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Changes in Decibel Scale Wavelength Properties of EEG with Alertness Levels While Performing Sustained Attention Tasks

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Abstract— **Loss of alertness can have dire consequences for people controlling motorized equipment or for people in professions such as defense. Electroencephalogram (EEG) is known to be related to alertness of the person, but due to high level of noise and low signal strength, the use of EEG for such applications has been considered to be unreliable. This study reports the fractal analysis of EEG and identifies the use of maximum fractal length (MFL) as a feature that is inversely correlated with the alertness of the subject. The results show that MFL (of only single channel of EEG) indicates the loss of alertness of the individual with mean (inverse) correlation coefficient = 0.82.**

I. INTRODUCTION

Alertness deficit is a major problem where the operator is monitoring powered equipment or is responsible for control of complex situations. It can lead to catastrophic consequences for people driving a car, monitoring power plant, and for air traffic controllers. Number of studies in past have shown that retaining a constant level of alertness is difficult or impossible for operators of motorized systems [5]. Attempts have been made to measure alertness using mechanical sensors and analysis of facial video. Large inter-subject variability and variability in the expressions across demographics, gender and age groups makes such techniques very unreliable. The unreliability is also due to issues of lighting conditions and movement of the subject.

Electroencephalogram (EEG) is the recording of the electrical activity in the brain. Numbers of researchers have identified the relationship of EEG with changes in alertness, arousal, sleep and cognition [12], [13]. One shortcoming of the use of EEG in real-world application is the associated clumsiness due to the use of gel with the electrodes and number of wires attached to the person, often in a car or in the workplace. Jung et al. have developed a wireless system that uses dry electrodes and can be kept in the regular looking cap of the individual [15]. Such a system makes it suitable for being used on a routine basis. Study by Jung et al. [3], [5] have estimated alertness of people driving a virtual automobile using EEG. Using the power spectrum of 8 channels of EEG and classified using a neural network, it was demonstrated that EEG could be used to identify loss of alertness.

One shortcoming with biosignals such as EEG is the very low signal to noise ratio. The typical signal strength of EEG signal is of the order of 1 micro-volt, and often the strength of artifacts and noise may be much greater than this. Artifacts such as electro-ocular gram (EOG) can often be an order of magnitude greater, making the use of EEG for automated analysis difficult and unreliable. Using wireless dry electrodes reduces the signal quality further due to the lack of gel that is rich in ions.

Earlier study by the author [5] has the mean correlation of 0.76 between measured alertness and as predicted using 8 channels of EEG. While that study has demonstrated the possibilities of the use of EEG in automobile or workplace environment, this accuracy may not be enough for a reliable automated system. There is also the need to reduce the number of channels because eight electrodes can make the system cumbersome and complex, even when there are no wires. One option is to identify features of EEG that are resilient to noise, and are reliable indicators of alertness of the person. The most commonly used indicator of the strength of bioelectric signals such as EEG is root mean square (RMS) or power spectral density (PSD). Both these simple measures are effective when the signal strength is relatively high compared with the background activity. Changes in RMS and PSD are a good indicator of the change in the overall activity. However these are not effective when the strength of the signal is weak.

Researchers have reported that EEG waveforms corresponding to different physio pathological conditions can be characterized by their complexity [3], [7]. One measure of complexity of a signal is the fractal dimension, (FD) which is a global property of the signal. Studies by Liu et al.[6] have demonstrated the fractal nature of EEG. These studies have determined changes in FD with various levels of handgrip force. Studies by the authors have also determined the fractal nature of other biosignals such as Electromyogram (EMG), where they have identified the relationship of FD with the size of the muscles. Work by the authors has also revealed the use of maximum fractal length (MFL) of biosignal as a measure of the signal strength [10]. Work by Oskoei and Hu [16] has compared number of different features of bioelectric signals when the signal is sparse and the signal strength is not high, and their work has identified wavelength as the most accurate measure of the strength of the signal when studying sEMG. Unfortunately, such a technique is also not noise resilient.

