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MULTIRESOLUTION WAVELET ANALYSIS AND HURST ESTIMATION USED FOR HIGHLIGHTING SENSORIMOTOR RHYTHMS

BY

ROXANA ALDEA[*]

“Gheorghe Asachi” Technical University of Iaşi
Faculty of Electronics, Telecommunications and Information Technology

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Abstract. The aim of this paper is to highlight the characteristics of sensorimotor rhythms (mu and beta) produced by right and left hand motor imagery. The electroencephalographic (EEG) data were recorded with 8 g.tec active electrodes by means of g.MOBIlab+ modulus. The EEG data are wavelet multiresolution decomposed into sub-bands of interest (7.5…15 Hz–mu rhythm,15…30 Hz–beta rhythm). We applied the Higuchi method for estimating Hurst exponent of this decomposed signals, with different types of wavelet, on C3 and C4 channels. The Higuchi method, for estimating the Hurst exponent, helps us to highlight, mathematically, the presence of the sensorimotor rhythms in the recorded signals.

Key words: brain-computer interface; Higuchi method; Hurst exponent; sensorimotor rhythms; wavelet.

1. Introduction

An electroencephalogram (EEG) signal is generated by the electrical activity of the billion nerve cells in human brain. The EEG signals are very helpful information for a unique interfacing technology between a human being and a machine, such as a brain–computer interface (BCI) (Mason *et al.*, 2003).

[*] *e-mail*: aldea_roxy@yahoo.com

The EEG signals are measured at the scalp through electrodes (the noninvasive method). The BCI system was implemented not only for healthy people, but also for patients who are suffering from severe motor deficiencies and numerous other diseases, and they cannot use any of the traditional methods to communicate, but they are cognitively intact (Wolpaw *et al.*, 2002). The imagination of motor movement for real applications' system can be realized by training the users (or subjects) to control his/her brainwaves. There are many researches who have proposed the EEG signals of motor imagery tasks for useful applications such as a robot control (Millan *et al.*, 2004), a virtual keyboard (Obermaier *et al.*, 2003), virtual applications or games, etc. However, most of the previous works, based on a binary command, since the imagination of left and right hand movement are mostly popular tasks.

The interpretation of biological systems as chaotic (or nonlinear dynamical systems) is recently of great interest in medicine and computational sciences. Thus, signals recorded from humans or animals can be characterized, general speaking, as having a noisy, nonstationary and nonlinear structure. If a variable, as a function of time, undergoes changes of characteristics that are similar, irrespective of the time interval over which the observations are made, the underlying process is defined as a fractal (Mandelbrot, 1982). In order to describe fractal systems, many definitions have been developed, *e.g.* Higuchi's fractal dimension (1988), the largest Lyapunov exponent (LLD), the Hurst exponent and the correlation dimension (CD) (Mandelbrot, 1982). The fractal dimension represents one possible parameter to characterize chaotic systems. The fractal dimension has been widely used as estimation of scale independent complexity or irregularity of a biological system over space or time (Phothisonothai *et al.*, 2007; Boostani *et al.*, 2004; Georgiev *et al.*, 2009).

Brain information is achieved by neural activity patterns that occur in electrical potentials known as action potentials on the cellular scale and in EEG waves on the macroscopic scale. Brain activity is typically aperiodic and unpredictable in the absence of stimulation. However, no one can bring mathematically stringent proof that brain activity is truly chaotic.

The event-related desynchronization (ERD) and synchronization (ERS) or ERD/ERS patterns are widely used to reveal the natural phenomena responses in EEG signal of imaging. Several methods have been proposed to detect the ERD/ERS. One of them is the method based on wavelet decomposition. This technique has always been a popular method for frequency-based extracting EEG signals. The C3 and C4 electrode signals were utilized for extracting the Hurst coefficients using Higuchi`s method.

2. Methods

2.1. Multiresolution Wavelet Analysis

Multiresolution wavelet transform allows the analysis of non-stationary signals. Wavelet transform can analyse these signals at different resolutions by decomposing them into frequency bands. This method was developed to solve the deficiencies of Short Time Fourier Transform (STFT). In the case of continuous wavelet transform, the signals are analysed by scaling and translating a mother wavelet function (Lazăr, 2001).Discrete wavelet transform (DWT) is the time-scale representation method based on digital filtering. DWT analyses the signal at different resolutions (multi-resolution wavelet analysis), by decomposing the signal into different frequency bands. In wavelet analysis it is spoken about approximations and details. Approximations are components of high scale and low frequency. Details are components of low scale and high frequency.

