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The Study of Stress Identification Using EEG Signals and the Response to Meditation †

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Abstract: Stress is a natural and common human response towards challenges and threats. Stress can be physical or emotional results from an event or thought that makes you angry, frustrated, depressed or nervous. Stress also arises when persons compelled to do work which they may not like. Acute stress sustains for long duration results in chronic stress. It has negative impact on central nervous system, physiological response and the reason for several neurological disorders. Early detection of stress can be done by different bio-markers like EEG, ECG, SCR and salivary cortisol. Among all bio-markers, EEG records electrical activity of human brain is more effective procedure to identify the stress factor and helpful for the identification of various psychological disorders. In this paper we have recorded stressed subject EEG measurement for the identification and analysis of stress, further the same subject is made undergone the meditation practice of 45 days then recorded the EEG for further stress analysis. Results and comparative analysis shows the significant reduction of stress factor in terms of spectral power cognitive ratio relative to alpha, beta, theta and delta waves.

Keywords: EEG; stress; meditation; cognitive ratio; relative power

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1. Introduction

People of all background experience stress for a specific duration of their life time. The way people experience and respond to stress including their physical and behavioral reactions greatly influenced by brain [1]. In certain environments, humans experience stress when they are exposed to conditions that are beyond their natural ability to regulate or predict [2]. Acute stress (stress for short duration) necessary for growth and development. Chronic stress results due to persistence of stress for a long duration, results in various psychological disorder like depression anxiety [1]. Patients who have better spiritual health tend to have lower level of stress, anxiety and depression since spiritual health and mental health are intimately associated. It is possible to prevent many mental diseases in chronic patients and improve their prognosis by practicing yoga [3]. There are many ways of stress management. Now a day's doctor suggests music therapy to improve the stress parameters [4]. But meditation is our ancient practice to calm down the mind and release stress. Even Tinnitus is the disorder, for hearing noises in ears when there is no outside source of the sounds can treated with meditation [5]. Vast research on mediation based on EEG (Electroencephalography)due to its non-invasive nature and low cost to access brain activity is going on. During natural disasters, yoga can be used as a psychological technique to lessen mental trauma [6]. The change in brain electrical activity after certain duration of practicing yoga and meditation can easily monitored by EEG [7]. There are several accessible datasets, biomarkers and EEG based methods for the detection and diagnosis of depression, bipolar diseases [8]. Long ago, there is relationship established between psychological stress and physiological disorder and 90 percent of the disease is psychosomatic. Spectral analysis of EEG is employed for the psychological stress analysis based on three phases like reactive, anticipatory and recovery [9]. The use of meditation techniques as potential therapies for psychological discomfort has drawn more attention now a days. Mindfulness meditation practice, which is being aware of one's thoughts, feelings and bodily sensations while being non-judgemental attitude towards others [10]. During COVID-19 pandemic in India, study examined the effects of stressful situations and stress levels among Raja Yoga practitioner had reduced stress levels and less stressful occurrences [12]. Hatha yoga is an age-old discipline that combines breathing, physical posture and meditation that helps to reduce anxiety and promoting feelings of calmness and relaxation [13]. Yoga-nidra has been better known in recent years due to its positive effects on mental health, which include lowered stress and anxiety levels as well as better sleep [14]. The brain changes during yoga and meditation and these changes can be detected using EEG. These EEG can be analysed using machine learning to reveal how brain functions alter during yoga and meditation [15]. The viability of modifying EEG baseline rhythms, functional connectivity and advanced nonlinear parameters for clinical use is examined who frequently experience anxiety and depression symptoms [16]. One of the yoga poses called Bhramari pranayama is uttering the sound "om" while inhaling through the nose demonstrated that practicing Bhramari pranayama on a daily basis can enhance PSD and functional connectivity in the alpha and theta frequency ranges. The benefits of Bhramari pranayama in lowering stress attributed to enhance quality of life [17]. In addition to perceptual reactions, the body releases stress-related harmones like cortisol to alter body's hormonal balance when it experiences stress. As a result, physical reactions might serve as markers for measuring or identifying stress. It has been demonstrated that physiological markers such as blood pressure, heart rate variability, skin conductance and EEG can be used to measure stress [18]. Computational analysis of cortical EEG bio-signals with neural dynamics is performed to find the patterns using machine and deep learning [19]. Other EEG measures such as delta, theta power, relative gamma and theta-alpha power ratio show less phase independence. Increases in beta power exhibit a relative stress phase independent trend but increases in alpha power are independent of stress phase [20]. Our experiment shows the delta stage sustenance for those subjects who practiced meditation regularly for six months that provides relaxation and tranquillity of mind whereas stressed subjects always dwell in higher beta and alpha in relative frequency range.

