Time-Frequency Analysis of EEGs Recorded during Meditation

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***Abstract*—Time-frequency analysis is one of the most important and commonly used analytical tools for evaluating physiological signals. In the past, many researchers investigated the effect of meditation on stress relief and disease improvement. In this research, we select 10 normal adults as the subjects, and divided them into two groups: more than 10 years of meditation experience and no experience. The task was mainly designed to trace the varying spectral characteristics of EEG recorded with 19 active electrodes at a sampling frequency of 250Hz during meditation. And then we analyzed the changes of EEGs during meditation quantitatively. To obtain new insights into the nature of the EEG during meditation, we analyzed the recorded signals using Fast-Fourier Transform (FFT). An important problem in EEG signal processing is efficient segmentation. The comparisons between the recording times at different electrodes exhibit behavior that is strongly dependent on time and frequency.**

Keywords-Meditation, EEG, time-frequency analysis

I. INTRODUCTION

Modern lifestyles characterized by a significant amount of mental stress owing to hectic work schedules, often leads to negative emotions, manic depression, insomnia and other symptoms after an extended period. Previous studies showed that meditation can significantly affect physical and mental relaxation [1-4]. Many individuals achieve such relaxation by practicing relaxation techniques, including deep breathing, meditation, and yoga, or by performing rhythmic exercises, such as running, cycling, or speed walking. Identifying ways to incorporate such activities into daily life can help to reduce daily stress and boost physical energy and strength. Meditation state refers to altered sensory, cognitive, and self-referential awareness that can occur during meditation practice, whereas trait refers to the lasting changes in these dimensions that persist in the meditator, irrespective of active engagement in meditation[5, 6].

Caton measured the electroencephalogram (EEG) of small animals in 1875, while Berger did so in humans in 1925. While describing the EEG signal generated by alpha (8–12 Hz) activity for the first time in 1929, Hans Berger established that closing the eyes decreased sensory input and increased alpha power over the occipital scalp[7]. Quantitative EEG analysis as a field includes a diverse array of procedures. A recent approach to quantify the EEG series has been developed based on nonlinear dynamics[8]. EEG studies have utilized these methods to portray the neurophysiological changes that occur in meditation.

Although the neuroelectric correlates of meditative altered consciousness states have not yet been firmly established, the preliminary findings have implicated increases in theta and alpha band power and decreases in overall frequency. Related studies also indicate widespread alpha EEG coherence across the cortex in meditation. Above data suggest that alpha-theta activity is predominant in meditation, whereas delta activity predominates in deep sleep. Although theta-wave activity suggests dreaming, alpha, the predominate wave form in meditation, is most closely associated with wakeful alertness.

However, most EEG signals are often extremely time varying[9]. The situation is more complex since a subsystem can change rapidly on a time scale. Thus, the temporal and spatial interaction among the subsystems of the brain must be investigated to thoroughly elucidate neural information processing of the brain. Generic coherent analysis limits the dynamic synchrony analysis of the physical quantity of non-stationary EEG signals is often represented using transient Fourier spectrum[10]. Different time and frequency set up the desired time-frequency representation.

Representations based on Fourier transform were applied earlier on in the automatic analysis of EEG signals. Meditation produces changes in certain frequencies bands, including δ (0.4–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–30 Hz), and γ activity (30-70 Hz) bands, have been obtained through means of time-frequency distribution (TFD). Since EEG signals are non-stationary and multicomponent in nature, such methods are inappropriate for the frequency decomposition of these signals. Previous studies have demonstrated that time–frequency (t-f) based methods outperform conventional methods of frequency analysis [11, 12]. This study examines the feasibility of using t-f analysis EEG segments during meditation. The proposed approach is based on t-f analysis of each EEG segment to obtain the power spectrum density (PSD) and extract its features, which correspond to the fractional energy of windows defined on the t-f plane.

The rest of this paper is organized as follows. Section II, summarizes the research method by elucidating the data acquisition process, preprocessing, feature extraction using FFT. Section III then summarizes the results of this study. Discussion is finally drawn in Section IV, along with recommendations for future research.