DWT is calculated by successive low-pass high-pass filtering and subsampling, a method known as *Mallat algorithm* (Mallat, 1999).

Impulse response of high-pass filter (HPF) is denoted by $h(n)$, and the low-pass filter (LPF) by $g(n)$. At each level HPF produces a signal, $d(n)$, of detail, while the LPF, associated with scaling function, produces a signal, $a(n)$, which is a rough approximation. After HPF and LPF filtering and subsampling by 2, we obtain the following signals:

$$y_L(n) = x(n)g(n) = \sum_{k=-\infty}^{\infty} x(k)g(2n-k)\,, \tag{1}$$

$$y_H(n) = x(n)h(n) = \sum_{k=-\infty}^{\infty} x(k)h(2n-k)\,. \tag{2}$$

2.2. Hurst Estimation with Higuchi's Method

The Hurst exponent occurs in several areas of applied mathematics, including fractals and chaos theory, long memory processes and spectral analysis.

The Hurst exponent is also directly related to the "fractal dimension", which gives a measure of the roughness of a surface. The relationship between the fractal dimension, D, and the Hurst exponent, H, is (Beran, 1994)

$$D = 2 - H. \tag{3}$$

The fractal dimension provides an indication of how rough a surface is. As eq. (3) shows, the fractal dimension is directly related to the Hurst exponent for a statistically self-similar data set. A small Hurst exponent has a higher fractal dimension and a rougher surface. A larger Hurst exponent has a lower fractal dimension and a smoother surface. In our case, a large value for Hurst exponent means desynchronization.

A fractal dimension is a statistical measure indicating the complexity of an object or a quantity that is self-similar over some region of space or time interval. It has been successfully used in various domains to characterize such objects and quantities, but its usage in motor imagery-based BCI has been more recent (Phothisonothai *et al.*, 2008). There are several fractal dimension estimation methods, some of which are not applicable to all types of data exhibiting fractal properties.

Higuchi's method (Higuchi, 1988) computes the fractal dimension of a sample. It consists of forming new waveform by iteratively selecting samples differing in their starting point, *m*, and their delay factor, *k*. We first select a maximum delay factor, say k_{max}. So for every delay factor, *k*, where *k* is varied from 1 to k_{max}, we form *k* new time series, x_m^k, where the starting point of the series is defined by *m* and samples at every *k* samples are selected to form the new waveform

$$x_m^k = \left\{ x(m), x(m+k), x(m+2k), ..., x\left(m + \left[(N - m)/k\right]k\right) \right\}, \tag{4}$$

where *m*, the starting point for each waveform, is varied from 1 to *k*, *k* being the delay factor between the sample and *N* – the window size. Then the length of each waveform is calculated as the sum of the distances between two consecutive points

$$L(m,k) = \frac{\sum_{i=1}^{[(N-m)/k]} \left| x(m+ik) - x[m+(i-1)k] \right| (N-1)}{[(N-m)/k]k} , \tag{5}$$

where $[(N-m)/k]k/(N-1)$ is the normalization factor and *N* – the window length. The lengths for the same delay factor, *k*, are then averaged as follows:

$$L(k) = \sum_{m=1}^{k} L(m,k) , \tag{6}$$

where *k* is varied from 1 to k_{max} and $L(k)$ is the averaged length for a particular delay factor, *k*. We would expect that for every smooth and regular waveform, as the delay factor is increased, the length of the waveform would decrease proportionally since increasing the delay factor between samples could be viewed as smoothening the waveform, and hence we would expect the length to decrease proportionally.

3. Basic Results

The EEG data was recorded by means of a g.tec Company acquisition system, namely g.MOBIlab+ module, and BCI2000 platform. We recorded data from five cerebral healthy subjects.

The patients received instructions regarding their behavior during recording. The subjects were seated in front of a monitor that displays, successively, left and right arrows. The subjects must carefully look at the arrows and try to imagine the movement of the hand indicated by the arrow. Each left and right arrow appears 30 times. Channels chosen for electrode placement are: CP3, CP4, P3, C3, Pz, C4, P4 and Cz. These channels are selected in the left and right hemisphere, due to the appearance of mu and beta rhythms in these areas and the reference electrode is placed on the right ear.

Firstly, we extracted the signals corresponding to left and right hand imagery, respectively, and then mediated them for the 30 trials.

