Fractal Components From Electroencephalogram Provide Features For Brain Computer Interface

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Abstract: This paper presents an application of nonlinear science to investigate the alteration of electroencephalographic (EEG) signals in two brain states, i.e. idle state and imagination of movement. Based on Coarse Graining Spectrum analysis (GCSA) we extract fractal components from the recorded EEG signal in the frequency domain. The aim of this work is to extract reliable features based on random fractal components to apply as features in a Brain Computer Interface (BCI). Data recorded from six subjects for a BCI system is used to evaluate the proposed method. The result derived from Soft Margin Support Vector Machine classification shows that there is significant discrepancy in spectral components that could be a powerful method in investigating brain activities.

1 Introduction

Interpreting biological systems as chaotic, i. e. nonlinear dynamical systems, meets increasing interest in medicine and computational life sciences. Thus signals recorded from living creatures can be characterized in general to have a noisy, nonstationary and nonlinear structure. If a variable as a function of time undergoes characteristic changes that are similar regardless of the time interval over which the observations are made the underlying process is defined as a fractal [5]. To describe fractal systems many definitions including dynamical and geometric measures, have been developed, e. g. Mandelbrot and van Ness set [12], Higuchi's fractal dimension [9], largest Lyapunov exponent (LLD), Hurst exponent, Hausdorf dimension, and correlation dimension (CD)[5]. The fractal dimension is one possible parameter to characterize chaotic systems. Analysis of time series is one of the most common means to find the fractal dimension from observations [2, 8]. Fractal dimension has been widely used as estimation of scale independent complexity or irregularity of a biological system over space or time [1, 2, 3]. A comprehensive comparison between several well-known methods on both synthetic data and intracranial electroencephalogram data is presented in [11].

Brain information is carried by patterns of neural activity that are manifested in electrical potentials known as action potentials on the cellular scale and in electroencephalographic (EEG) waves on the macroscopic scale. Brain activity is typically aperiodic and unpredictable in the absence of stimulation. However, one cannot prove mathematically stringent that brain activity is truly chaotic, nor can it be proven that it is not [18]. Yet, EEG signals are eminently claimed as examples of fractal geometry [1, 2]. The change of fractal attributes has been discussed in several studies like cognitive tasks, sleep, and different types of diseases as well as mental states. For instance in [3], a higher dimensionality, i.e. complexity, of imaginary EEG states was recorded as compared to actual perceptual processing. However in most cases, biological signals do not consist solely of fractal dynamics. They include well-defined harmonic oscillations as well [4, 6]. Pereda et al. [10] discussed that in the natural signals the value of index β is very similar in linearly correlated noise and chaotic system. Both CD and LLE have been demonstrated to act as poor indices to discern between different mental tasks [14]. In the frequency domain, these oscillations are recognized as relatively sharp peaks in the power spectra although the peaks are usually superimposed on some type of noise spectrum which has been though to reflect the underlying fractal dynamics [15].

Considering this fact, we employ in the following Coarse Graining Spectral Analysis (CGSA) introduced by Yamamoto et al. [4] to calculate random fractal components in the frequency domain of human EEG signals set to two different brain states. The method is capable to separate simple harmonic and fractal components from each other in the frequency domain [4]. An EEG-based Brain Computer Interface could benefit from this remarkable property. The ultimate goal of any Brain Computer Interface is to establish a direct, robust and reliable communication channel between human brain and computer bypassing the natural muscular and nervous pathway [16]. By analyzing the EEG signal, we investigate the applicability of extracted features using CGSA in distinguishing the predefined brain states. In a multidimensional feature space we compare the classification accuracy over different combination of feature groups included the power band features and fractal components. For assessing the quality of features, a machine leaning technique has been applied. Soft Margin SVM was used to classify extracted features from the recorded EEG from an experiment carried out with six subjects, distinguishing between two classes, motor imaginary and relaxation. Results show a promising performance in four subjects, corroborating the idea of truly chaotic nature of brain activity.

2 Methods

2-1 Coarse Graining Spectral Analysis (CGSA)

The method is based on the calculation of fractal exponents from the power spectral density in signals characterized by a frequency power law. Biological signals may possess periodic components in addition to $1/f^{\beta}$, it is also a well-known phenomenon in EEG signal. CGSA was introduced to separate simple harmonic and fractal components from each other in the frequency domain. It is based on the spectral analysis of windowed signals using a Fast Fourier transformation partially modified according to Yamamoto [4].

