Sunil Hirekhan[1], Ramchandra Manthalkar[2]

Temporal Correlation of Meditation EEG Signals

Abstract: - Meditation is an ancient technique that has been in practice for thousands of years which develops a sense of wellbeing. Meditation is a purely mental practice that has been shown to induce neuroplasticity, or changes in the body. Because of its beneficial impacts on modern human existence, meditation has recently become the subject of scientific studies. To investigate the effectiveness of these complementary and alternative medicine approaches, it is necessary to understand the underlying neuronal dynamics using Electroencephalogram (EEG) analysis/imaging techniques. In order to extract the long-range temporal correlation of EEG signals the DFA (Detrended Fluctuation Analysis) exponent, alpha (α),of alpha band of EEG signal, pre and post mindfulness (Vipassana) meditation retreat is computed. Previously, the DFA exponent alpha has been used widely for diagnostic purposes in clinical settings. It has been observed that, as a measure of complexity, the detrended fluctuation analysis exponent alpha (α) of EEG signals decreases in 10 (67%) of 15 subjects during meditation. The increase in the complexity of neural rhythms is shown by the decrease in the DFA exponent. Increased neural oscillation is a sign of appropriate homeostasis regulation, which enhances the equilibrium between sympathetic and parasympathetic nervous system activity. The occipital and frontal regions show an overall rise in EEG alpha and beta band power. Calm, relaxation, and pleasant affect are linked to an increase in alpha band power. An alert mental state is indicated by a higher beta power.

Keywords: complexity, indicated, mindfulness, diagnostic, DFA

1. INTRODUCTION

The Long-Range Temporal Correlation(LRTC)is considered to be a better method for quantifying the scaling behaviour of time series, compared to traditional autocorrelation analysis or power spectral density analysis[1].The long-range temporal correlation of a time series may be obtained by computing the detrended fluctuation analysis(DFA) and the power law exponent, alpha(α). It is a powerful technique used by the researchers to distinguish a healthy human system compared to a diseased one, and is applied as a complexity metric[2]. Complexity of a time series gives an idea of the amount of information needed to describe the series. More the internal structure in a time series less information is needed to describe it, i.e. it is less complex series.DFA analyses degree of internal structure in a time series by detecting the long-range temporal correlation in the time series as a measure of memory. Stronger the memory, higher the DFA values, lower the complexity of a time series [3].The traditional theory suggests that the human physiological systems achieve homeostasis, reflected in terms of the complexity of the physiological signals. A healthy system automatically maintains (a rise) complexity of the signals, while a diseased one is not able to keep it. The rise in the complexity is indicated by the reduction in alpha (α) values of the log-log plot of the $F_{DFA}(s)$ vs (s) of the physiological time series[2]. The method is being employed for diagnostic purposes in clinical settings[4]–[10]. It has been observed that the DFA scaling exponent for healthy subjects is found to be lower in magnitude as compared to the diseased one.

It is proposed that the Long- Range Temporal Correlation (LRTC) analysis of meditation EEG signals shall be helpful to explore the trait effects of meditation. It is expected that the detrended fluctuation analysis (DFA) exponent (α) of meditation EEG signals shall be lower in magnitude after the meditation retreat since the subjects attain better health through neuroplastic changes[11], [12]. The EEG data have been obtained before and after the Vipassana (mindfulness) meditation retreat. The alpha sub band of neuronal oscillations exhibits long range temporal correlation[13], [14].The artefact free 07 sec.EEG epoch is pre-

[1]Dept. of Electronics Engineering, Govt. College of Engineering, Aurangabad, India
[2]Dept. of Electronics Engineering, SGGS Institute of Engineering &Technology, Nanded, India

processed, and detrended fluctuation amplitude is calculated. Further, the log-log plot of the DFA amplitude, F_{DFA} against window(epoch) size, 's' is obtained. Slope of this linear relationship log(DFA) vs log(s), exponent alpha (α) is computed[15]–[17]. It is observed that the DFA exponent alpha (α) is found to be lower in magnitude in case of 10 meditators out of total 15 participants after the meditation retreat. The reduction in the DFA exponent indicates the enhanced complexity and attainment of better balance of the neuronal oscillations after the meditation retreat[2], [18].

