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Fractal Dimension-Based EEG Biofeedback System

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Abstract— **Biofeedback plays an increasingly important role in mainstream computer applications, including hands-free human-machine interaction. The most obvious use of this technology is to help disabled people interact with their environment. The main challenge in brain computer interfaces is to identify the particular EEG signal components that can be successfully used as control commands. In this study, we show that the fractal dimension of EEG is such a component. This is verified via the experiments carried.**

The fractal dimension is known to be a good measure of the chaotic behavior of the EEG signal. An algorithm proposed by Higuchi is used to estimate the fractal dimension. Visual and auditory information extracted from the EEG signal of each subject are fed back to himself. Each subject was asked to perform any mental activity so as to alter the value of his EEG's fractal dimension.

Our experiments show the feasibility of the EEG biofeedback method to change the fractal dimension of the EEG signal. Our study introduces the fractal dimension as a new feature that can be controlled by a person and used in brain computer interface systems.

Keywords—**Biofeedback, BCI, fractal dimension, EEG**

I. INTRODUCTION

Research concerning with harnessing brain electrical activity so it can control and communicate with the environment is growing rapidly. The ability to consciously change specific components of one's brain signal forms a new challenge in recent research. Existing research in Brain Computer Interface (BCI) is composed of two main areas. The first area is concerned with analyzing existing patterns of the EEG signals. The second area aims at training the subject to emit a specific brain activity. A review of current BCI systems can be found in [1].

The former research area studies the natural changes in the EEG signal, for example the changes occurring in the EEG's Mu rhythm when a person starts or imagines a movement. Such an activity can be used to control a cursor on a screen. The second research area is concerned with training a subject to consciously alter some features of his EEG signal. These feature(s) are then used to activate a certain action, e.g. to operate a computer display. These research areas, especially the second area overlap with a form of clinical EEG biofeedback therapy [2,3]; this therapy has been used in the last 2 decades to treat certain kinds of disorders and diseases such as learning disabilities [4] and ADHD (Attention Deficit Hyperactivity Disorder) [5].

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The EEG signal is the resultant of the interaction of millions of neurons observed at the surface of the head. From various experiments, it is now well established that the EEG recordings as well as the neural activity of the brain show many characteristics of chaotic behavior. In other words, the overall system that gives origin to the EEG potentials, namely the brain, is in a chaotic state [6].

Most of the methods for analyzing the brain dynamics are largely based on linear models and on Fourier spectra. Recently, nonlinear dynamics theory is being applied to EEG signal analysis. This opens a new window for understanding the chaotic behavior of this signal [7], [8]. Although relatively new, the use of this theory in EEG signal analysis can provide new subtle information about the functional states of the brain.

A chaotic system often alternates in a seemingly random way, but if we depict its trajectories in a suitable graphical way, we notice that the trajectories of the system concentrate in one or more areas known as chaotic attractors. The Fractal Dimension (FD) explains the behaviour of the chaotic attractors of the dynamical system and can characterize different pathophysiological conditions [9]. The FD refers to the minimum number of independent variables needed to describe the dynamical system.

A variety of algorithms are available for computing the fractal dimension. Some of these algorithms operate directly on the signal in the time domain and the others operate on the phase space domain of the signal [10]. Algorithms that need the construction of the phase space, such as Grassberger and Proccacia's algorithm [10], are slow. On the other hand, the algorithms that operate directly in the time domain are considerably fast and these are suitable for online analysis. In this study, one of the most common methods for estimating the fractal dimension of a biomedical signal, the Higuchi's algorithm [9], is employed. This method deals with the signal in the time domain by considering the time series as a geometric object [7].

The aim of this research is to study whether or not a person can change a given feature in his EEG signal and if yes, to what degree. The ultimate objective is to study the feasibility of using this feature e.g. as a command input in BCI systems. Two types of experiments are conducted in this study. The first experiment forms a preliminary study to investigate the ability of a person to change the theta-band power of his/her EEG signal. Auditory and visual information representing the theta-band power are instantaneously fed back to the subject. The subject is asked to change the value of that power. The second experiment deals with the ability of the subject to change the value of the fractal dimension of his EEG signal. Auditory and visual feedbacks representing the FD are instantaneously provided to the subject to inform him about the value of the FD of his EEG. Our experiments aim at studying the ability of a person to consciously change the fractal dimension of his brain signal and the possibility of using this feature (FD) in developing BCI systems. We also investigate the relationship between the FD and the power of the different frequency bands of the EEG signal.