If the total spectral power of a signal consists of both harmonic and non-harmonic (fractal) components, it is possible to isolate the latter, because the fractal component is scale-invariant when rescaled. It will still retain its power when cross correlated with the original data [10, 12]. Non-linear nature of EEG exhibits random fractal structure with $1/f^{\beta}$ spectrum (1< β<3). In contrast, rescaling of harmonic components causes a complete loss of spectral power when cross-correlated with the original. Here, β can be obtained as negative slope of the fractal power versus frequency, in a log-log scale [10]. The frequency range of 4-45 Hz was selected because it includes frequency band usually connected to cognitive and imaginary tasks and the spectra presents the clearest $1/f - \beta$ dependence within it.

Due to the definition introduced by Mandelbrot and van Ness [12], fractal time series $x(t)$ satisfy the eq. (1) for any $h > 0$ and t_0 , where $\stackrel{\text{def}}{=}$ implies that the distribution function is equal in both sides and H is the Hurst exponent[4]. It explicitly demonstrates the nature of random fractal time series, where changing the time scale doesn't affect the dynamic of the signal.

$$x(ht + t_0) - x(t_0) \stackrel{\text{def}}{=} h^H\{x(t + t_0) - x(t_0)\} \tag{1}$$

Without loss of generality, we assume $x(t_0) = 0$, thus we have $x(ht + t_0) = x_h(t, t_0)$. That means the original time series is related to renormalized version of it [4], consequently the discrete version of this relationship can be defined as:

$$X_h(i, i_0) = X(hi, i_0) \stackrel{\text{def}}{=} h^H X_1(i, i_0) \tag{2}$$

Where $X(i)$ is the discrete version of $x(t)$. The new time series $X_h(i, i_0)$ is called "coarse grained" subset and the new sequence is formed by selecting every h sample from the original time series. An auto power spectrum and cross power spectrum from $S_{XX}(n)$ and $S_{XX_h}(n)$ then can be calculated as:

$$S_{XX}(n) = \frac{1}{N_{subset}} \sum_{i_0}^{N_{subset}} \left\| \frac{1}{N_{data}} . \sum_{k=0}^{N_{data}-1} X_1(k, i_0). e^{-j2\pi kn/N_{data}} \right\| \quad (3)$$

Where $n = 0, 1, \ldots, N_{data} - 1$ and N_{subset} is the number of different i_0 chosen from a given time series.

$$S_{XX_h}(n) = \frac{1}{N_{subset}} \sum_{i_0}^{N_{subset}} \left[\begin{array}{c} \frac{1}{N_{data}} . \sum_{k=0}^{N_{data}-1} X_1(k, i_0). e^{-j2\pi kn/N_{data}} \times \\ \left(\frac{1}{N_{data}} . \sum_{k=0}^{N_{data}-1} X_h(k, i_0). e^{-j2\pi kn/N_{data}} \right)^* \end{array} \right] \quad (4)$$

In a simple harmonic signal the value of $S_{XX_h}(n)$ that is equivalent to Fourier transform of the cross correlation function between two orthogonal sinusoid, tended to be zero when $N\_data \to \infty$. On the other hand, it is proven that the corresponding value in a fractal motion defined in Eq. (2) never goes to zero. Indeed it could be concluded that $\| S_{XX_h}(n) \| / h^H$ can be considered as a fractal component in the autopower spectrum without contribution of simple harmonic motions [4]. For random fractals, the spectral exponent β is linked to H with the relationship of:

$$\beta = 2H + 1 \quad (5)$$

We tried to extract and measure the linear correlation between CD and β in both idle and imagination of movement states. Features computed in this fashion represent the fractal part of EEG signal.

2-2 Soft Margin Support Vector Machine

In this work, by calculating fractal component (β) via CGSA from EEG signal, we introduce a set of features for classification of two different brain states. In order to assess the quality of features, a machine leaning technique has been applied where the computer learns a decision function based on the training dataset.

