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EEG based epileptiform pattern recognition inside and outside the seizure states

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ABSTRACT

Automatic diagnosis of epilepsy by computers based on Electroencephalography (EEG) analysis is a beneficial practice which increases recognition rate, speeds up diagnosis and saves physicians from long hours of EEG inspection. Most studies on this subject report results on detecting seizures; but seizures, which appear during the ictal states are very rare to catch. Therefore, an efficient algorithm must be able to detect epilepsy during nonseizure periods, or in other words interictal states as well. We present a novel algorithm to detect epileptiform patterns during both states: ictal and interictal. For this purpose, we use wavelet packet analysis (WPA) rather than traditional time and frequency domain methods. WPA, by providing arbitrary time-frequency resolution, enables analyzing signals of stationary and non-stationary nature. It has better time representation than Fourier analysis and better high frequency resolution than Wavelet analysis. WPA subimages are analyzed further to obtain feature vectors of Log Energy Entropy, Norm Entropy and Energy. These features are fed into a classifier, multilayer perceptron (MLP). We test our method on a well-known and widely studied database which includes healthy, ictal and interictal EEG recordings. Normal vs. Ictal and Interictal vs. Ictal zone classifications are realized at 100% accuracy by using any of the three features. Nonseizure vs. Seizure state classification is realized with 100% accuracy using Norm entropy. Normal vs. Interictal zone classification is achieved with 100% accuracy using Log Energy Entropy. Normal vs. Interictal vs. Ictal Zone classifications are considered as two-step binary classifications of Nonseizure vs. Seizure state followed by Normal vs. Interictal zone both of which are realized at 100% accuracy. Therefore, jointly use of Log Energy Entropy and Norm entropy is able to realize all possible classifications with 100% accuracy. We make the most comprehensive comparison of results belonging to all possible classification categories reported on the same datasets. The proposed method outperforms all the other results in all possible classifications by achieving 100% accuracy in all possible classifications. The method presented is the only single method that achieves this. Overall, the method provides us with a promising tool for the detection of epileptiform patterns during and outside the seizure states.

1. Introduction

Epilepsy is a widespread disease accompanied by sudden seizures in the brain. Its diagnosis relies on long term examination of electroencephalograms (EEG) looking for seizures. Since seizure states are very rare to catch, it is essential to find automatic diagnosis tools that can detect epileptiform patterns during nonseizure times as well.

Epilepsy-diagnosis related analysis of EEG signals has been studied using various tools in the literature. The features that are used during these analysis can be summarized as follows: Nigam et al. used relative spike amplitude and spike occurrence frequency [28]; Srinivasan et al. used time domain and frequency domain features [29]; Kannathal et al. used entropy estimators [30]; Polat and Güneş used principal component analysis and FFT [31]; Tzallas et al. used time-frequency analysis [32]; Guo et al. used multi-wavelet transform based approximate entropy [33]; Iscan et al. used combined time frequency features [34]; Acharya et al. used non-linear and wavelet based features [35]; Orhan et al. used discrete wavelet transform [36]; Wang et al. used statistical features from wavelet packet decomposition [37]; Acharya et al. used principal component analysis [38]; Alam and Bhuiyan used higher order statistics in the EMD domain [39]; Das et al. used normal inverse Gaussian parameters in the dual-tree complex wavelet transform domain [40]; Riaz et al. used EMD based temporal and spectral features [41]; Kaya et al. used 1D-local binary pattern based feature

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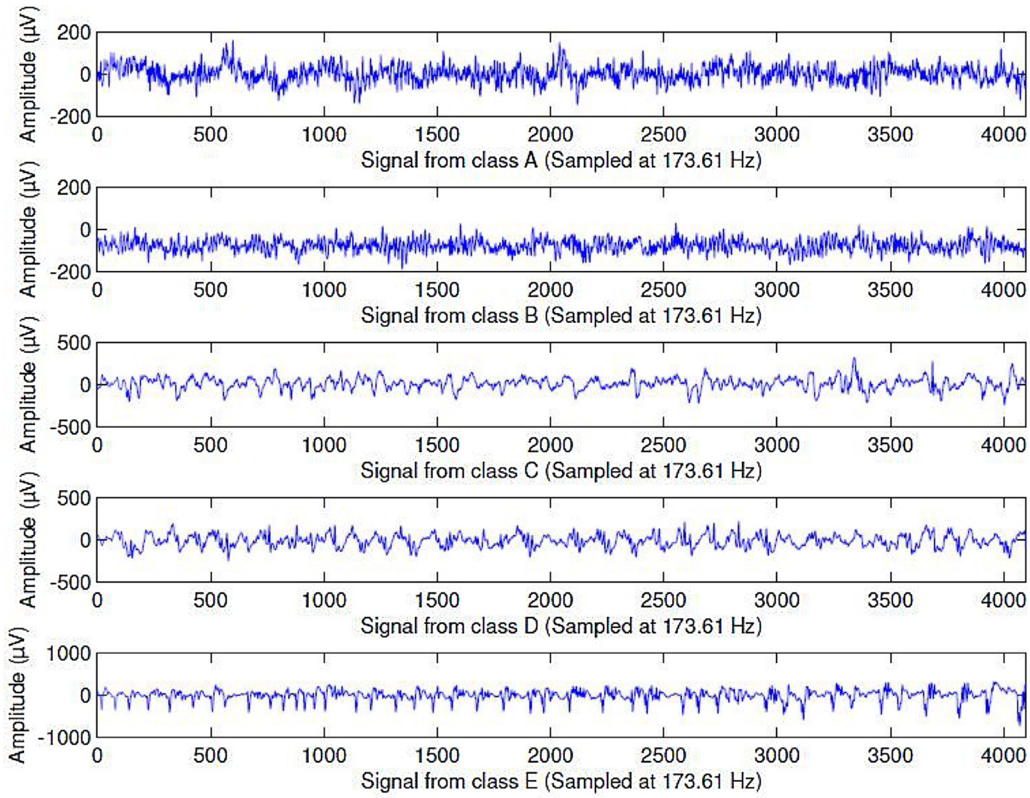