The multiresolution wavelet analysis was performed by means of the *Biorthogonal3.5*, *Daubechies2*, *Daubechies4* and *Coiflet4* types, some suited mother's wavelet for sensorimotor rhythms. As the best results are reported using the EEG records from C3 (right hand motor imagery) and C4 (left hand motor imagery) channels, we applied our software only for these ones.

Taking into account that the frequency components of the EEG signal are situated in the 0…120 Hz range, while the spectrum of the mu rhythm lies around 8…12 Hz and beta rhythm around 12…30 Hz, a fourth level decomposition of the signal was necessary.

The time series representation of multiresolution wavelet decomposition is not relevant in this case because sensorimotor rhythms are not observed by visual analysis of signals, therefore we plotted the frequency response of the decomposed signal corresponding to the frequency bands of mu and beta rhythms.

Fig. 1 presents the frequency responses of the signal recorded during left hand movement imagining *versus* rest at the 0…30 Hz frequency band that fits both mu and beta rhythms. This plot will not provide relevant results. We cannot distinguish relevant spikes in 8…12 Hz and 12…30 Hz bands corresponding to mu and beta rhythms, so we will apply the Higuchi method for estimating Hurst exponent and highlight, mathematically, the presence of these rhythms in the recorded signals.

The calculation of the Hurst exponent is realized for the decomposed signals with different types of wavelet on C3 and C4 channels. The signals used are: detailed coefficient of fourth level with 7.5…15 Hz frequency band (corresponding mu rhythm), detail coefficient of third level decomposition with 15…30 Hz frequency band (corresponding beta rhythm) and detail coefficient of second level, 30…60 Hz.

In Tables 1…4 we calculated the average values of Hurst exponents for five subjects. In Table 1 the signals were decomposed using the Biorthogonal3.5 wavelet. Channels C3 and C4 are the most suitable for emphasizing sensorimotor rhythms. Note that, on C3 channel, the average signal corresponding to right hand motor imagery has higher values than the rest signal or left hand motor imagery signal. The highest value is at the range of 7.5…15 Hz frequency; therefore mu sensorimotor rhythm is predominant.

Better values for left hand motor imagery signal are obtained on C4 channel at 15…30 Hz frequency band, in this case mainly the beta rhythm.

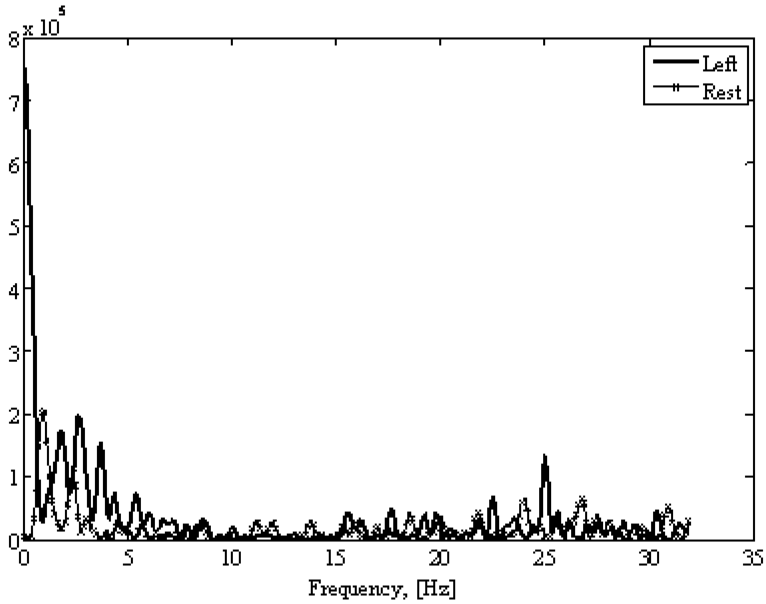

Fig. 1 – Frequency response of approximation coefficient at level 2 for left hand motor imagery signal *vs*. rest signal.

Table 1
The Average of Hurst Exponent (Multiresolution Wavelet Decomposition with Biorthogonal3.5)

Biorthogonal3.5	7.5…15 Hz	15…30 Hz	30…60 Hz
C3			
Right	**0.8252**	**0.4817**	0.5055
Left	0.7550	0.2739	0.4313
Rest	0.7278	0.4745	0.4948
C4			
Right	0.6523	0.4574	0.5902
Left	0.6469	**0.5699**	0.4312
Rest	0.5772	0.3121	0.4161

Table 2 contains the signals decomposed using Daubechies2 mother wavelet. In this table, the difference between values is very obvious, and we have a maximum of 0.8015 for right hand motor imagery signal on C3 channel at 15…30 Hz, and 0.7024 for the left hand motor imagery signal on C4 channel at the same frequency of 15…30 Hz. The results are considered very good.

