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Stationarity and variability in eyes open and eyes closed EEG signals from able-bodied and spinal cord injured persons

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Abstract— **This paper examines the assumption of stationarity used in EEG brain activity analyses, despite EEG data often being non-stationary. Transformations necessary to obtain stationary data from measured non-stationary EEG data and methods to assess non-stationarity are illustrated using eyes open (EO) and eyes closed (EC) data. The study shows that even short time EEG records of 10s duration exhibit non-stationary behavior. Examination of the change in variance when going from the EO to the EC state for both able bodied and spinal cord injured participants show that the difference in variance is consistently positive and statistically significant only when stationary data is used. This has implications for brain computer interfaces that utilizes changes in EO and EC EEG signals.**

I. Introduction

The changes that occur in alpha (8-13Hz) brainwave activity from a reduced and desynchronized state during visual stimulation (eyes opened), or mental effort, to a dominant synchronized form during a relaxed state, or eye closure, is a well known phenomenon [1]. The increase in alpha activity during eyes closed has been shown to be produced voluntarily by most people [2]. There has been much interest in using eyes open and eyes closed EEG by researchers as it has often been associated with arousal levels [3] and has been used as a marker for daytime sleepiness [4] as well as a switching mechanism in brain-computer interfaces (BCI). For instance, eyes open (EO) and eyes closed (EC) alpha wave activity has been used in the Mind Switch environmental control System (MSECS) by detecting increased alpha wave power during eye closure. The MSECS uses this increase as an on-off switch for electrical devices [5,6]. For the MSECS, Fast Fourier Transforms (FFT) is used to decompose the EEG signal to separate frequency bands; changes in EEG alpha activity are then used as a switch. Similarly the NEU-II BCI [7] also utilizes the change in alpha wave activity as an on-off switch for electrical devices using wavelet transforms. Aside from BCI devices, research has also focused on using changes in alpha wave activity to detect mental stress [8] as well as utilizing the ratio between eyes open and eyes closed alpha activity as a marker for daytime sleepiness [4].

EEG signals can be represented as time series data measured on a dynamic system that represents brain activity [9]. It is well known that EEG signals are non-stationary [9,10]. However, EEG signals are often analyzed using methods that assume stationarity in the signal, such as FFT. Non-stationary data is unpredictable and cannot be modeled or used for forecasting. The results obtained using non-stationary data could lead to results that are inconsistent, unreliable and not characteristic of the system. The power spectral density and cross spectral density are often used in the analysis of an EEG signal in the frequency domain and this works only if the signal is, in a weak sense, a stationary process [11]. Thus, the use of non-stationary time series can lead to erroneous results, unless appropriate analysis techniques are used where the stationarity assumption is not invoked.

This paper focuses on the assessment of non-stationary behavior of the EEG signal and the transformation necessary to obtain stationary data. The transformations that give rise to stationary data from non-stationary data are then applied to study the effect it has in the differences in variance between EO and EC conditions for both able-bodied and spinal cord injured (SCI) participants. The two conditions, that is, the EO and EC states is of interest since assistive technologies like the MSECS are based upon reliable changes between the EO and EC conditions [5,6].

II. Methods

A. Participants and EEG Procedure

EEG data used for this study were obtained from thirty able-bodied participants (17males and 16 females) with mean age of 38.4 years (SD= 10.3), and 17 SCI participants (16 males and one female) with mean age of 33.7 years (SD= 10.1). The SCI group was a mixture of tetraplegic (n=7) and paraplegic (n=10) participants mostly with complete breaks (n=2 incomplete). All participants consisted of volunteers from the community. The study was approved by the institutional research ethics committee and participants were only entered into the study after informed consent.

