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Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction

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ABSTRACT

This study proposes a new model which is fully specified for automated seizure onset detection and seizure onset prediction based on electroencephalography (EEG) measurements. We processed two archetypal EEG databases, Freiburg (intracranial EEG) and CHB-MIT (scalp EEG), to find if our model could outperform the state-of-the art models. Four key components define our model: (1) multiscale principal component analysis for EEG de-noising, (2) EEG signal decomposition using either empirical mode decomposition, discrete wavelet transform or wavelet packet decomposition, (3) statistical measures to extract relevant features, (4) machine learning algorithms. Our model achieved overall accuracy of 100% in ictal vs. inter-ictal EEG for both databases. In seizure onset prediction, it could discriminate between inter-ictal, pre-ictal, and ictal EEG with the accuracy of 99.77%, and between inter-ictal and pre-ictal EEG states with the accuracy of 99.70%. The proposed model is general and should prove applicable to other classification tasks including detection and prediction regarding bio-signals such as EMG and ECG.

1. Introduction

Epilepsy is a neurological disorder affecting over 50 million people worldwide. The archetypal modality for studying the human brain activity and brain-related disorders is electroencephalography (EEG). The need for an automated detection technique becomes more evident as there are no strong differences between seizure and seizure-free EEG recordings. From this vantage point, every third epileptic patient cannot be effectively cured by existing treatments, such as anti-epileptic drugs and surgeries. Patient's everyday activity is negatively influenced by the unpredictable nature of epileptic seizures, which, moreover, increases a risk of severe injuries. Thus, a patient's quality of life could be considerably improved if we can develop an effective alarm system for upcoming seizures [1]. This study suggests such (possible) system.

In order to evaluate the performance of such systems, the interval-based and segment-based paradigms are considered [2,3]. The former is characterized by sensitivity and false detection rate – FDR (or false prediction rate, FPR, in case of seizure prediction), whereas the latter is evaluated according to the sensitivity and specificity values. Sensitivity and specificity are expressed in percentages, while FDR (FPR) represents the number of false detections (predictions) per hour. Many interval-based approaches also suggest the latency as a measure. However, the development of seizure onset and termination detector is not an objective of the present study. In addition, the aim is not the development of interval-based seizure prediction system either. Therefore, the FPR criterion will not be used for the performance evaluation as in [4–6]. The objective of this study is the development of an effective segment-based approach for classifying EEG signals that can be utilized in designing the automated interval-based seizure prediction (or onset detection) systems.

Electrophysiological studies usually include EEG to monitor the neural (brain) responses. It should be noted that intracranial EEG (iEEG) produces brain signals of the better quality, but its less attractive side is its invasiveness. Contrary to iEEG, scalp EEG became more attractive, but potentially useful information may be lost due to the lower signal quality. This implies that it is reason-

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able to have a model for the seizure onset detection and prediction applicable to both modalities. We evaluate our models on both modalities: iEEG modality used in Freiburg data recordings and scalp EEG modality used in CHB-MIT data recordings.

The first seizure prediction approach using Freiburg database were designed by adjusting thresholds for particular features extracted from (intracranial) EEG segment, generating an alarm if the features violated an absolute or adaptive value [1]. In [7], a plethora of univariate and bivariate features were investigated for the use in threshold-optimized prediction methods. As various features hold discriminative information related to different cerebral states (inter-ictal, pre-ictal, ictal, and post-ictal), many machine learning algorithms were normally implemented to enhance seizure prediction rates [8–11]. In [8], six different types of neural network architectures were compared by using 14 features extracted from EEG of two patients to classify brain states into four classes: inter-ictal, pre-ictal, ictal and post-ictal. The accuracies of up to 99% were achieved. Tafreshi et al. [9] analyzed 19 patients from Freiburg database and achieved average success rate of 89.68% by combination of Empirical Mode Decomposition (EMD) features and AR model coefficients. Another but more successful approach using EMD features was presented in [11]. EMD features were combined with discrete cosine transformation (DCT) features and then classified by least square support vector machine (SVM) to achieve average accuracy of 99.1%. Aarabi & He [10] presented a rule-based seizure prediction system for focal neocortical epilepsy using 5 univariate and one bivariate feature to achieve sensitivity and specificity of 90.2% and 97% respectively.

