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A novel robust diagnostic model to detect seizures in electroencephalography

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A B S T R A C T

Identifying seizure patterns in complex electroencephalography (EEG) through visual inspection is often challenging, time-consuming and prone to errors. These problems have motivated the development of various automated seizure detection systems that can aid neurophysiologists in accurate diagnosis of epilepsy. The present study is focused on the development of a robust automated system for classification against low levels of supervised training. EEG data from two different repositories are considered for analysis and validation of the proposed system. The signals are decomposed into time-frequency subbands till sixth level using dual-tree complex wavelet transform (DTCWT). All details and last approximation coefficients are used to calculate features viz. energy, standard deviation, root-mean-square, Shannon entropy, mean values and maximum peaks. These feature sets are passed through a general regression neural network (GRNN) for classification with K-fold cross-validation scheme under varying train-to-test ratios. The current model yields ceiling level classification performance (accuracy, sensitivity & specificity) in all combinations of datasets (ictal vs non-ictal) in less than 0.028 s. The proposed scheme will not only maximize hit-rate and correct rejection rate but also will aid neurophysiologists in the fast and accurate diagnosis of seizure onset.

1. Introduction

1.1. Background

Epilepsy is a chronic neurological disorder characterized by sudden recurrent and transient disturbances in behavior or perception. These disturbances are hallmarked by paroxysmally abnormal bursts of electrical discharges in the brain termed as ‘epileptic seizures’ (more commonly known as fits). The clinical manifestations range from major motor convulsions (e.g., grand mal seizures) to brief periods of lack of awareness (petit mal seizures). It is estimated that epilepsy is prevalent in about 1–2% of the world’s total population i.e., about 65 million people worldwide suffer from epilepsy (Moshé, Perucca, Ryvlin, & Tomson, 2015). Hence, diagnosis and treatment of epilepsy holds utmost clinical significance around the world.

The EEG recordings are often visually inspected by experienced neurophysiologists or trained neuro-clinicians to detect seizure onsets (Moshé, Perucca, Ryvlin, & Tomson, 2015). However, visual inspection of standard EEG recordings collected over several hours significantly hinders the diagnosis procedure (Duque-muñoz, Espinosa-oviedo, & Castellanos-dominguez, 2014). Furthermore, the EEG data are subjected to contamination from background noise, artifacts and interfering expressions from other neurological symptomatology. Henceforth, visual scoring of the epileptic activity from EEG signature proves to be very time-consuming and challenging even for an experienced neurophysiologist. About 80% of epilepsy cases are reported to come from developing countries (http://www.who.int/mediacentre/ factsheets/fs999/en/), where the patients admitted to the hospitals far outnumber the available neurophysiologists. This state of affairs further makes the current visual scoring method prone to human errors (Duque-muñoz et al., 2014; Gandhi, Panigrahi, Bhatia, & Anand, 2010) and can lead to improper diagnoses. For these reasons, a method for automated

Abbreviations: EEG, electroencephalography; DWT, discrete wavelet transform; DTCWT, dual-tree complex wavelet transform; GRNN, general regression neural network; TTTR, train-to-test ratio; ERD, energy; RMS, root-mean-square; STD, standard deviation; ENT, entropy; MXP, maximum peak; CA, classification accuracy; SE, standard error; SN, sensitivity; SP, specificity; CT, computation time.

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detection of epileptic seizures could serve as a fundamental clinical tool for the scrutiny of EEG data in a more robust, accurate and computationally efficient manner.

1.2. Related work and existing lacunas

Various algorithms for detection of epileptic seizures have been proposed in literatures. Some of the seminal studies are summarized here. Gotman (Gotman, 1999) had applied mimetic techniques, using the characteristic attributes like inclinations, crests, time-durations and sharpness measures in EEG. Most of the subsequent research work have adopted a dual scheme i.e. feature extraction and its classification for the development of automated epileptic seizure detection system. Frequency domain analysis using fast Fourier Transform (Polat & Güneş, 2007) and time-frequency domain approaches like short-time Fourier transform (Duque-muñoz et al., 2014) and especially wavelets (Acharya, Vinitha Sree, Swapna, Martis, & Suri, 2013; Faust, Acharya, Adeli, & Adeli, 2015; Gandhi, Chakraborty, Roy, & Panigrahi, 2012a; Swami et al., 2016) have often been used for extraction of discriminating features in the EEG signals. Features like entropy, energy (Gandhi et al., 2010; Gandhi, Panigrahi, & Anand, 2011), statistical parameters (Gandhi et al., 2011; Swami, Bhatia, Anand, Panigrahi, & Santhosh, 2015), chaotic parameters (like Largest Lyapunov exponent, correlation dimension, etc.) (Shayegh, Sadri, Amirfattahi, & Ansari-Asl, 2014), Hjorth parameters (Päivinen et al., 2005), principal component analysis (PCA) vectors (Subasi & Gursoy, 2010), independent component analysis (ICA) vectors (Subasi & Gursoy, 2010), have shown noteworthy performance for characterizing subtle changes in EEG signals. In addition, optimization algorithms like harmony search (Gandhi, Chakraborty, Roy, & Panigrahi, 2012a), etc. have also been proposed for feature selection.