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II. METHODS

A. Subjects

Individuals who practiced meditation daily for 10 years (Tibetan meditation method, Nyingma) were compared with a group with no experience in meditation. Five healthy experienced meditators (2 F, 3 M) between 34 to 47 years old (mean =42.8 ± 5.31 years) and five healthy non-experienced meditators (2 F, 3 M) between 21 to 29 years old (mean =24.2 ± 3.42 years) participated as the study subjects. The subjects had no history of neurological or psychiatric disorders, and none of them were medication. The experiment paradigm was explained fully, and written consent was obtained from each participants.

B. EEG Recordings

The EEG data were recorded from 19 active electrode positions (Nicolet Clinical EEG) on the scalp (Fp1-F3, F3-C3, C3-P3, P3-O1, Fp2-F4, F4-C4, C4-P4, P4-O2, Fp1-F7, F7-T3, T3-T5, T5-O1, Fp2-F8, F8-T4, T4-T6, T6-O2, T3-C3, C3-Cz, Cz-C4, C4-T4) according to the International 10-20 system of electrode placement, referenced to the linked ear lobe electrodes.

EEG was recorded in an electrically shielded room at a sampling frequency of 250 Hz. Signals were analog band-pass filtered between 0.2 and 100 Hz, and notch filters were applied at 60 Hz to substantially remove external noise related to line power frequencies.

C. Experimental Paradigm

The experimental and control groups establish the initial physical parameters of the first 4 min. The procedure was followed by three experimental tests, each consisting of meditation 5 min and opening the eyes for 2 min. Carried out in a quiet room, the entire procedure lasted approximately 25 min, including preparation of the subject.

D. Time-Frequency Analysis

Spectral decomposition of the EEG by calculating the Fourier transform has been performed since the early development of electroencephalography. The rhythmic nature of many EEG activities explains the need for this analysis. Fourier transform allows one to separate various rhythms and estimate their frequencies separately of each other, a difficult task in order to determine visually if several rhythmic activities occur simultaneously. Spectral analysis can also quantify the amount of activity in a frequency band.

Spectral analysis of EEG signals is a highly effective means of comparing short samples of data from patients against age-matched normative values, as well as in sleep stage analysis and quantification of drug, metabolic effects, and various diseased states.

EEG spectral analysis results are often grouped into the conventionally adopted frequency bands, i.e., δ (less than 4 Hz), θ(4-7 Hz), α(8-13 Hz), β(14-30 Hz), and γ activity (above 30 Hz). Although much physiological and statistical evidence suggests the independence of several of these bands, their boundaries can vary only slightly based on the particular experiment under consideration; in addition, they can be adjusted as required. The conventional means performing frequency analysis applies the fast Fourier transform (FFT) algorithm directly to a segment of digitized data. Fig. 1 shows the FFT of EEG signals during meditation with a frequency ranging from 1 to 125 Hz and time scale from 1 to 6 sec. Fig. 2 presents a sample power spectrum density with the analogous grid used to extract the feature.