A SVM q-norm soft margin classifier was introduced to handle the high dimensional classification problems where the data are not linearly separable [13]. If the training set is not linearly separable, the standard approach is to allow the wide decision margin to make a few mistakes. In this case some points, outliers or due to noise, could be placed inside or on the wrong side of the margin. Then a cost should be paid for each misclassified example, which depends on how far it is from meeting the margin requirement given in Eq. 4. We implement this by slack variables ξ_i. The formulation of the SVM under the condition for the optimal hyper-plane can be modified by including an extra term:

$$y_i(X_i^T W + b) \geq 1 - \xi_i \,, \quad i = 1, \ldots, m \quad (6)$$

For minimum error, $\xi_i \geq 0$ should be minimized as well as $\|W\|$, and the objective function becomes:

$$\min \quad W^T W + C \sum_{i=1}^{m} \xi_i^q \quad (7)$$

Subject to:

$$y_i(X_i^T W + b) \geq 1 - \xi_i \,, and \;\; \xi_i \geq 0; \quad i = 1, \ldots, m$$

Here C is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the training error. Small value of C tends to emphasize the margin

while ignoring the outliers in the training data, whereas large C may overfit the training data [13].
Note that the condition $\xi_i \geq 0$ is dropped, as if $\xi_i < 0$, we can set it to zero and the objective function is further reduced.) Alternatively, if we let $k = 1$, the problem can be formulated as:

$$\min \quad W^T W + C \sum_{i=1}^{m} \xi_i \tag{8}$$

Subject to:

$$y_i(X_i^T W + b) \geq 1 - \xi_i \,, and \;\; \xi_i \geq 0; \quad i = 1, \dots, m$$

This is called 1-norm soft margin problem. The algorithm based on 1-norm setup, when compared to higher-norm algorithm, is less sensitive to outliers in training data. When the data is noisy, the 1-norm method should be used to ignore outliers. Typically, the support vectors will be a small proportion of the training data. However, if the problem is non-separable or with small margin, then every data point which is misclassified or within the margin will be non-zero. If this set of points becomes large, then, for the nonlinear case, this can be a major slowdown for using SVMs at test time.

In this research the classification has been fulfilled over the multidimensional feature space calculated offline using recorded data in seven sessions for each subject. We considered 20% data as training data for each subject and repeated the calculation over each training group of data following the cross validation scheme to verify the results.

2-3 Experimental Setup

To classify two states of brain activity, relaxation and concentrating in imaging a hand movement, a special scenario containing those states for data collection was designed. The data recorded from our previous work has been applied to evaluate the proposed scheme [17]. In our BCI system a subjects try to control their attention according to a predefined paradigm in imagination of hand movement and relaxation periods. Every trial lasts 5s and contains one specific brain activity and each run consists of two trials related to different brain activity. Subjects sat on a relaxing chair with armrests. At the start of trial, a black screen was shown to the subject for 2 s. After 2 s, an open hand was displayed on the screen and the subject had to try to keep it open for 5 s (i.e. relaxation phase). This is the idle state in which the subject does not perform any specific mental task. Following the relaxation phase, a ball began to fall and by touching the virtual palm, at 8 s, an active feedback phase lasting 5 s was started, here the user should try to grasp the ball by imagination of hand grasping. In this study we employed the recorded data from two channels C3 and C4 of the 10-20 system sampled at 256Hz. The EEG obtained during each trial experiment is divided into 1s short windows, overlapping by 125 ms, and a moving average of the amplitude spectra of these is created. Then the features were extracted from each window and classified. Data was collected from 6 healthy university students (2 male, 4 female, mean age: 24.3) volunteering for the study.

3 Results

Results are shown both in tabular and graphical formats. Fig 1. illustrates the ensemble average of fractal power spectra in idle and imaginary states. The first feature set was formed from the spectral power of EEG signal in alpha, lower beta, upper beta, and gamma frequency bands. The second feature set is constructed out of fractal components. Tab1. shows the different classification accuracy employing each feature space and their combination. Results were driven as the average over all sessions for each subject.

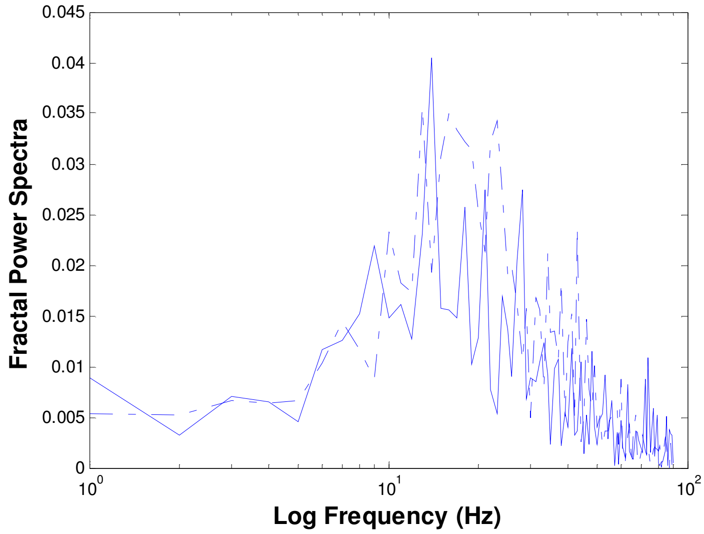

Fig 1. Ensemble average of EEG fractal power spectra obtained from CGSA in relax (solid) and imaginary (dashed) state