This paper reports the experimental study of the maximum fractal length (MFL) of EEG and measures the changes of these features against alertness. MFL is similar to wavelength but is on the decibel scale and is based on the fractal

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properties of the signal. It is proposed that MFL be an estimate of the operator's global level of alertness. The correlation between MFL of the EEG signal and the task performance measure for three subjects has been reported. The results indicate that MFL is linearly correlated with the fluctuations of the subject's task performance and putative alertness level with mean inverse correlation coefficient of 0.82 compared with 0.76 achieved using power density of EEG, tested on the same data. Further, this correlation is achieved with the use of only one channel of EEG compared with eight channels in the earlier studies by the author.

II. Background

Bio-signals such as EEG are a result of the summation of action potentials that travel through tissues and undergo spectral and magnitude compression. Burst within burst behaviour of these signals in time has the property that patterns observed at one sampling rate are statistically similar to patterns observed at lower sampling rates[6]. These patterns suggest that EEG has self-similarity. Researchers have studied fractal methods to characterize normal and pathological signals[4].

When the density of the action potential is high, there is substantial overlap and features such as RMS and PSD are an indicator of the density of the action potential, and thus a measure of the strength of the activity in the vicinity of the electrodes. By measuring the change in the feature, the impact of the background noise is largely eliminated. However, these features are not suitable when the number of action potentials is small and the signal is sparse.

Inspection of EEG recorded from the Cz and midway between Pz and Oz locations demonstrates that the signal is sparse. This paper recommends the use of wavelength of the signal to identify the singularities that corresponds with the number of action potentials. To reduce the impact of background noise and action potentials from distant sources, the logarithmic value of the wavelength is considered. The logarithmic value of the wavelength also corresponds with the maximum value of the fractal length, the length of the signal at the smallest scale.

The authors propose a new feature, the maximum length of the signal i.e., MFL as a measure of the alertness changes. Based on the experimental results, this research has discovered that maximum fractal length (MFL) measured as the absolute value of the length of the signal at the lowest scale follows the small changes in activity or alertness levels. Based on this, it is proposed that MFL, a novel feature, as a measure of small changes in EEG in relation to the level of alertness. One obvious application of these properties of EEG is the identification of small changes to determine the level of alertness using EEG recordings.

III. Methods

A. Subjects

Three healthy subjects (aged from 18 to 34) participated in a dual-task simulation of auditory sonar target detection. All had passed the standard Navy hearing tests or reported having normal hearing. Each subject participated in three or more simulated work sessions that lasted 28 minutes. Each participant was given an oral and written summary of the experimental protocol.

B. Alertness Measure

Auditory targets were classified as *Hits* or *Lapses* depending on whether or not the subject pressed the auditory response button within 100 ms to 3000 ms of target onset. To quantify the level of alertness, auditory responses were converted into *local error rate*, defined as fraction of targets not detected by the subject (i.e., lapses) within a moving time window. A continuous measure, local error rate, was computed by convolving an irregularly spaced performance index (hit = 0/ lapse = 1) with a 95 s smoothing window advanced through the performance data in 1.64s steps.

Each error rate time series consisted of 1024 points at 1.64 s intervals. Error rate and EEG data from the first 95 s of each run were not used in the analysis. For each window position, the sum of window values at moments of presentation of undeteced (lapse) targets was divided by the sum of window values at moments of presentation of all targets. The window was moved through the session in 1.64s steps, converting the irregularly-sampled, discontinuous performance record into a regularly-sampled, continuous error rate measure within the range (0,1).

C. EEG recording and processing

EEG data were recorded at a sampling rate of 312.5 Hz from two midlines sites, one central (Cz) and other midway between parietal and occipital sites (Pz/Oz), using 10 mm gold-plated electrodes located at sites of the Inernation 10-20 system, referenced to the right mastoid. EEG data were first preprocessed using a simple out-of-bounds test (with a $\pm 50\mu V$ threshold) to reject epochs that were grossly contaminated by muscle and /or eye-movement artifacts. Moving averaged spectral anlysis of the EEG data was then accomplished using a 256-point Hanning-window with 50% overlap. Windowed 256-point epochs were extended to 512 points by zero-padding. Median filtering using a moving 5s window was used to further minimize the presence of artifacts in the EEG records. Two sessions from each from the three of the participants were chosen for analysis on the basis of their including more than 50 detection lapses.

