilepsy. From figs. 2-a and 2-b we can see a meaningful change in global coherence for the range of frequencies of 20-60 Hz before and during seizure, while the results of the global coherence for non-seizure file (Fig. 2-c) do not show the pattern in preictal files.

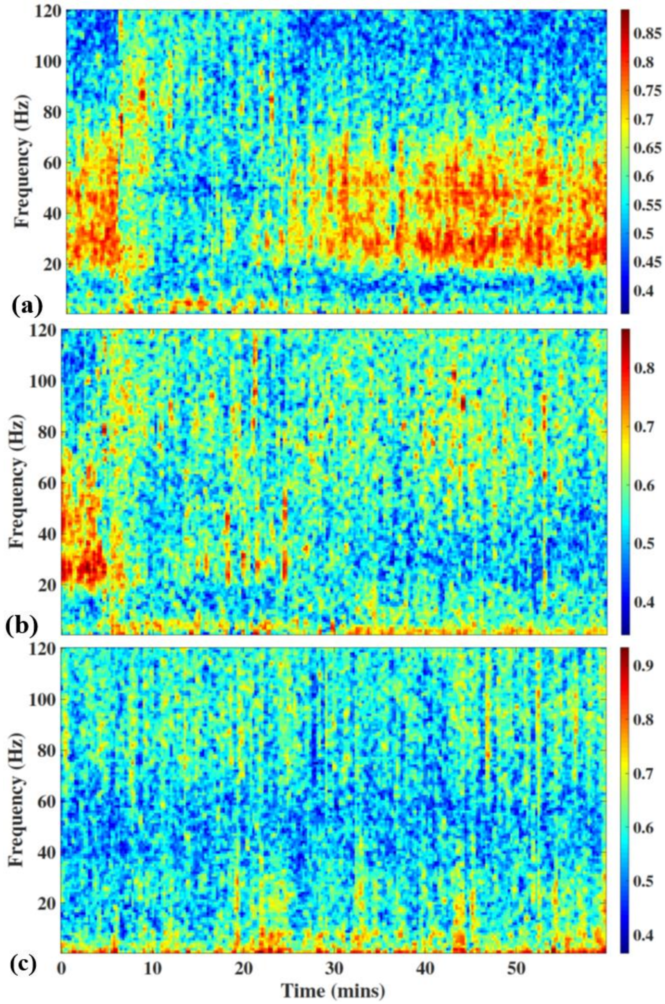

Figure 2. Global coherence for various frequencies of a frontal lobe epilepsy patient a) one hour data contains seizure from 356 to375 seconds and precede a seizure b) A seizure occurs between 287-305 seconds c) one hour interictal file

Based on the results of the global coherence for patient #1, we can conclude that, prior to seizure, the range of frequencies from 20 to 65 Hz can be important for patients suffering from a frontal epilepsy (Beta and Gamma sub-bands). In addition, during the non-seizure activity, the frontal lobes generate a range of frequencies where dominant ones are Delta and Alpha.

Fig. 3 shows the global coherence of preictal and interictal portions (one hour each) for a patient with temporal epilepsy. Figs. 3-a demonstrates that there is a wide range of frequencies that should be considered prior to the seizure, whereas Fig. 3-c can confine this broad range. Our results confirmed that high-gamma frequencies (>60 Hz) are a promising biomarker during ictal phase for temporal lobe epilepsy [25-28].

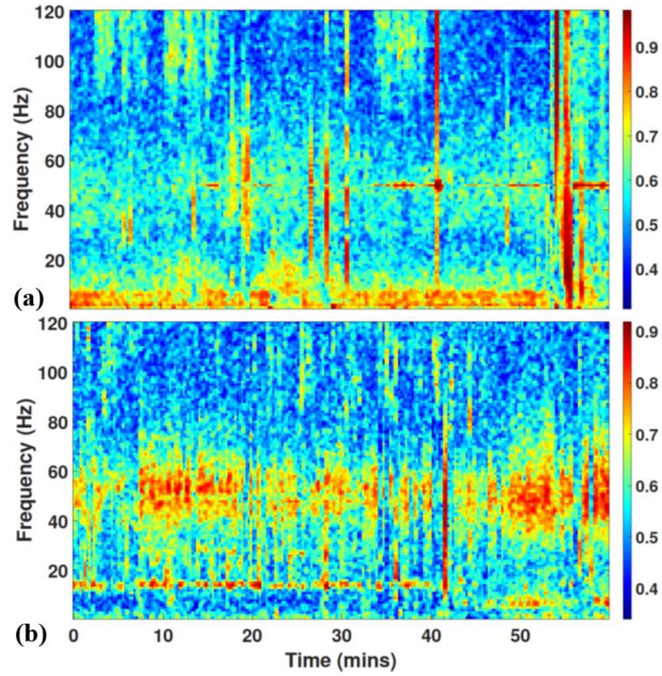

Figure 3. Global coherence for various frequencies of a temporal lobe epilepsy patient a) one hour EEG signal contains the seizure from 53 to 56 minutes b) one hour interictal file

We employed the Kruskal Wallis (KW) feature selection technique, which is a nonparametric test, without making prior assumptions about the data distribution, unlike the One Way ANOVA [29-30].

By applying Kruskal Wallis on six EEG sub-bands, we ranked these features based on their medians for both lobes of the brains. The results, shown in Fig. 4, illustrate that Alpha sub-band is the most important feature among other sub-bands for the frontal lobe while, for the temporal lobe one, we were faced with a higher range of frequencies, which required to take into account various sub-bands. Consequently, Alpha oscillation is strong for the Frontal lobe whereas for the temporal lobe various sub-bands may change the dynamics of the brain.

IV. Conclusion

The proposed work demonstrated that the global coherence can be a promising measure prior to the seizure, in the range of Alpha sub-band for the frontal lobe epilepsy. For a temporal lobe epilepsy, we should consider a wider range of frequencies (various brainwaves) in the preictal stage.

The above approach will be applied to other available patients on the dataset in order to explore how the neural activity is coordinated and associated before and during seizure in order to understand how the brain functions during those states (while investigating changes in the eigenvectors and Hermitian angles).

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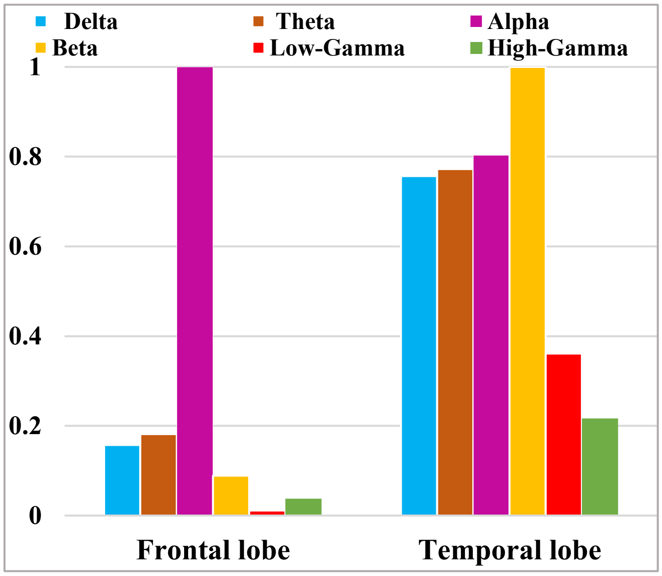

Figure 4. Ranking the features, 6 EEG sub bands, with Kruskal Wallis for both lobes of the brains.

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