The first machine learning approach has been developed by using the CHB-MIT database [12] is reported in [13]. The subject-oriented approach detected the onset of 96% of 173 test seizures in interval-based assessment, with latency of 3 s and false detection rate (FDR) of 2 false detections per hour. Other studies have been published [14,15] to improve the onset detection performance presented in [13]. On the other hand, there were some studies that tried to pull a mark of separation between seizure and seizure-free activity using CHB-MIT database. In [16], an automated epileptic seizure detection using wavelet based feature extraction technique is evaluated on 23 patients with 195 seizures with a 96.5% classification accuracy. A supervised machine learning method for seizure detection using multiple subject records is presented in [17]. A few subject-oriented seizure detection approaches developed on Freiburg EEG database have been discussed and explained in [18]. Specificity and sensitivity values above 90% were reported in majority of these studies. An efficient seizure detection approach was developed in [19], achieving specificity and sensitivity of 99.82% and 87.5% respectively. In addition, differential windowed variance (DWV) algorithm have been successfully combined in an automatic detection of seizure onset on Freiburg dataset in [20]. Sensitivity of 91.525%, average delay of 9.2 s after the onset, and FDR of 3/24 h were achieved. Eight novel empirical measures have been introduced to avoid false detections. Liu et al. [21] developed wavelet-based automatic seizure detection method with effective features and support vector machine for classification. A post-processing step was performed on the raw classification results to get more accurate results achieving a sensitivity of 94.46%, a specificity of 95.26%, and a FDR of 0.58/h for seizure detection in Freiburg EEG dataset.

The aforementioned studies suggest that an automated system for seizure onset detection and prediction can be designed. However, there is still room to investigate whether a different model could carry out seizure detection and prediction with higher performances in terms of statistical measures such as accuracy, sensitivity, and specificity. In addition, can shorter time interval (shorter segments) result in a comparable or a higher performance? Thus, the contribution of this study lies in the development of a model for seizure onset detection and prediction with very high confidence. This finding has implications for general design principles of epilepsy-based systems.

In order to cope with nonlinear and non-stationary signals, such as EEG, the classical frequency methods have rather strict restrictions. Therefore, time–frequency techniques have been developed to eliminate these restrictions. Such techniques for signal decomposition include Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT), and Wavelet Packet Decomposition (WPD). The model suggested in the present study consist of four modules: (1) multiscale principal component analysis (MSPCA) to remove artefact contaminated parts from EEG measurements, (2) three different decomposition methods (EMD, DWT and WPD) to find the most suitable set of frequency bands, (3) statistical values (lower and higher order statistics) to extract the relevant features from EEG frequency bands decomposed with EMD, DWT and WPD, and (4) machine learning methods (classifiers) to discriminate between different states (inter-ictal, pre-ictal and ictal). The rationale to select MSPCA for artefact removal (de-noising) is that its proven superiority when applied to different biomedical signals, such as ECG [22–24], EMG [25], EEG [18]. The rationale to select the suggested three decomposition methods (EMD, DWT and WPD) is plethora of their application in the different fields. The rationale to extract statistical features is to capture important information while keeping the low data dimensions. The selected classifiers are well-known classifiers with wide range of applications. We checked the aforementioned module combinations with four machine learning techniques to find the best system for seizure detection and prediction.

Hence, the aim of this study is to develop a segment-based system for classification of EEG signals that can be applied in automated interval-based seizure prediction (or onset detection) systems by using two omnipresent and archetypal EEG databases: Freiburg (iEEG) and CHB-MIT (scalp EEG). Our findings clearly indicate that the models suggested in the preset study are suitable for automated seizure onset detection and prediction systems.

The rest of this article is organized in the following way. Section 2 provides the materials and methods employed in this study. It explains databases used in this study, de-noising module, feature extraction and dimension reduction methods. In Section 3, EEG signal classification methods are shortly explained. The experimental results are presented in Section 4, whereas Section 5 concludes the paper.

2. Materials and methods

2.1. Experimental setup

2.1.1. Freiburg and Physionet CHB-MIT EEG databases

Freiburg EEG data was recorded at the Epilepsy Center of the University Hospital of Freiburg during the period of invasive presurgical epilepsy monitoring. The Freiburg EEG database is composed of invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and a 16 bit analogue-to-digital converter was used to sample the EEG data. Each patient had between two to five seizures and at least 24 h of seizure-free (inter-ictal) recordings. Every patient's data is organized into “ictal” and “inter-ictal” datasets. The former contains seizure files and at least 50 min of pre-ictal data, whereas the latter holds one day of seizure-free EEG-recordings [26].

CHB-MIT Dataset consists of 23 different subsets containing EEG records from 22 different pediatric patients. This dataset contains 182 seizures. Generally, each of these digitized records is one hour long. Sampling frequency is 256 Hz with 16-bit resolu-