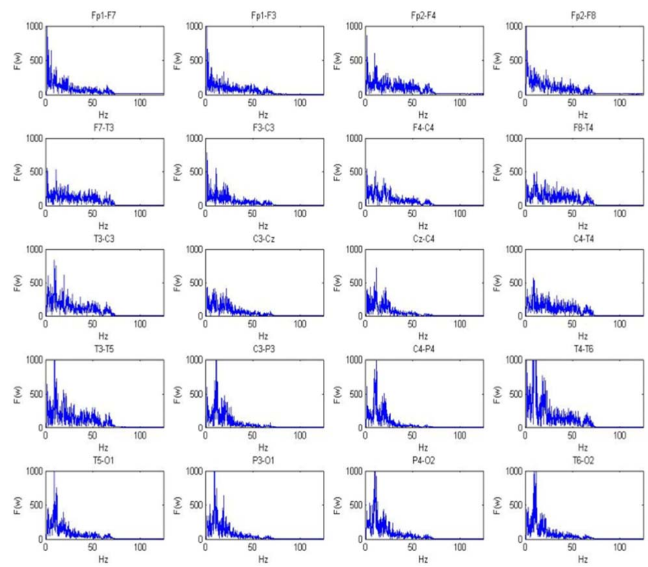


Figure 1. FFT of EEG signals during meditation

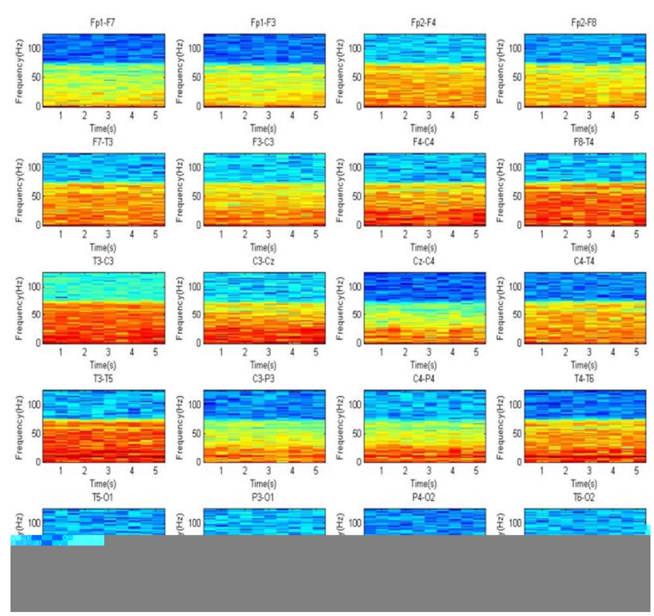


Figure 2. Time windows and frequency subbands used to extract the feature

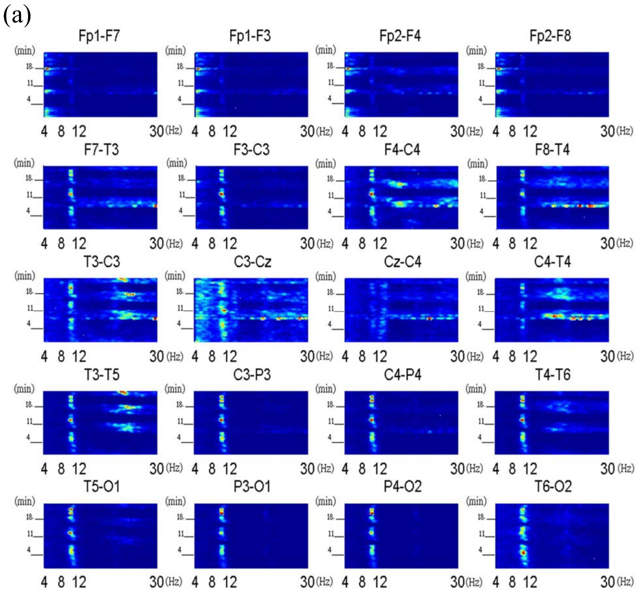
III. RESULTS

Analytical results are derived from the comparative interpretation of the time and frequency spectrum arrays, for both control and experimental subjects. Highly experienced

Tibetan Buddhist meditators and novices are compared while engaged in three times of meditation, with attention paid without object.

Meditation is an internally-invoked, personal practice, in which an individual can do independently. Long-term meditators have a slower mean frequency and greater theta–alpha power at rest than novices do, as well as widespread increases in theta and early alpha power, and enhanced theta coherence at frontal– central locations.

(a)



(b)

