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Epilepsy and seizure characterisation by multifractal analysis of EEG subbands

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ABSTRACT

Electroencephalography (EEG) is often used for detection of epilepsy and seizure. To capture chaotic nature and abrupt changes, considering the nonlinear as well as nonstationary behaviour of EEG, a novel nonlinear approach of MultiFractal Detrended Fluctuation Analysis (MFDFA) has been proposed in this paper to address the multifractal behaviour of healthy (Group B), interictal (Group D) and ictal (Group E) patterns. Following wavelet based decomposition of EEG into its frequency subbands, multifracatal formalism has been applied to extract four features, namely, spectrum width ($\Delta\alpha$), spectrum peak (α_0), spectrum skewness (B) and Hurst's exponent (H). The effectiveness of the parameters has been also tested through statistical significance across the subbands. It has been found that no parameters in alpha subband exhibit significant differences across all the Groups, whereas, all the parameters for band-limited EEG significantly distinguish the Groups. However, at least one Group was found to be significantly isolated from the parameters across all the subbands. Furthermore, support vector machine (SVM) has been trained to classify the Groups with the multifractal features for different EEG subbands. An accuracy of 99.6% has been observed for the band limited EEG.

1. Introduction

Epilepsy is a short electrical spikes generated in the brain resulting in convulsions, muscle spasms, emotional and behavioural discrepancies and loss of consciousness [1]. It affects people of all ages spreading through 1% of children and 0.5% of adults [2], making it as fourth most common neurological disorder. Since childhood, it hampers education, employment and socialism by diminishing sense of self-worth. Primary diagnosis of epilepsy bases on the experiences from an eyewitness. For faster and accurate diagnosis of the types of epilepsy, EEG is one of the most useful analysis method [2]. Usually, by visual inspection of EEG recording, epilepsy can be detected. But it is a very time consuming and tedious work and moreover, chances of misreading are very high. So, an automated detection method is very essential for accurate and faster detection of epilepsy. In spite of several researches, there still exist several difficulties in the detection of epilepsy. Low accuracy, considerable false alarms and missed detections are inherent with most of the established methods [3]. Reliable epileptic data are also scarcely available to be utilised to test a developed algorithm.

For the detection of epilepsy as well as seizure, several approaches have been evaluated by the researchers. Spatio-temporal-spectral analysis is most sought after for analysis of any EEG. However, inherent nonlinearity in the synaptic interactions across frequency bands in brain and central nervous system [4], encompassed the requirement of nonlinear methodologies to address them [5]. Various nonlinear methodologies were implemented to extract information from EEG signals in different studies [6–8]. Nonlinear dynamics based on chaos has been extensively used in identification of disorders from neuronal activities [9,10]. In detection of epilepsy also, fractal dimension (FD) [11,12], approximate entropy (ApEn) [13,14], largest Lyapunov exponent (LLE) [15,16], correlation dimension (CD) [15,16] and intrinsic mode functions (IMFs) [11] have been explored for their suitability. Adeli et al. [15] have concluded that LLE is low in band limited EEG and alpha subband of epileptic EEG. Similarly, CD is also reduced for beta and gamma subbands of epileptic EEG. In case of ApEn, Bai et al. [17] also observed reduction in value for epilepsy. However, first four IMFs were found to be higher for epilepsy as reported by [11]. Study done by Accardo et al. [12] on usefulness of FD in epilepsy detection, has ambiguity due to strong noise contaminations.

EEG is nonstationary in nature and it has large and small fluctuations. In this paper we have explored multifractal behaviour of EEG via multifractal formalisms. Detrended Fluctuation Analy-

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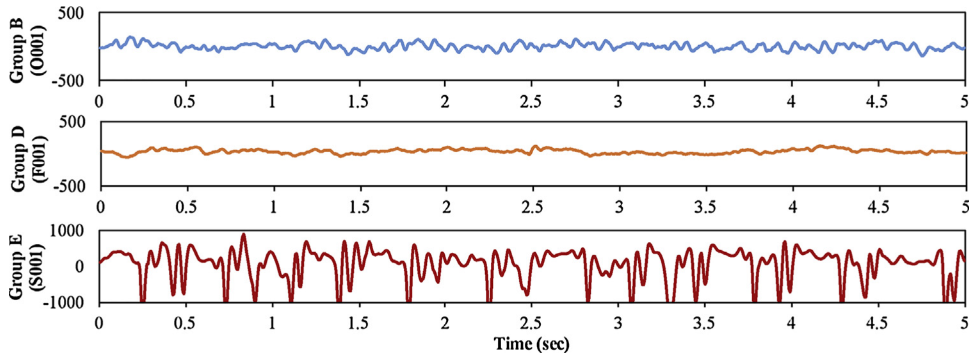

Fig. 1. Schematic representation of multifractal spectral parameters.

