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Entropy features for focal EEG and non focal EEG

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ABSTRACT

Electroencephalogram (EEG) is the recording of the electrical activity of the brain which can be used to identify different disease conditions. In the case of a partial epilepsy, some portions of the brain are affected and the EEG measured from that portions are called as Focal EEG (FEEG) and the EEG measured from other regions is termed as Non Focal EEG (NFEEG). The identification of FEEG assists the doctors in finding the epileptogenic focus and thereby they can plan for surgical removal of those portions of the brain. In this work, a classification methodology is proposed to classify FEEG and NFEEG. The Bern Barcelona database was considered and entropies such as Approximate entropy (ApEn), Sample entropy (SampEn) and Fuzzy entropy (FuzzyEn) as features which are fed into several classifiers. It was found that Non Nested Generalized Exemplers (NNge) classifier gave the highest classification accuracy of 99%, sensitivity of 99% and specificity of 99%, which is good comparing to proposed methods in the literature. In addition to the above, the maximum computation time of our features is 1.14 s which opens the window towards real time processing.

1. Introduction

Epilepsy is a neurological disorder in the present world today. This causes involuntary convulsion to the patient's muscles and at times lead to loss of consciousness. In this world about 50 million people are living with epilepsy [1–4].

Electroencephalogram (EEG) is widely used for various analysis of brain activity [1–3,5,6]. Epilepsy is clinically analysed using EEG. Some people with epilepsy become resistant to drugs and thus they need surgical removal of those parts of the brain which causes epilepsy to get rid of this disease. That portion of the brain which causes epileptic seizures is called as the epileptogenic foci. Such surgery is common in the present society now. The outcome of the surgery has successfully removed or significantly reduced the occurrence of the epileptic seizure in the patients [7]. Hence there is a precise need to find the exact region of the brain causing the epileptic seizures for surgical planning [8]. Presently locating the epileptogenic foci is being performed manually by the physician by clinical procedure which is subjective. This type of treatment is done in the case of partial epilepsy or partial seizures. In partial seizures, some portions of the brain are affected by the epileptic seizures and other portions are normal. In this context, FEEG is the EEG that is recorded from the brain areas where the first ictal EEG (seizure) changes were detected. And NFEEG is that EEG that is recorded from the brain areas that were not involved at the seizure onset [9].

Hence an automatic identification between these two signals – FEEG and NFEEG will assist doctors in identification of the epileptogenic foci for their surgical evaluation of the regions of the brain. In attempt to this, Bern Barcelona database [9] is considered and used it towards building algorithms for automatic classification of FEEG and NFEEG. In the literature, there are only a very few works who used this database for this purpose. The highest accuracy reported in the literature is 87% [10]). Here a simple method is presented in comparison to the existing methods that achieved the highest accuracy of 100%, 100% sensitivity and 100% specificity.

The paper is organized as follows. Section 2 presents the details of the data, brief information about the entropies used as features and the various classifiers which have used in this work. Section 3 presents the results obtained in this work. Section 4 presents a discussion on related studies of this database and compares our results with other methods and results in the literature. The conclusion is given in Section 5.

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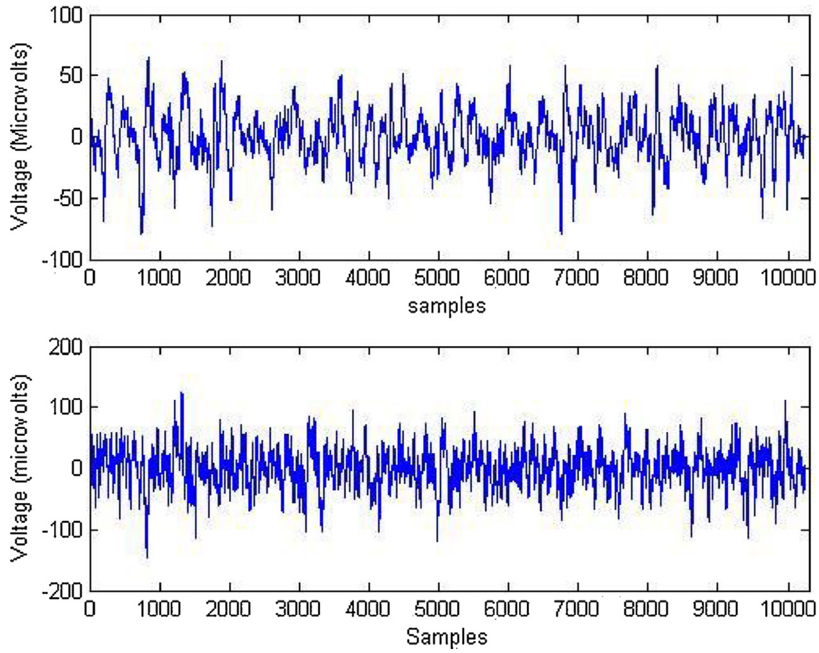