Able-bodied EEG data was collected using the Neurosearch-24 data acquisition system (Lexicor Medical Technologies, Boulder, CO, USA). All silver/silver chloride

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electrodes were referenced to linked earlobes and impedances were kept below 8kΩ. EEG data signals were acquired at a sampling rate of 128 Hz and the gain set at 16K to ensure waveform resolution was not lost. Low-pass filter was set at 50Hz to reduce any electrical noise, high pass filter of 1Hz was applied to reduced drift noise. The SCI EEG data was collected using the Biosemi^{TM} Active-OneSystem. EEG signals were recorded following the International 10-20 Montage system sampled to 256 Hz covering the major areas of the brain [6]. Both datasets were collected for different studies exploring EO and EC changes for the purpose of the MSECS, and hence the different systems. SCI data were down-sampled to 128Hz to allow for comparisons. In both the able-bodied and SCI group only EEG activity from the cortical site O2 was used. An occipital site (O2) was chosen for two reasons: (1) alpha activity is usually larger in the occipital regions as it is linked with visual perception and (2) there are fewer artifacts (eg. ocular muscle activity) in this region compared to frontal scalp regions. All participants were assessed for their EEG activity in sessions of two minutes, which included three consecutive measures of 20s EC and 20s of EO. For the able-bodied participants, EC was at t=22, 62 and 102 s. In the case of SCI participants, EC occurred at t=8, 48 and 88 s. In the case of able-bodied participants with 33 participants there were 99 consecutive pairs of EO and EC periods, while there were 51 pairs in the case of the 17 SCI participants. In our analysis, the first 10s of EEG in each of EC and EO periods were used. Transformations were applied separately to each known EO and EC state.

B. *Assessment of non-stationary behavior and transformations to stationary data*

In this section the transformations required to obtain stationary data from non-stationary data and assessing stationarity are described. A time series is said to be stationary if the distribution of the variable is the same as after some lag. Wherever one looks at the distribution for some segment of the data at time *t* it should be the same as that observed for a similar length segment at a different time *t* [12]. A time series is said to be weakly stationary if the mean, variance or the autocorrelation structure does not change with time. The presence of such changes is indicative of non-stationary behavior. Time series where there is a trend, cycle, random walk or combination of the three are examples of non-stationary behavior. Such series have a variance and mean which varies with time.

To obtain stationary data from non-stationary data, two main steps are involved: detrending and differencing. Detrending will remove the deterministic trend while differencing the trend in variance. Detrending is carried out by removing the best fit line in the least square sense from the data. First order differencing involves forming a series:

$\{y(1),y(2),\ldots y(n-1)\}$ where $y(i)=x(i)-x(i-1)$

The series $\{x(1),x(2),\ldots x(n)\}$ is the detrended series.

Second order differencing involves forming a series:

$\{z(1),z(2),\ldots z(n-2)\}$ where $z(i)=y(i)-y(i-1)$, $\{y(1),y(2),\ldots y(n-1)\}$ being the first order differenced and detrended series.

Each time differencing is carried out a data point is lost. The same process is then repeated to achieve a higher order differencing. The amount of differencing is the lowest order differencing that yields a time series that fluctuates around a well defined mean and variance. The presence of positive autocorrelations out to a high number of lags (10 or more) is indicative of a need for higher order differencing [13]. Differencing tends to introduce negative correlation. It reduces the autocorrelations and drives the lag 1 autocorrelation to a negative value. If the series is over differenced the lag 1 autocorrelation tends to have a value more negative than -0.5. Another indication of over differencing is an increase in the variance rather than a reduction when the order of differencing has increased [13]. This is a useful result to ensure that the data is not subjected to over differencing. A useful corollary is that the amount of differencing required to ensure a data is stationary is a measure of the correlation present in the detrended data.

III. Results

A. *Detrending and Diffferencing*

The procedure of detrending and differencing is demonstrated in the representative sample below. Figure 1 shows a representative EEG record of 10s duration sampled at 128Hz during the EO condition. The plot is shown after detrending and removing the mean. The bottom plot is the autocorrelation function. Figure 2 shows the autocorrelation for the four orders of differencing 1, 2, 3 and 4 in the order of top to bottom. The first, second, third and fourth differencing is denoted as D(1), D(2), D(3) and D(4) respectively. From the data, the presence of positive autocorrelations out to a high number of lags is indicative of non stationary behavior. This is confirmed by evaluating the mean and variance of overlapping 2s segments separated by 0.0781s (10 samples). If the data is stationary the mean and variance of these segments should fluctuate around the mean and variance of the full record. This is not the case, and confirmed with the results shown in Table 1.