Fig. 1. EEG Signals from Classes A, B, C, D and E.

extraction [42]; Martis et al. used nonlinear parameters on different frequency bands [43]; Zhu et al. used fast weighted horizontal visibility graph constructing algorithm [44]; Nicolaou et al. used permutation entropy [45]; Acharya et al. used higher order cumulant feature [46]; Acharya et al. used recurrence quantification analysis [47]; Acharya et al. used continuous wavelet transform, higher order spectra and texture [48]; Xie et al. used Wavelet-based sparse functional linear model [49]; Fu et al. used time frequency image [4]; Chen used dual-tree complex wavelet-Fourier features [9]; Li et al. used wavelet based nonlinear analysis [14]; Subasi used wavelet based feature extraction [15]; Kumar et al. used discrete wavelet transform based fuzzy approximate entropy [39]; Acharya et al. used entropies [16]; Acharya et al. used entropies [17]; Kumar et al. used wavelet entropy [19]; Zhou et al. used lacunarity and Bayesian LDA [21]; Kumar et al. used local binary pattern [22]; and Samiee et al. used rational discrete STFT [23].

Time domain, frequency domain (Fourier) and time-frequency domain (Wavelet) analysis are the main tools used for analyzing signals but Fourier analysis has poor time representation, and wavelet analysis has poor resolution at high frequency. WPA overcomes both of these, and the arbitrary time-frequency resolution enables analysis of signals of both stationary and non-stationary nature.

Wavelet packet analysis has been used successfully in various biomedical problems in the literature. For example: Hu et al. used relative wavelet packet energy to classify surface EMG signals [1]; Wang et al. used relative energy of harmonic wavelet packet to classify surface EMG signals [2]; Hariharan et al. used Energy and Shannon entropy of WPA for pathological infant cry analysis [5]; Arjimandi et al. used energy and Shannon entropy of WPA for pathological voice quality assessment [6]; Sekine et al. used power of detail signals of wavelet packet decomposition (WPD) to classify waist acceleration signals [8]; Ting et al. used energy of WPD for EEG feature extraction to be used in brain computer interfacing [10]; Zhang et al. used relative energy and Shannon entropy of WPD to automatically recognize cognitive fatigue from physiological indices [11]; Crovato et al. used Shannon entropy of WPD for classification of dysphonic voices [12]; Subasi et al. used wavelet packet energy to classify EMG signals [13]; Raghu et al. [20] used log energy and norm entropies; and Wang et al. [37] used statistical features to classify EEG signals for seizure detection.

In this work, we propose a novel method for the automatic detection of epileptiform patterns during ictal and interictal states. For this purpose, we analyze EEG signals by WPD. Then we extract three features: Log Energy Entropy, Norm Entropy and Energy which are useful signal processing tools that are able to extract useful information from a signal. We feed these feature vectors to a multilayer perceptron (MLP) for classification. MLP is a kind of neural network which is able to learn patterns from a dataset and generalize to a new set. It has been shown to be robust and powerful in pattern recognition and classification problems. We test our approach on a well-known and widely studied database of normal, ictal and interictal EEG recordings.

2. Material

EEG signals we test our method with are from the Bonn Epileptologie database which is used to report many results using different techniques. It is explained by Andrzejak et al. [18]:

Five sets named A-E each of which contains 100 single channel EEG recordings of length 23.6 s are used. Sets A and B are from surface EEG recordings that were taken from five healthy volunteers in an awake state with eyes open (A) and eyes closed (B). C, D and E are from the archive of presurgical diagnosis which were taken from five patients. Segments in D were recorded from within the epileptogenic zone, and in set C they were recorded from the hippocampal formation of the opposite brain hemisphere. C and D contain seizure-free intervals (interictal) and E only contain seizure