Fig. 1. Top: A sample signal from the Focal EEG Bottom: A sample signal from the Non Focal EEG.

2. Methods and materials

This section describes the methods employed for automatic classification of FEEG and NFEEG.

2.1. Data

The EEG database of Bern Barcelona database is used in this work. The details of this data can be referred in [9]. The EEG data is from five patients with temporal lobe epilepsy. The sampling rate of the acquisition is 512 Hz. The dataset contains 3750 pairs of FEEG and NFEEG signals with 10, 240 samples each. We have used the first 50 pairs of data for evaluating our algorithm. We took 50 pairs of FEEG and NFEEG signals and made it to form 100 signals in each group namely Focal and Non focal EEG group. An example of these signal pairs from FEEG and NFEEG is shown in Fig. 1.

2.2. Features

The concept of entropy was originated in 1803 by a mathematician Lazare Carnot as he discovered that energy is lost due to dissipation and friction [11,12]. This thermodynamic entropy was later brought into the field of information theory with the name information entropy only in 1948 by Shannon [13]. Since then, there are lot of varieties of entropies have come in the literature. In this work namely Approximate entropy (ApEn), Sample entropy (SampEn), Reyni's entropy (RE) and Fuzzy Entropy (FuzzyEn), as features.

2.2.1. Approximate entropy (ApEn)

Approximate entropy (ApEn) is widely used in the literature. ApEn is an algorithm proposed by Pincus [14] which measures the regularity of a signal. ApEn is used in earlier works and the details of ApEn can be referred from them [15,16]. ApEn has also been used widely in the literature for EEG by a number of researchers [17–20].

2.2.2. Sample entropy (SampEn)

SampEn is a modified form of ApEn. This also measures complexity for a given time series data. The advantage about the SampEn is that it does not depend on the length of the data and gives improved relative consistency. SampEn was used in our earlier work [21]. SampEn has been used widely in the literature towards epilepsy detection Molinari et al., 2012; [22].

2.2.3. Reyni's entropy (RE)

Reyni's entropy was introduced by Alfred Reyni in 1961 [23]. Reyni's entropy estimates the spectral complexity of the given signal about an event *f*. It is given by [10],

$$RE = -\log\left(\sum_{f} p_f^2\right)$$

This complexity measure has been already used in the literature towards detection of epileptic seizures [24].

2.2.4. Fuzzy entropy (FuzzyEn)

FuzzyEn has been in the literature for a long time [25,26]. This work has used the method formed by [27] to calculate FuzzyEn. A more detailed information about FuzzyEn can be referred from [27].

2.3. Classifiers

Six classifiers namely Naïve Bayes classifier (NBC), Radial basis function (RBF), Best First Decision tree classifier (BFDT), K nearest neighbourhood classifier (KNN), Support vector machines (SVM) and Non Nested Generalized Exemplars (NNge) decision rule classifier are proposed which are briefly explained as follows.

2.3.1. Naive bayes classifier (NBC)

This is a standard classifier with the base on Bayes theorem. The variables involved are considered as independent random variables. With this consideration, it computes the probabilities as of the Bayes theorem for the given data.