This study introduces the FD of EEG as a new parameter that can be controlled by a person. Furthermore, using nonlinear dynamics theory in the EEG signal analysis can provide us with valuable information about the chaotic behavior of this signal.

II. EXPERIMENTS

The aim of the experiments is to study the ability of a person to change his/her mental state with the help of provided auditory and visual feedbacks. In this section, we introduce the experimental setup and the protocol under which the experiments are conducted.

A. Experimental setup and data acquisition

Seven healthy subjects (all males, 20-29 years old) participated in this study. The subjects did not suffer from any neurological or muscular disorders.

Cortical potentials were recorded using electrodes placed over the C4 and F4 locations on the scalp according to the 10-20 international system with right mastoid reference.

The EEG channels were amplified using a custom made amplifier with a pass band of 0.1-100 Hz and was sampled with 256 Hz and digitized to 12 bits per sample.

Fig. 1 shows the block diagram of the experimental setup. As the figure shows, the EEG signal is recorded from the subject. A feature is extracted from the EEG signal instantaneously. Then visual (a bar graph that its height is a function of the extracted feature) and auditory (beep signal which its on-off period is a function of the extracted feature) signals are fed back to the subject. In fact, this system acts as a kind of sixth sense, which allows the subjects to 'see' and 'hear' the activity inside their brains [3].

B. Experimental paradigm

Each subject was seated on a comfortable armchair. To minimize the movement artifacts, the subject was asked not to move his body during the experiments. The experiments were conducted with the subject having either closed eyes or open eyes. The subject was asked to avoid eye blinking as much as possible to minimize the effect of EOG artifact.

Each experiment lasted about 15 minutes. Each subject was asked to change the extracted feature from his EEG with the help of the provided feedbacks. The provided features for feedbacks for subjects 1 and 2 were their theta-band power. For the other subjects, it was the fractal dimension of their EEG signal. Subjects 1 and 2 were asked to perform any mental activity so as to increase their theta-band power. Subjects 3-7 were asked to decrease the FD of their EEG signal. All the subjects participated in 6 sessions of biofeedback except subject 3 who participated in 8 sessions.

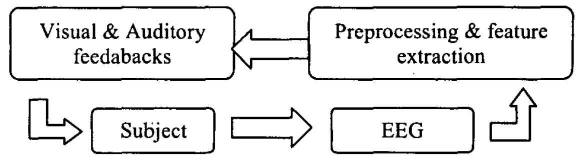

Fig. 1. Block diagram of the experimental system

III. DATA PROCESSING

In section A. below, we will explain Higuchi's method for estimation of the FD of a time series. The second part explains the procedures used for calculating the theta-band power and the FD of the EEG signal in this study.

A. Higuchi's Algorithm

Consider $x(n) = \{x(1), x(2), \ldots, x(N)\}$ the time sequence to be analyzed. For a known k, k lengths ($L_m(k)$) are computed as:

$$L_m(k) = \left((N-1)/\left(\lfloor (N-m)/k \rfloor k\right)\right) \sum_{i=1}^{\lfloor N-m/k \rfloor} \left|x(m+ik) - x(m+(i-1)k)\right| \quad (1)$$

$$m = 1, 2, \ldots, k$$

Where m indicates the initial time value, k indicates the discrete time interval between points (delay), $\lfloor \alpha \rfloor$ means integer part of α, N is the total length of the time sequence and $(N-1)/(\lfloor (N-m)/k \rfloor k)$ is the normalization factor.

Compute the average length as:

$$L(k) = 1/k \sum_{m=1}^{k} L_m(k) \quad (2)$$

This procedure is repeated for each k from 1 to $k_{\max}$.

The average length for scale k, $L(k)$, is proportional to k^{-D}, where D is the FD estimated by Higuchi's method. In the curve of $ln(L(k))$ versus $ln(1/k)$, the slope of the least-squares linear best fit, is the estimate of the FD [9].

$k_{\max}$ is an integer number and depends on several parameters such as sampling rate of the signal. In this study, the best results were obtained for the synthetic data with $k_{\max} = 10$.