Based on our previous research and the literature discussed, it is asserted that discrete wavelet transform (DWT) is one of the most commonly used techniques for feature extraction. DWT allows capturing and localizing the transient changes in EEG recordings. However, the fundamental disadvantage of using discrete wavelets that has been overlooked in the past is its property of *shift variance* (Selesnick, Baraniuk, & Kingsbury, 2005). This means that even a slight shift in the signal greatly perturbs the resultant wavelet coefficients. It has been well known that the dual-tree complex wavelet transform (DTCWT) technique, which applies specially designed filter banks (Chen, 2014; Kingsbury, 2001; Selesnick et al., 2005) for implementing wavelet-domain processing, eliminates the aforementioned problem. Based on our survey, very limited research has been reported on processing epilepsy signals using DTCWT (Chen, 2014; Das & Bhuiyan, 2014; Das, Bhuiyan, & Alam, 2014). Present work demonstrates the extraction of time-frequency domain features of normal and epileptic EEG signals using DTCWT technique.

Once the feature sets are extracted, classification methods are employed in the next stage for deciding the class of the input features. Various classification methods are available in literatures. It ranges from rule-based decision making (Gotman, 1999), linear classifiers (Iscan, Dokur, & Demiralp, 2011), support vector machine (SVM) (Swami et al., 2014) and artificial neural network (ANN) (Gandhi et al., 2012b; Tzallas, Tsipouras, & Fotiadis, 2009) with multi-dimensional decision boundaries to logistic regression (Tzallas et al., 2009), naïve Bayes classifiers (Iscan et al., 2011), decision trees (Polat & Güneş, 2007), etc. Implementation of any classification algorithm uses a certain number of features for training and the remaining for testing. The majority of the proposed expert systems have used 7:3 as a train-to-test ratio (TTTR) (i.e. 70% of feature sets are used for training and the remaining 30% are used for testing), whereas many researchers have even achieved the estimated performance by using 9:1 as TTTR. In either case, however, using such a high percentage of features for training makes the system's performance 'predictably' high. To the best of our knowledge, although noteworthy expert systems have been developed for seizure detection, none of the investigations have so far tested the robustness of the computational performance with varying TTTRs. These shortcomings form the main research focus of the proposed technique. In addition, there is a striking incongruity between the measures of sensitivity and specificity (Carney, Myers, & Geyer, 2011) with slow or unmentioned computation timings. Here, we demonstrate an improved seizure detection scheme that overcomes the aforementioned lacunas and holds ground for solving the discrepancies observed in the classification of convulsive patterns.

The proceeding section of this paper describes the materials and methods. This section illustrates the datasets used in this study and systematic methodology employed for developing the proposed expert model. Later, Sections 3 and 4 explain the outcome of the proposed methods and draw comparisons with few existing methods. Finally, Section 5 culminates the important findings of this work and briefly describes its future scope.

2. Materials and methods

2.1. Source datasets

Two different EEG datasets are used for the present work. The first dataset used in this study is publically available in the EEG database of University of Bonn (UoB), Germany (Andrzejak et al., 2001). This database has become a benchmark for developing seizure detection models. The details of this dataset are summarized in Table 1. Starting from top to bottom, a sample segment from each subset A, B, C, D and E respectively is shown in Fig. 1. Sets A and B contain seizure-free data recorded from five healthy subjects. These datasets were acquired using gold plated surface electrodes placed according to 10-20 international electrode placement system. During the acquisition, the volunteers were relaxed and awake with eyes open (dataset - A) and eyes close (dataset - B). Sets C, D, and E consist of data recorded from epilepsy patients for pre-surgical diagnosis purpose using intracranial electrodes. The datasets C and D were recorded during seizure-free interictal trials from electrodes placed opposite to the epileptogenic zone and within the epileptogenic zone, respectively. The dataset E represents epileptic seizure (ictal) signals collected from electrodes placed within the epileptogenic zone. In general, non-ictal signals from UoB database consist of EEG segments without any epileptic seizure activity i.e., normal and interictal segments.

Each subset of the UoB database contained 100 EEG segments, each lasting for 23.600 s duration with 4097 samples and sampling rate (*Fs*) of 173.610 Hz. Similar to DWT, the implementation of DTCWT requires the number of samples to be of the power of two (Chen, 2014; Das et al., 2014). Hence, we used the initial 4096 samples from each subset.

In the present research, we have considered seven different combinations of the datasets available from UoB database. These combinations include:

2.1.1 *Set A* versus *E:* Combination of A and E datasets. Here, only the EEG segments from A and E datasets are used and they are classified into two categories viz. non-ictal intervals (belonging to set A) and ictal intervals (belonging to set E).
2.1.2 *Set B* versus *E:* Combination of B and E datasets. Here, only the EEG segments from B and E datasets are used and they are classified into two categories viz. non-ictal intervals (belonging to set B) and ictal intervals (belonging to set E).
2.1.3 *Set C* versus *E:* Combination of C and E datasets. Here, only the EEG segments from C and E datasets are used and they