sis (DFA) [18] has been established as an important tool to obtain monofractal scaling properties of a time series [19]. But, DFA may not provide local extreme large magnitude within time periods of large fluctuations. Due to the presence of multifractality in EEG, FD may not be useful in EEG analysis as used by Accardo et al. An alternative approach of Multifractal Detrended Fluctuation Analysis (MFDFA) has been developed to estimate multifractality [20]. A large dataset has been used consisting three different Groups of EEG signals namely Group B (healthy), Group D (interictal) and Group E (ictal) to explore multifractal features through MFDFA. The EEGs were first decomposed into the five subbands, namely, *delta* (0–4 Hz), *theta* (4–8 Hz), *alpha* (8–12 Hz), *beta* (12–30 Hz) and *gamma* (30–60 Hz). Four multifractal parameters spectrum width ($\Delta\alpha$), spectrum peak (α_0), spectrum skewness (B) and Hurst's exponent (H) were extracted from each subbands of EEG of each Groups and tested for their effectiveness in separability between the Groups through analysis of variance (ANOVA). Furthermore, the significant parameters were tested with Tukey's honest significant difference (HSD). Finally, fivefold cross validated multiclass one-against-one cubic polynomial kernel based SVM was trained for each subbands and band-limited EEG to classify the Groups based on the multifractal features.

2. Materials and methods

2.1. Data

EEG data for both healthy and epileptic subjects by Dr. Ralph Andrzejak of the Epilepsy Center at the University of Bonn, Germany are used in this study [19]. From the database, three different groups of EEG data were analysed: Group B (healthy subjects), Group D (interictal), and Group E (ictal). In this dataset, Group B data were taken from the five healthy subjects with international 1020 electrode placement system. Group D and Group E data were obtained from interictal and ictal segments of epilepsy patients. The interictal segments were recorded during seizure free intervals from the depth electrodes that were implanted into the hippocampal formations. The ictal segments were recorded from all sites exhibiting ictal activity using depth electrodes and also from strip electrodes that were implanted into the lateral and basal regions of the neocortex [21].

100 single channel EEG segments of 23.6 s duration were recorded using a 128-channel amplifier system, digitised with a sampling rate of 173.61 Hz and 12-bit A/D resolution, and filtered using a 0.53–40 Hz (12 dB/octave) band pass filter. Fig. 1 shows the sample EEG signal one from each group.

There are five broad spectral subbands of EEG signal of clinical interest: delta (0–4 Hz), theta (4–8 Hz), alpha (8–15 Hz), beta (15–30 Hz) and gamma waves (30–60 Hz). A traditional low pass finite impulse response (FIR) filter was employed on EEG to get band-limited EEG at 0–60 Hz band. For further decomposition into individual EEG subbands, a DWT, based on fourth order daubechies (*db4*), was used. Major advantages of using wavelet transform include its excellent multiresolution representation encompassing time-frequency localisation and scale-space analysis [22,23]. Moreover, employment of variable window size further enhances feature-extraction from non-stationary signals (e.g. EEG) by frequency based stretching or compressing of the wavelet [15,23]. For faster and efficient computation, dyadic (powers of 2) scales and positions were followed in this study. First level decomposition of band-limited EEG (0–60 Hz) yielded detail coefficients as Gamma (30–60 Hz) and approximate coefficients (0–30 Hz). These approximate coefficients were further decomposed to get higher resolution components as Beta (15–30 Hz) and lower resolution components (0–15 Hz). After similar decomposition of these lower resolution components, Alpha (8–15 Hz) subbands were extracted along with the approximate coefficients (0–8 Hz). These approximate coefficients were decomposed further for high resolution Theta (4–8 Hz) and low resolution Delta (0–4 Hz). So, altogether 4 level decomposition was done.

2.2. Wavelet based decomposition

Wavelet transform analyses a signal at different frequency subbands, with different resolutions by decomposing the signal into a coarse approximation (approximation coefficients, CA) and detail information (detailed coefficient, CD). Repeated filtering of the signal with a pair of low pass and high pass filter divides the signal in frequency domain into two halves. CA can be subdivided again iteratively to get different levels of decomposition.

2.3. Multifractal Detrended Fluctuation Analysis (MF-DFA)

MFDFA algorithm for a signal time series x_k of length N is divided into following five steps.

Step 1. Cumulative deviation of x_k for the 'profile' $Y(i)$ is determined

$$Y(i) = \sum_{k=1}^{i} [x_k - \langle x \rangle], \quad i = 1, \ldots, N \tag{1}$$

where

$$\langle x \rangle = \frac{1}{N} \sum_{k=1}^{N} x_k \tag{2}$$

This signal x_k is converted into random walk like time series $Y(i)$ to highlight its self similar fractal characteristics for further DFA.

Step 2. Profile $Y(i)$ is divided into N_s non overlapping segments of length s ($N_s \equiv int(N/s)$). This is repeated from reverse order too to