2. MATERIALS AND METHODS

The EEG Acquisition: EEG data is obtained using a 32-channel, ENOBIO-32 machine with a sampling frequency of 500 Hz, and resolution of 24 bits. The data is recorded from novice meditators who have attended the 10-days Vipassana (Mindfulness) meditation retreat for the first time. The EEG data recording and analysis of 15 participants (07 Male + 08 Female) in the age group 20-30 yrs, is carried out. The EEG data is obtained from the participants seated in the chair in relaxed posture with eyes open. The informed consent is obtained from all the participants before the experiment. This EEG experimentation is approved by the ethical committee of the institute.

2.1 Data Pre-Processing and Analysis:

After visual inspection of recorded EEG data, an artifact free, 07 second data segment is extracted for analysis. Total of 20 EEG electrodes covering the whole scalp have been considered for data analysis.. The EEG sub band is extracted using the basic FIR filter, with a filter order of 310. The dc bias is removed, and all the epochs are normalised in order to achieve the common amplitude range amongst the varying EEG electrodes and subjects, before undertaking further analysis. The EEGLab open source platform is utilised to carry out visual data inspection and preprocessing. In order to estimate the long-range temporal correlation in the EEG segment, the detrended fluctuation analysis is implemented, as follows.

2.2 Detrended Fluctuation Analysis:

The EEG time series is Hilbert transformed to obtain the signal profile, whose absolute values gives the amplitude envelope[8], [15], [19]. The amplitude envelope is divided in p equal windows. The no. of windows varies from 08 to 256, where the window size varies from 448 – 14 time points, respectively. Within each window a least square fit on amplitude envelope is performed to subtract the local trend, as to maintain only the intrinsic fluctuation in EEG. This variance of the intrinsic fluctuation, {y(n)}, from the trend line $y_P(n)$, in P^{th} window is, $F^2(s)$

$$F^2(s) = \frac{1}{s}\sum_{n=(P-1)s+1}^{Ps}[\{y(n)\} - y_P(n)]^2 ;$$

It is the measure of local detrended fluctuation in P^{th} window. The square root of the average fluctuation of $F^2(s)$ over all windows is the RMS fluctuation from the local trend in p windows, each of s time points, is DFA,

$$F_{DFA}(s) = \sqrt{\frac{1}{p}\sum_{P=1}^{p} F^2(s)} ;$$

The above computations for a single EEG electrode, is performed for all the electrodes and are repeated for all subjects, pre and post-intervention. The study of dependence of $F_{DFA}(s)$ on window size, s, is the essence of long-range temporal correlation, i.e. DFA.

If $F_{DFA}(s) \propto s^{\alpha}$, the EEG time series follows a power-law behaviour and there exists the long-range temporal correlation. The exponent α is an indicator of the nature of long-range temporal correlation, i.e. fluctuations in EEG time series[16], [20].

The detrended fluctuation analysis is implemented for the alpha EEG sub band[13]. The alpha sub band (8 - 12 Hz) is filtered out for every EEG electrode before and after meditation retreat for each participant. The FIR band pass filter for the pass band range (8 -12 Hz), with a filter order, n (n=310) is used. The magnitude and phase response for this FIR filter is as shown in figure no. (1). The X-axis spread is from 0 to nyquist frequency, the sampling frequency is 500 Hz.

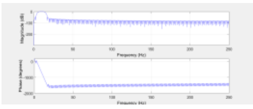

Fig.(1) : Magnitude and Phase response of Band Pass FIR Filter

The amplitude envelope of the alpha sub band EEG signal is obtained by taking the absolute value of the Hilbert transform[20], is shown in the figure (2).