D. Experimental procedure

Experimental procedure was designed in order to determine the level of alertness from EEG recordings. Each subject participated in three or more 28-min experimental sessions on separate days. During the experiment, the participants mimicked audio sonar target detection. The participants were asked to respond to given auditory commands. The subjects pushed one button whenever they detected an above-threshold auditory target stimulus (a brief increase in the level of the continously-present background noise). To maximise the chance of observing alertness decrements, sessions wer conducted in a small, warm and dimly-lit experimental chamber, and subjects were instructed to keep their eyes closed.

The experiments were conducted at Swartz centre and have been reported in other publications [3], [5]. This experimental data was obtained from Swartz Center for Computational Neuroscience, Institute for Neural Computation, University of California, San Diego [3], [5].

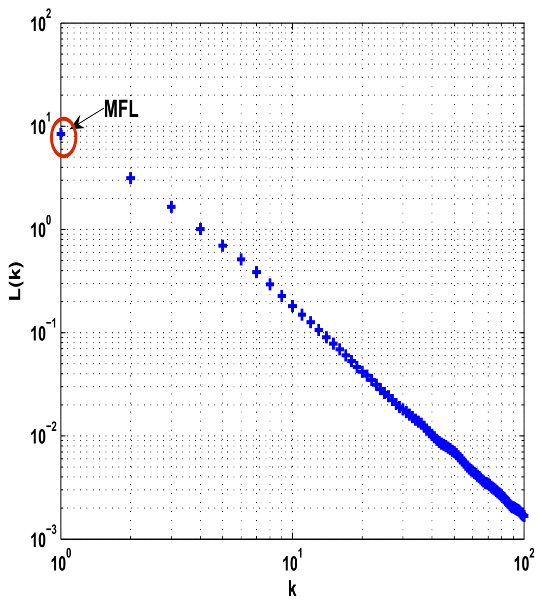

Fig. 1. Computation of Maximum Fractal length and Fractal dimension

E. Data Analysis

For the sake of comparison, MFL, FD and PSD values were computed for all the recordings and these were correlated with the detection lapses (error data) to determine which of these techniques was suitable for identifying the lack of alertness. The FD was calculated using Higuchi's algorithm [2], [11]. The MFL was determined based on the value of the length at the lowest scale as shown in the Fig.1. The results of the experiments were analyzed statistically to determine the alertness levels in relation to the small changes in EEG using the correlation method. MFL and FD were computed from the EEG data using a moving window in steps of 1.64s and were analysed to determine the correlation with the local error rate. The MFL and FD were fitted to the data points using polynomial fit for each session.

IV. Results and Observations

Fig.2 and Fig.3 show the plot of correlation between the fractal dimension, MFL and error rate function for channel 1 and channel 3 respectively. From the plots, it is observed that using fractal features it is reliable to determine or indicate the level of alertness. The fractal features were correlated (negative) with corresponding local error rate to determine the alertness measure. The negative correlation coefficients between the MFL & FD with Error function is shown in Table I. The results (Table I) demonstrate that the fractal features and local error rate have high negative correlation coefficients (Mean = 0.82/SD = 0.028).

TABLE I

Correlation coefficients for MFL and local error rate

Experiment Nos	Correlation coefficient		
	MFL	FD	PSD
Subject A - No.3648	-0.84	-0.76	+0.87
- No.3674	-0.80	-0.73	+0.73
Subject B - No.3654	-0.83	-0.76	+0.83
- No.3656	-0.81	-0.73	+0.76
Subject C - No.3665	-0.80	-0.73	+0.76
- No.3673	-0.79	-0.71	+0.70

The results indicate that MFL is linearly and inversely correlated with the fluctuations of the subject's task performance and putative alertness level with mean negative correlation coefficient of 0.82. It is also observed that other features such as fractal dimension and PSD also correlate with the subject's task performance, but to a lesser degree. The correlation accuracy of FD was 0.74 while that of PSD was 0.77.