Classification accuracy (%)	Power band Features	Fractal components	Combination of two Feature groups
S1	67.50	73.72	72.14
S2	75.48	84.59	85.90
S3	80.06	87.95	88.73
S4	69.33	71.90	73.01
S5	79.36	79.54	78.45
S6	83.72	90.01	91.32
Average	**75.90**	**81.30**	**81.52**

Tab 1. Classification accuracy using three different feature space

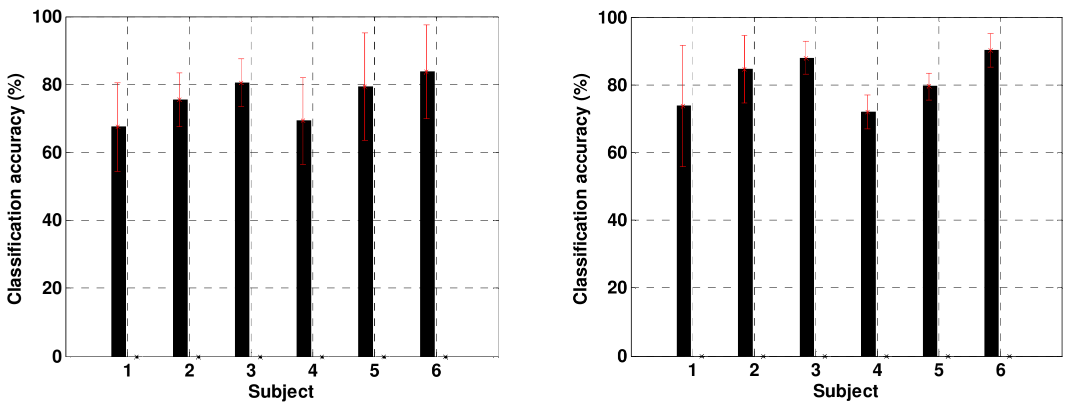

Fig 2. Average classification accuracy for each subject using power band (a) and fractal power spectra (b) as feature and 1-norm soft margin Support Vector machine as classifier

A satisfactory improvement has been achieved over the data collected from Subject S2, S3 and S6. The average classification accuracy is low for S4 in both cases. Only in one case, S5, recruiting the new features did not yield to significant improvement. The mean values and standard deviation (SD) of the classification accuracy of each scheme is illustrated in Fig 2.

4 Discussion

The capability of using fractal based features in a BCI system has been proposed in [6]. Fractal components extracted from the logarithmic power spectrum have been used as an index of complexity of the signal, demonstrating the non-linear nature of EEG or non linear dynamic of brain. An application of chaos and fractal properties, that are the most important tools in nonlinear analysis, has been presented in analyzing two different brain states including idle state and imagination of hand movement in the human EEG. We tried to extract and measure the linear Correlation between CD and β in these two states. However due to its lower computational cost, use of β is more appropriate in online application.

In order to investigate this demand over real EEG data, we extracted the fractal components in frequency domain and compared the effects of imagination of motor activation tasks of the human EEG compared to idle state. In the idle state a lucid frequency power dependency is visible and fractal components are appeared to be lower in movement imaginary compared to the baseline condition. Applying these components as features to a Soft Margin SVM classifier, yields to evaluate how much the fractal based attributes are informative. We achieved average 81.3 % accuracy in classification over entire the sessions for all six subjects. Combining the extracted features with common oscillatory features in a high dimensional space, we tried to mine maximum information related to brain state hidden in EEG signal. Questions of robustness of the method and data requirements could be yet discussed.

5 Conclusions

Experimental results show that the extracted fractal components using GCSA are suitable discriminators of EEG signals. They are able to extract significant differences between two predefined brain states in most of subjects. However a nonlinear classifier has been trained and tested over feature space. It is concluded that fractal analysis could be powerful methods in investigating brain activities during motor movements and is a promising option to design BCI systems.

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