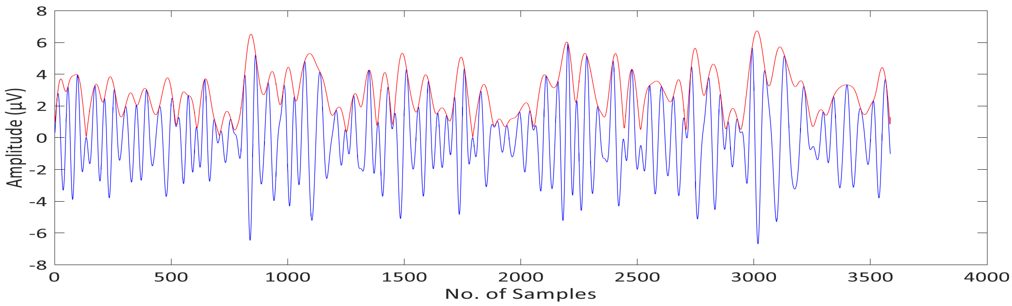

Fig.(2) : Amplitude Envelope of EEG Sub band-Alpha

Any characteristic scale signal can be represented using statistical features like mean, mode standard deviation, etc. but, a non-stationary signal like EEG can be conveniently described using the power law exponent pertaining to varying scales through the long-range temporal correlation. Hence, the detrended fluctuation of the signal on different scales is computed[16], [21], [22]. The log-log plot of the DFA(s) vs. (s) is linear in nature on increasing time scales, as shown in figure(3), indicates that the EEG signal obeys the power law.

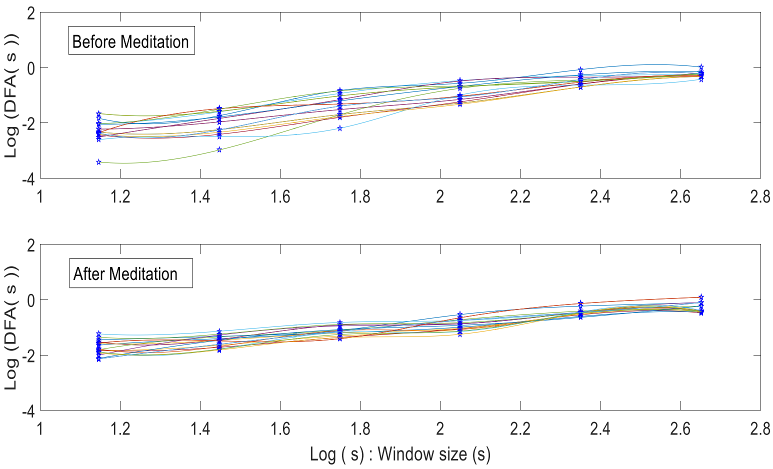

Fig.(3) : Log(DFA(s)) vs. Log(s) for all (20) EEG electrodes of a female meditator(1)

The above Figure(3) shows that the log-log plot of all the twenty EEG electrodes exhibits the long- range temporal correlation on increasing time scales.

Following figure no.(4) depicts the log-log plot of a male meditator for the EEG electrode PO3, before and after the 10-days meditation retreat.

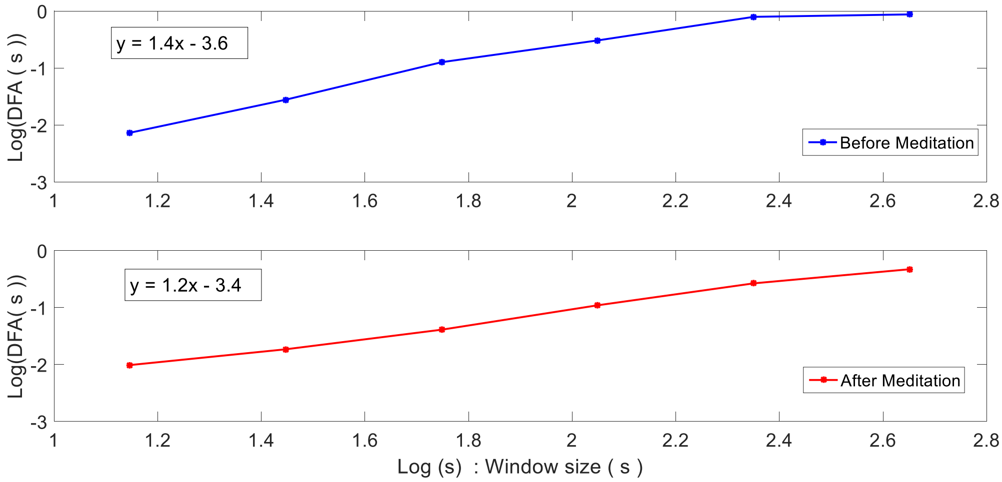

Fig.(4) : Log(DFA(s)) vs. Log(s) for electrode PO3 of a male meditator (3)