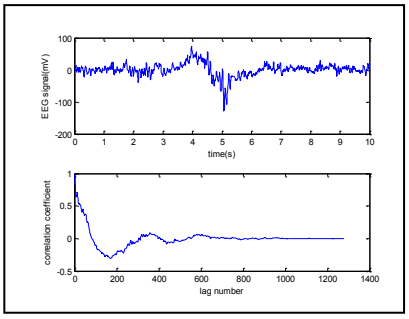

Figure 1. Top plot is 10s of an EEG record with eyes open after detrending and removing mean. The bottom plot is its autocorrelation function.

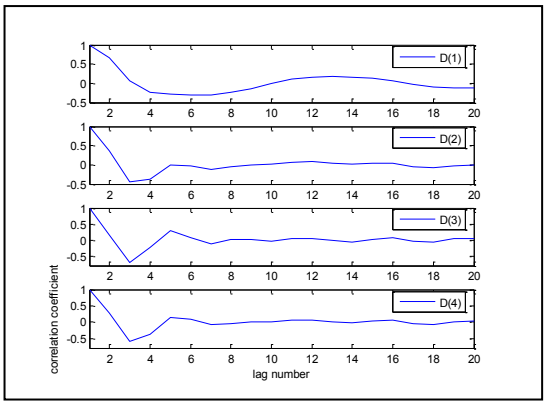

Figure 2. Autocorrelation for different orders of differencing. Lags are only shown up to a value of 20, since beyond it the differences are minimal.

TABLE I. AVERAGE MEAN AND STANDARD DEVIATION FROM THE DIFFERENT SEGMENTS AND THE FULL EO EEG RECORD

Type of EEG record	Average (mean of all segments) ± Std	Average (variances of all segments) ± Std	Mean of full record	Variance of full record
Detrended and removed mean	0.314 ± 8.609	428.6 ± 492.7	0	417.4
Detrended, D(1), and removed mean	0.005 ± 0.132	33.3 ± 18.8	0	30.3
Detrended, D(2) and removed mean	0.002 ± 0.031	21.8 ± 7.3	0	20.9
Detrended, D(3) and removed mean	-0.005 ± 0.026	26.4 ± 7.3	0	26.2
Detrended, D(4), and removed mean	0 ± 0.051	83.8 ± 23.8	0	81.2

TABLE II. AVERAGE MEAN AND STANDARD DEVIATION FROM THE DIFFERENT SEGMENTS AND THE FULL EC EEG RECORD

Type of EEG record	Average (mean of all segments) ± Std	Average (variances of all segments) ± Std	Mean of full record	Variance of full record
Detrended and removed mean	0.584 ± 2.668	541.2 ± 117.6	0	516.2
Detrended, D(1), and removed mean	-0.028 ± 0.131	122.2 ± 26.0	0	117.2
Detrended, D(2) and removed mean	-0.007 ± 0.064	58.8 ± 12.9	0	56.5
Detrended, D(3) and removed mean	0.001 ± 0.040	55.6 ± 12.5	0	53.2
Detrended, D(4), and removed mean	0.016 ± 0.107	202.9 ± 47.8	0	194.4

The results for EO indicate that detrending and differencing to an order of two are the optimum steps necessary to produce a stationary series. A similar procedure as before is then carried out on a 10 seconds EEG data with the participant during the EC condition. The results are shown in Table 2. The results for EC indicate that detrending and differencing to an order of three are the optimum steps necessary to produce a stationary time series. This is an order higher than that used for differencing compared to the EO data set. This indicates the presence of more autocorrelations in the EEG of eyes closed data set compared to the eyes open data set.

B. Detrending and Diffferencing results in the able-bodied sample

The above procedure of detrending and differencing was then carried out on a larger set of EO, EC pairs from both able-bodied and SCI participants. Figure 3 shows the differencing order for EO and EC plotted for different consecutive pairs for the able-bodied participants. The results show that the differencing order necessary to obtain stationary data is not fixed for all EO or EC but varies. The mean for EO is 1.3232 while that of EC is 1.8788.