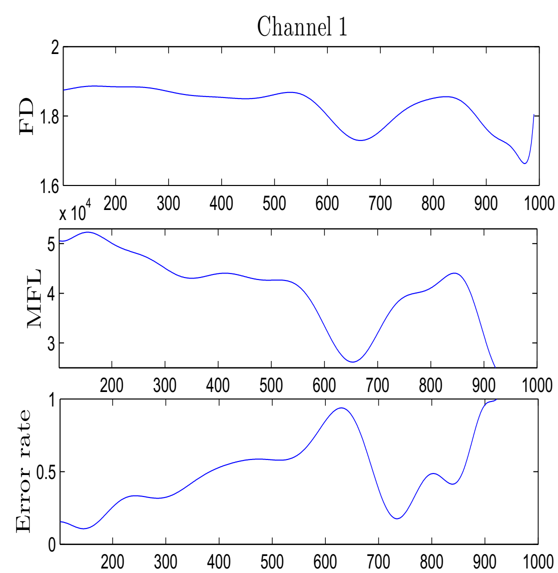

Fig. 2. Plot of FD and MFL (during session no. 3654) inversely correlated with the local error rate using polynomial fit(X label = Samples).

The data was also analyzed for the intra session variations for the different participants as shown in the bar plot (Fig.4). This bar plot shows that the negative correlation coefficients are more similar in two sessions. It suggests that the MFL is reliably correlated with error function in two sessions. The alertness changes are reliably measured during the two sessions using the minimum number of channels (in this case two channels).

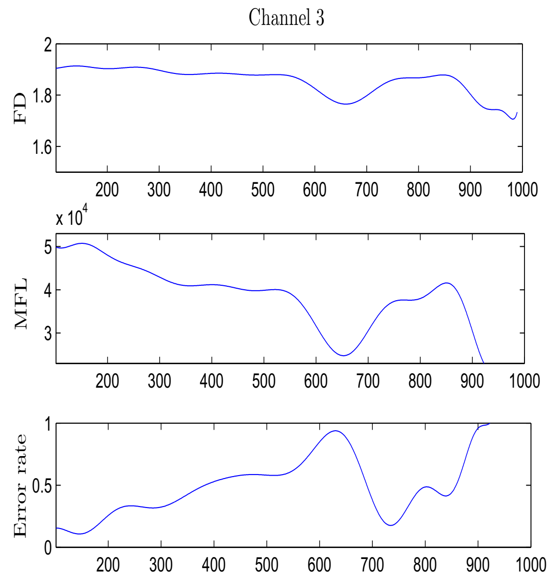

Fig. 3. Plot of FD and MFL (during session no. 3654) inversely correlated with the local error rate using polynomial fit(X label = Samples).

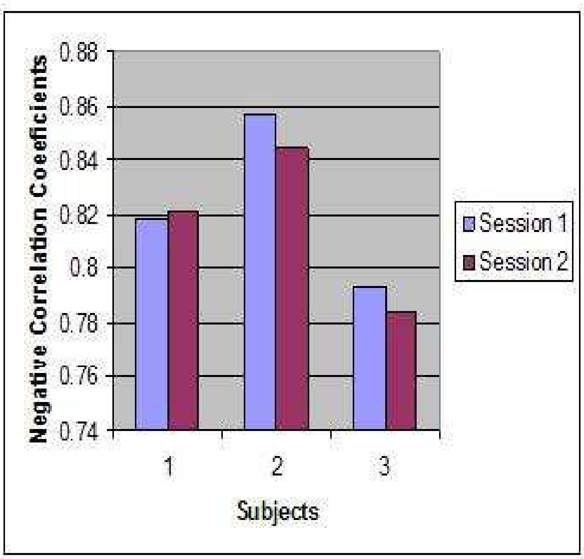

Fig. 4. Bar plot to determine the intra session changes for different participants.

V. Conclusion

This study has identified changes in the maximum fractal length (MFL) of EEG recordings in response to the changes in alertness of the subject. This study has identified that in comparison with PSD and FD, MFL correlates best with the alertness of the subject. It has also been found that with only one scalp EEG channel, the system is able to predict the changes in alertness level of the subjects with a negative correlation coefficient of 0.82. The outcomes of this study can be extended and would be useful for developing non-linear models and analysis tools for EEG and other similar biosignals.

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