It may be observed that the slope of the log-log plot, is alpha(α) =1.4 (before meditation), and alpha(α) =1.2 (after meditation). The lower value of slope alpha (α) of these log-log plots 'after meditation' can be observed with 10 meditators out of 15 participants who attended the meditation retreat, as depicted in table no.(1). As observed in the literature the effect of meditation may lead to the reduction in the values of DFA exponent alpha (α) in the alpha sub band of EEG signal[13]. The analysis of variance (ANOVA) of the EEG data before and after the meditation retreat is carried out in order to determine the level of significance across the data. The F-ratio and the significance level in each participant EEG data has been computed and shown in the table..

Table No. (1): No. of Electrodes with reduction in DFA exponent alpha(α) (%)

Sr.No. of Meditator	Male/Female Meditator	Percentage of EEG electrodes with reduction in exponent alpha (α) (%)	F-ratio F(1,39) at a significance level of 0.05	p-value, ANOVA Significance, (Pre & post)
1	Female	92.3	3.8	0.05
2	Male	80	14.32	0.0005
3	-"-	78.9	20.75	0.0005
4	Female	75	12.95	0.009
5	Male	65	3.78	0.05
6	Female	63.1	0.45	0.5
7	Male	58.8	0.35	0.55
8	-"-	55.5	0.15	0.7
9	-"-	55.5	13.8	0.0007
10	Female	54.5	4.73	0.03
11	-"-	40	5.11	0.02
12	-"-	40	3.65	0.06
13	Male	20	3.89	0.05
14	Female	15	0.9	0.34
15	-"-	13.3	3.86	0.05

It may be noted that, out of 10 meditators who had reduction in alpha (α) exponent values in more than 50 % of electrodes, the DFA values for 7 subjects (70%) has significance of 5 % level pre and post –meditation. Also, out of 5 meditators, who do not have reduction in alpha (α) exponent in more than 50 % of electrodes, 4 subjects have significance of 2 % -6 % level, whereas, only1 subject do not have less than 5 % level, as shown in table no.(1).

3. EEG SUB BAND POWER

The comparison of EEG sub band power in all the sub bands delta, theta, alpha, beta and gamma before and after meditation is implemented. It has been observed, in general, that there is an increase in the sub band power in almost all the brain lobes, after the meditation. This increase in sub band power is noticed in almost all the subjects, prominently in alpha and gamma sub band. The change in sub band power in all the 20 EEG electrodes of a meditator (no. 1) is shown in figure no.(5).

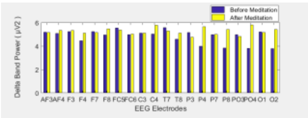

Figure No. (5a) :Change in Delta Sub Band Power of a Meditator

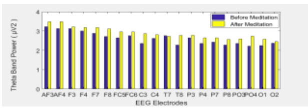

Figure No. (5b) :Change in Theta Sub Band Power of a Meditator

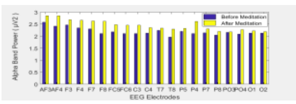

Figure No. (5c) :Change in Alpha Sub Band Power of a Meditator

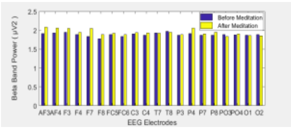

Figure No. (5d) :Change in Beta Sub Band Power of a Meditator

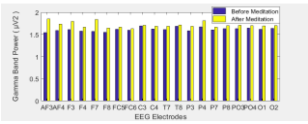

Figure No. (5e) :Change in Gamma Sub Band Power of a Meditator

It may be noted from figure no. (5a-e), that there is an overall increase in the power in almost all the electrodes, and in all brain lobes. The increase in delta sub band power in 13 electrodes, theta sub band power in 19 electrodes, alpha sub band power in 20 electrodes, beta sub band power in 15 electrodes and gamma sub band power in all the 20 electrodes, is observed..

Similarly, in order to find the total effect of sub band-wise increase in power, the average of the no.of electrodes with increase in power in each sub band for all the meditators, together is obtained. This gives the overall effect of the increase in no. of EEG electrode power in each sub-band is as shown in the figure no. (6a).