However, since it is the change in going from EO to EC in each consecutive pair that is of interest in BCI applications, the change in the variances in going from EO to EC for each consecutive pair after differencing (to obtain stationary data) was tested. This was tested using t-test to determine whether the null hypothesis can be rejected where it is assumed the change in variance from EO to EC is greater than zero.

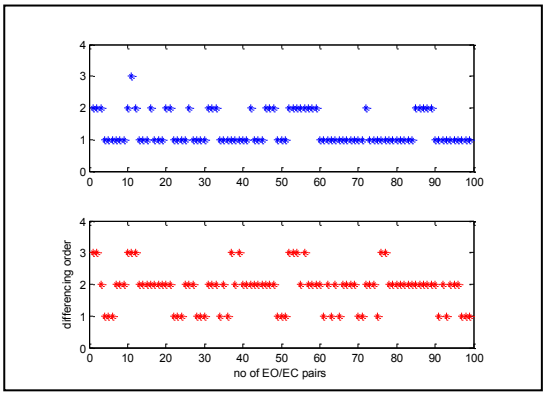

Figure 3. The differencing order for EO (blue*, top plot) and EC (red*, bottom plot) for EO, EC pairs in able-bodied participants

The results from the t- test show that, for the stationary data, the null hypothesis can be rejected with a p value less than 0.0001 with the lower limit of the 99.99% confidence interval being 2.5 and the upper limit being infinity. The confidence interval is the range which encloses the true hypothesized difference at the chosen probability. It is evident that this range does not include zero and is always positive. However for the non–stationary data, the p value is 0.84 and the confidence interval includes the zero. The null hypothesis is therefore not rejected.

C. Detrending and Diffferencing results in the SCI sample

Results from the analysis of the differencing order necessary to obtain stationary data of consecutive EO and EC pairs from the SCI data set showed that they do not differ from each other, except in three cases where the order for EC is 2 and EO is 1. For all other EO, EC data sets the differencing order obtained were equal and had a value of 1. Thus the autocorrelations presented in EO and EC are similar for SCI participants.

Next, the change in the variance when going from EO to EC in each consecutive pair was examined and a t-test carried out to determine whether the null hypothesis can be rejected. The alternate hypothesis is that the change in variance when going from EO to EC is greater than zero. The results from the t-test show that for the stationary data that the null hypothesis can be rejected with a p value of 0.017. The lower limit of the 98% confidence interval is 0.11 with the upper limit being infinity. Again, as evident from this result, the range does not contain zero and has only positive values. As for the non-stationary data, the p value is 0.28 and the confidence interval includes the zero. The null hypothesis is therefore not rejected.

IV. Discussion

This paper examined the transformations required to obtain stationary data from measured EEG data. The results showed that even a 10s segment of EEG data exhibited non-stationary behavior with the presence of positive autocorrelations out to a high number of lags. Often in EEG studies, to avoid non-stationarity, shorter time series are used in EEG analyses. However, the length of the time series to exhibit stationary behavior is not clear. A procedure to overcome this ambiguity could be to utilize the transformations presented in this paper on the non-stationary data to make it stationary.

This paper also aimed to test the effect of non-stationarity when there is a change from EO to EC. Changes between the EO and EC conditions have importance in the function of assistive technologies such as the MSECS. The study showed that differences between the two conditions can be altered depending on whether the data used was stationary or not. The results found differences in the autocorrelations amongst the EEG time series between EO and EC states were significant for able bodied participants but not for SCI participants. Analysis of the changes in the variances in going from EO, EC states of able bodied to SCI participants for non-stationary and stationary data were also studied. The results of able bodied subjects showed that statistically significant differences were observed with the variance in the EC state greater than in the EO state for the stationary data, but not so if non-stationary data was used. A similar result was found for the SCI participants. This finding is important given that there is known altered brain activity seen in persons with SCI [14,15] and this may impede their use of BCI based assistive technologies. The transformation of non-stationary SCI EEG data to a stationary form vastly improves the detection between EO and EC conditions based on change in variance.

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