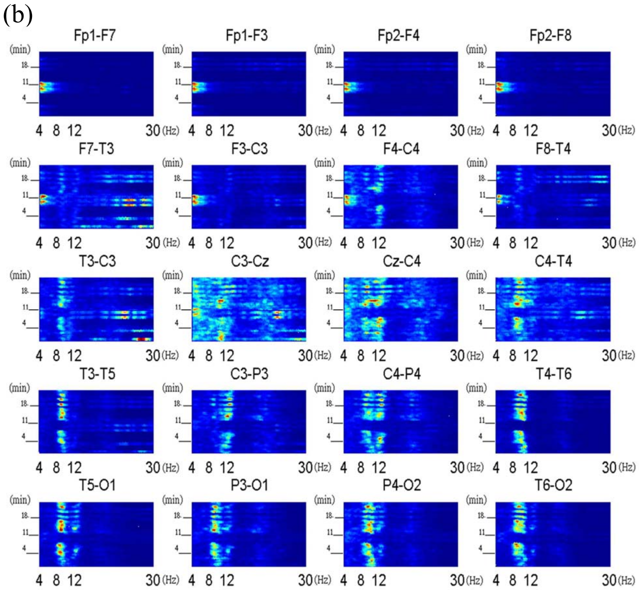


Figure 3. (a) Time-frequency analysis of EEG data for the experienced meditator, (b) shows time-frequency analysis of EEG data for the inexperienced meditator

Theta coherence is most pronounced in the left frontal pole, and the theta power correlates positively with a self-reported blissful effect and negatively with thought appearance rates.

This study also analyzes EEG data based on As Recorded MONTAGE. In the frequency axis is between 4-30Hz, this experimental data of interest are in the brainwave data. In the time axis which is the experimental time. Fig. 3 (a) summarizes time-frequency analysis of EEG data for the experience meditator, while Fig. 3 (b) summarizes time-frequency analysis of EEG data for the inexperienced meditator, only a small portion of their simple learning method. The time-frequency analysis graph reveals that meditation can be induced α waves.

When the experimental group and the control group are in meditation, α wave can be induced in the posterior regions of head. Our results also indicate that an experienced meditator focuses more on the α wave 8-10Hz; while for the inexperienced meditator, α wave is more spread throughout the 8-13 Hz. According to our results, for an extended meditation experience, α-wave is more concentrated in the data; meanwhile, for an inexperienced meditator, the energy spectra of experience in the θ (4-8 Hz), and β (12-30 Hz) have appeared. No obvious α wave of data is found in the prefrontal and frontal lobes. In T3-C3, C3-Cz, Cz-C4, C4-T4 electrode, an energy spectrum between 4-30 Hz can be found.

Experimental results suggest a positive correlation between thalamic activity and alpha power at some, but not all locations. Although an integrated model of the neural generators for alpha and other frequencies has not yet been established, alpha appears to be a dynamic signal with diverse properties that is sensitive to presentation and expectation of a stimulus.

Alpha power often increases when meditators are evaluated during meditation compared with control conditions. This band is stronger at rest in the meditators than with non-meditator controls, implying that state and trait alpha changes emerge from meditation practice. This outcome is related to early biofeedback studies, in which greater levels of alpha activity are found to be correlated with lower levels of anxiety and feelings of calm and positive effects. In sum, increases in alpha power are related to relaxation, which is observed in some individuals when meditating compared with the baseline.

IV. DISCUSSION

Brain response of meditation practice is measured based on the assumption that various conscious states are accompanied by different neurophysiological states. Many meditation practices are characterized by a meta cognitive shift in the relationship between thoughts and feelings. Moreover, non-meditators cannot keep themselves in a state of physical immobility for the extended periods of time that time trained meditators can exhibit, making comparisons with the prolonged meditation state of a meditator impossible.

Having largely disregarded the above issues, attempts to assess state versus trait effects have used protocols that omit counterbalancing of meditation versus non-meditation states, minimized the duration of non-meditation simulations, or only compared meditators and controls at rest to determine trait effects.

In this study, the two-minute break involves querying the subjects with open eyes to ensure that the subjects are not sleeping. Therefore, additional experiments are necessary to ensure the accuracy of EEG waveform. Simultaneously, time-frequency analysis reveals that for individuals experienced in meditation, this study analyzes the future of the object, not only for a stable α wave with a trend to teach, but also in the γ activity generated in power spectrum.

Long-term meditators involved in non-meditator controls exhibit trait higher theta and alpha power, possibly related to a specific meditative technique and a slower baseline EEG frequency. However, self-selection effects cannot be ruled out, because EEG slowing is often found for both state and trait meditation effects.

In sum, meditation practice may alter the fundamental electrical balance between cerebral hemispheres to modulate individual differences in affective experience. Additional studies are warranted to confirm this possibility.

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