Table 2
The Average of Hurst Exponent (Multiresolution Wavelet Decomposition with Daubechies2)

Daubechies2	7.5…15 Hz	15…30 Hz	30…60 Hz
C3			
Right	**0.4439**	**0.8105**	0.4952
Left	0.2256	0.6143	0.4478
Rest	0.1269	0.3646	0.4210
C4			
Right	0.4542	0.6824	0.2215
Left	0.3976	**0.7024**	0.4425
Rest	0.4641	0.5389	0.4809

In Table 3 are represented the signals decomposed using Daubechies4 wavelet. Note that on C3 channel, at frequency band of 15…30 Hz for the right signal we have a Hurst exponent value of 0.6147, higher than the rest and left signals but with 0.018 less from the value of frequency 30…60 Hz. In the case of the left signal, on C4 channel we have a maximum value of 0.5855 at 7.5…15 Hz frequency band.

Table 3
The Average of Hurst Exponent (Multiresolution Wavelet Decomposition with Daubechies4)

Daubechies4	7.5…15 Hz	15…30 Hz	30…60 Hz
C3			
Right	0.3980	**0.6147**	0.6328
Left	0.3675	0.2361	0.4499
Rest	0.6064	0.4812	0.5579
C4			
Right	0.3565	0.5256	0.4662
Left	**0.5855**	0.3830	0.3214
Rest	0.4211	0.4297	0.5018

Table 4
The Average of Hurst Exponent (Multiresolution Wavelet Decomposition with Coiflet4)

Coiflet4	7.5…15 Hz	15…30 Hz	30…60 Hz
C3			
Right	**0.4622**	0.3335	0.3932
Left	0.2435	0.3255	0.3371
Rest	0.4044	0.3788	0.3573
C4			
Right	0.4209	0.4085	0.4520
Left	**0.6235**	0.4289	0.5063
Rest	0.3361	0.4114	0.5723

In Table 4 are displayed the results of signals multiresolution wavelet decomposition, using Coiflet4. A maximum value for the right signal is on C3 channel at 7.5…15 Hz frequency band. On C4 channel the maximum value is for the left signal also at 7.5…15 Hz frequency band.

4. Conclusions

We applied our analysis on C3 and C4 channels of the EEG signals recorded for five subjects. We have performed a multiresolution analysis of these signals by means of four types of wavelets. Multiresolution wavelet analysis allows us to decompose the signal into sub-bands components. The method allows reducing the dimension of the data and this is an important advantage.

We have obtained good results for Hurst exponent with Higuchi's method and that highlights the features of sensorimotor rhythms. These rhythms occur in the contralateral side of the hand movement. Therefore, when imagining the right hand movement, in the left side of the brain, a desynchronization occurs on C3 channel, while in the case of left hand imagining movement, desynchronization occurs in the right side of the brain, on C4 channel. The best values for the Hurst coefficient were obtained with Daubechies2 mother wavelet.

In future research, we intend to employ other methods for estimating the Hurst exponent.

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EVIDENŢIEREA RITMURILOR SENZORIMOTOARE CU AJUTORUL ANALIZEI WAVELET MULTIREZOLUŢIE ŞI A ESTIMATORULUI HURST

(Rezumat)

Scopul acestei lucrări este de a pune în evidenţă ritmurile senzorimotoare (mu şi beta) produse în timpul imaginării mişcării mâinii drepte sau stângi. Semnalele electroencefalografice (EEG) au fost înregistrate cu ajutorul modului g.MOBIlab+ prin intermediul a 8 electrozi activi plasaţi pe scalp. Semnalele au fost descompuse wavelet multirezoluţie în sub-benzile de interes 7,5...15 Hz ritm mu şi 15...30 Hz ritm beta. Pentru semnalele descompuse cu diferite waveleturi, se aplică metoda Higuchi de estimare a exponentului Hurst, pe canalele C3 şi C4. Acestă metodă permite evidenţierea, pe cale matematică, a prezenţei ritmurilor senzorimotoare pe semnalele înregistrate.