The FD of a simple line is equal 1. FD of a curve, which nearly fills out the plane, is close to 2. As we can show the EEG signal in time domain as a curve, the FD of the EEG signal has a value between 1 and 2.

B. Preprocessing and Feature Extraction

The signal is filtered with a band-pass filter (0.5-70 Hz) and a notch filter at 50Hz that discards the effect of power lines. For both the band-pass and notch filters, 20-point linear phase FIR filters were employed. Fig. 2 shows the procedure for estimating the EEG's theta-band power.

We used a 2-second Hanning window with 50% overlap. The provided feedbacks are refreshed every one second. A low pass filter is also used as a smoother to discard fluctuations in the computed power due to the nature of calculations and artifacts. This filter discards sudden changes in the provided feedback, which may confuse the subject.

Fig. 3 shows the procedure for calculating the fractal dimension. The signal was windowed with a 2-second (512 point) Hanning window with 50% overlap and a LPF was used to smooth the computed FD.

IV. Results

A. Biofeedback

As mentioned before, for subjects 1 and 2, the provided feedbacks were based on the power of the theta-band. The subjects were asked to increase their EEG's theta-band power. Fig. 4 shows subjects' performances in increasing the theta-band power of their EEG signals through the six biofeedback sessions. The value shown for each session is the percentage of change in the theta-band power during that session. As shown in Fig. 4, the performance of each subject is enhanced as he attended more sessions. For example, in the first session, subject 1 couldn't increase his theta-band power. Even a decrease in this parameter is observed in the first session. However, in sessions 5 and 6, he was able to increase the theta-band power of his EEG.

Five other subjects, subjects 3,4...7, attended the experiments concerned with decreasing the FD of their EEG

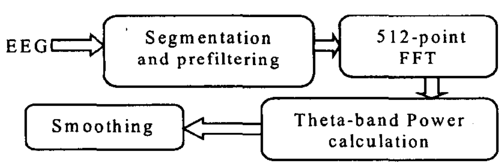

Fig. 2. Procedure for calculating theta-band power

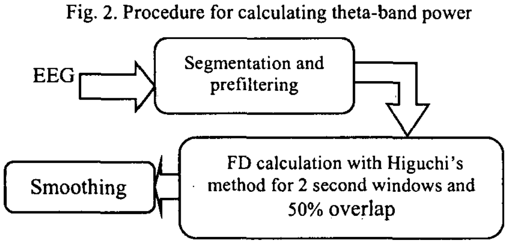

Fig. 3. Procedure for calculating Fractal Dimension

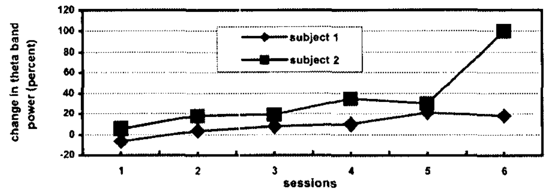

Fig. 4. Percentage of change in theta-band power in each session for subjects 1 and 2

signals. In Fig. 5, we can see the FD of subject 3's EEG during the first and eighth sessions of biofeedback. In the first session, the subject did not have significant control over the FD of his EEG. But as shown in Fig. 5, he showed a good performance in decreasing the FD of his EEG in the last session. In other words, he trained himself to consciously change the FD after eight training sessions.

Fig. 6 shows the performances of the 5 subjects in each session. The values in Fig. 6 show the FD of the EEG signal at the end of each session minus the value of this parameter at the beginning of that session.

Subjects 3, 4 and 7 had a significant capability of changing the FD of their EEG in the last sessions and their performances were enhanced with time. Subject 6 had a little control over his FD but still his performance improved by time and he might get better results if he had participated in more sessions. Subject 5 couldn't decrease his FD during the sessions and he complained from the type of the provided feedbacks. Probably providing other types of auditory and visual feedbacks can help this subject and even other subjects to improve their performances.

B. Changes of FD and power spectrum of EEG

In Fig. 7, on the left hand side, we show the FD and the delta, theta, alpha, beta and gamma band powers of subject 3 during the first and eighth sessions. As can be seen, subject 3 decreased his FD without introducing any significant changes in the power bands except for the slow wave (the delta) band. In Fig. 7, on the right hand side, we show the same data for subject 5. As shown, the increase in the FD of this subject's EEG coincides with the decrease in the power of fast waves (i.e., beta and gamma waves).