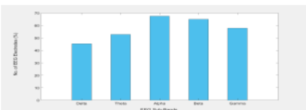

Fig. (6a) : No. of EEG Electrodes(%) with sub band-wise increase in Power

It can be observed from the above figure that the maximum increase in the EEG electrode power has been in alpha band and beta sub band. The minimum increase in electrode power is in delta band after the meditation retreat.

Also, to find the total effect of brain lobe-wise increase in power, the average of the EEG electrodes with increase in power in each brain lobe region is obtained for all the meditators. This gives the total effect in a brain lobe region-wise increase in power, as shown in figure (6b).

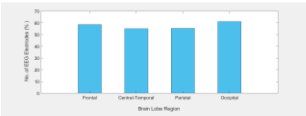

Figure No. (6b) : No. of EEG Electrodes(%) with Brain Lobe-wise increase in Power

The figure (6b) indicates that the maximum increase in EEG electrode power has been in Occipital region, followed by Frontal region. The least increase in electrode power has been observed in the Central-Temporal (C3-C4,T7-T8) electrodes region.

4. DISCUSSION AND CONCLUSION

The objective of the present work is to analyse the trait effect of meditation through long-range temporal correlation analysis and other associated parameters. The EEG signal exhibits long range temporal correlation as it follows power law by maintaining the same DFA exponent alpha (α) for varying window sizes. The DFA exponent alpha (α) acted as a complexity metric in many of the physiological processes[2], [18], [26].It has been found that the DFA exponent alpha is lower in magnitudes in healthy human systems compared to diseased one[6], [27]. As has been mentioned previously the meditation practice instils a sense of health and happiness in the human being, the DFA exponent are expected to be reduced after the meditation practice, as has been observed here. These participants may have achieved neuroplastic changes in the brain resulting in reduced DFA exponent alpha (α)[11], [23]. In this work, the DFA analysis has been implemented to analyse the change in the alpha brain rhythm before and after the Vipassana meditation retreat, for the first time. It is found that the DFA exponent, alpha is reduced in the EEG alpha rhythm of 10 meditators out of 15 participants, as mentioned in table no. (5.1).The one-way analysis of variance(ANOVA) have been computed in the groups of before and after meditation average DFA values, for each subject. The result of this analysis indicates that the 11 subjects have significant level of 5 %, for the DFA values, with degrees of freedom (1,39), is as shown in table no.(1).This indicates that the sets of DFA values computed before and after meditation retreat of the same participant are significantly different for 11 meditators, which may happen due to the neuroplastic changes associated with the Vipassana meditation retreat. This also signifies the prominence of the LRTC analysis for extracting the neural correlates of Vipassana meditation.

There has been observed an increase in sub- band power, after the meditation retreat, particularly, in occipital and frontal region. These power samples are averaged in the window to compute the electrode power in $\mu V^2/Hz$. The electrode power magnitudes for each electrode in the respective brain lobe hemisphere/region are computed. It is found that on an average, the band power for occipital and frontal regions are increasing after meditation retreat. The increase in sub band power may be noted from bar charts of a meditator displayed in figure(5a-e). The generalised increase in brain lobe power is asserted through the group average of all the meditators together for all the EEG electrodes, as shown in figure (6a-b). The maximum increase in alpha band power. The alpha band power is associated with feeling of calm, relaxation and positive effect. It is also denoted as alpha synchronization represents reduced state of active information processing [28]. Alpha synchronization may be considered as an indicator of top-down information processing, indicating cognitive or neural processes specifically related to creative cognition [28]. Alpha synchronization has been interpreted as a functional correlate of inhibition (or top-down control). According to that view, alpha increases may reflect an inhibition of cognitive processes that are not directly relevant for task performance [29].

It may be concluded that the long-range temporal analysis of the EEG signals confirms the reduction in the DFA exponent alpha(α) after the meditation retreat of novice participants, is an indicator of better health and happiness. Increase of overall sub band power, with maximal alpha sub band power in occipital, frontal region, indicates higher creative ideation, original thinking, leading to a more stable, enhanced contentment after the meditation retreat.

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