It is believed that chaotic quantifiers such as the FD can reveal subtle changes in brain waves as only one parameter and are related to higher cognitive tasks.

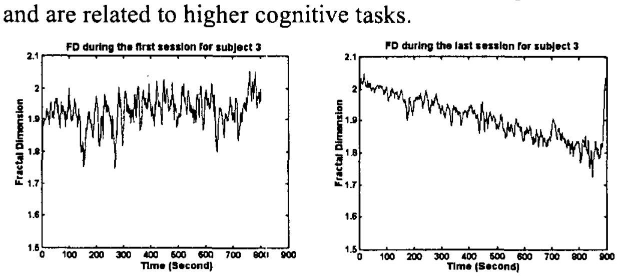

Fig.5. FD during the first (LHS) and last sessions (RHS) for subject 3

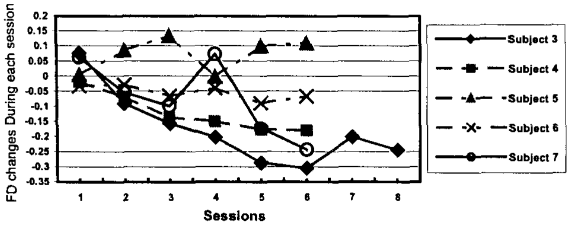

Fig.6. Changes of FD during the sessions for each subject

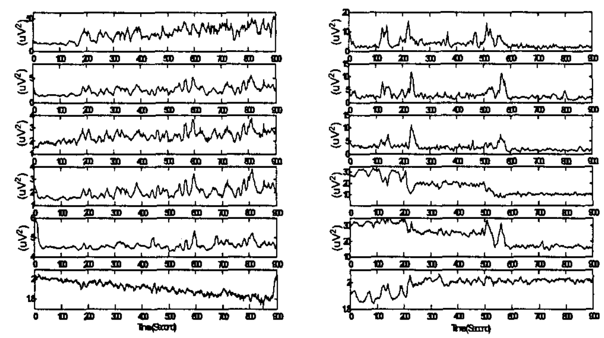

Fig.7. Fractal dimension and power of frequency bands of EEG (Left: subject 3 during last session, Right: subject 5 during 5th session 1st row: delta-band power, 2nd row: theta-band power, 3rd row: alpha-band power, 4th row: beta-band power, 5th row: gamma-band power, 6th row: FD)

V. Conclusion

We developed a system that evaluates the ability of humans to change the FD or the theta-band power of their EEG signals. Our system measures the complexity of the EEG by estimating its FD and sets up the feedback loop by showing this feature to the subject. The aim of this study is to identify new features that could be used in BCI systems.

To identify new features, we use the fact that the EEG signal reflects the interaction of millions of neurons and that the brain follows a chaotic behavior. Thus it is logical not to use conventional methods that assume linear models for this behavior. We use dynamics system theory to estimate the FD that has significant information about the EEG and its spectrum [8]. The FD shows the complexity of the EEG signal, which reflects the neuronal activity of the brain and can be a good quantifier for recognizing different brain states. Unlike other algorithms used for calculating the FD, Higuchi's algorithm, which is used in this study, does not need the reconstruction of the phase space and allows us to provide the feedback instantaneously.

The results show that most of the subjects could learn the ability to change their EEG's FD during few sessions of training. Some of them showed a performance of about 20% in decreasing their EEG's FD, while not being able to do it in the first session.

In this study, one of the subjects (subject 5) couldn't decrease his EEG's FD during the biofeedback sessions. This may be a result of different factors such as the type of the provided feedback, the experimental paradigm, the feedback parameter, etc. To obtain better and more robust results that evaluate the performance of this quantifier, we believe that this study should be conducted with more subjects. Studying the effects of different experimental paradigms and different types of visual and auditory feedbacks can also be very useful and interesting in general for many research labs in this field to establish an efficient approach for Brain Computer Interaction experiments.

Another useful lesson from our research is that in the study of EEG signal analysis, it is beneficial to consider the chaotic behavior of the brain and employ analysis methods that take this behavior into account. Regardless of the existence of strange attractors in the brain activity, neuroscience should benefit greatly from alternative methods recently developed for the analysis of nonlinear systems that exhibit chaotic behavior.

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