2. Methodology

Figure 1 shows the complete procedure of the stress identification and analysis experiment based on the standard clinical EEG measurement method includes in acquisition, preprocessing, feature extraction classification and stress identification sequences, following sub-sections describes the procedures.

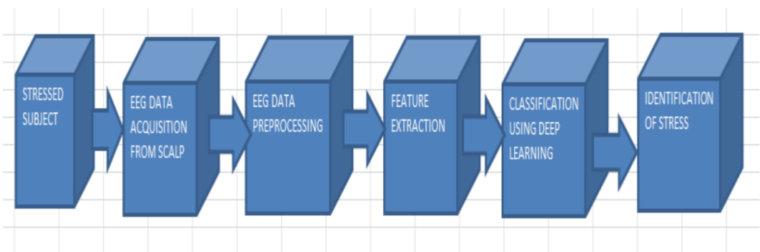

Figure 1. Block Diagram of Acquisition of EEG and classification of stress.

2.1. Data Collection

After being made aware of the laboratory tasks, participants completed an informed permission form. An EEG recording while at rest was made in a quiet room. Participants were recorded with their eyes closed and in a stressful state of mind. Every participant took two minutes to complete the task. Using electrode patches, scalp sites were located in accordance with the international 20 standards after applying the electro-conductance gel for proper contact. Three electrodes (FP1, FP2 & FPz) were used to capture capture EEG data. Participants were informed of the laboratory tasks and signed informed consent. Twenty five stressed subjects were taken for conducting experiment of age group 20–25 years. Resting state EEG recorded in a isolated dim room for two minutes each with eyes closed. After that, participants asked to practice meditation for 20 min daily for 45 days. Participants practiced meditation early morning for ten minutes and before going to bed in night for ten minutes for 45 days. We taught them focussed meditation to keep attention in master pituitary gland only. After 45 days, their EEG was recorded again. EEG signals were recorded from 3 electrodes-FP1, FP2 and FPz with reference to earlobes. EEG data was sampled at 250 Hz.

2.2. Data Pre-Processing

The EEG signals were pre-processed using Simulink, where techniques like a notch filter were applied before the raw signals has been converted into the required file format before noise removal and feature extraction. To remove power cable noise of 50 Hz from raw data, notch filter is used. Each participant's EEG data were saved as a file for offline processing on a personal computer, allowing for further analysis in MATLAB and Python. Each Raw EEG data consists of nearly 50,000 rows of data. Raw EEG data limited to 4800 rows for artefact removal. Then passed by zero-order band-pass filter from 0.1 to 40 Hz after which large untenable spikes and noisy EEG channels were eliminated. Further, artefacts were removed and a band pas filter was applied. Artefacts were eliminated by setting a threshold, retaining only signals between −100 μV and 100 μV to ensure the signal remained informative and meaningful. Subsequently, the filtered data underwent independent component analysis (ICA) to separate biological and electrical artefacts including muscle, eye movement and line noise aberrations. This can also remove EMG disturbances and EEG signal drift.

The use of a band-pass filter with a windowing function reduces the impact of spectral leakage, improving the accuracy of Fourier-related transforms and enhancing the extraction of spectral data from the signals. The default rectangular window is ineffective at supressing noise, leading to spectral leakage where parts of the signal's energy spread into neighbouring frequencies. As a result, spectral information from Fourier-related transforms can appear at incorrect frequencies. Next, we applied the wavelet technique to remove electrooculogram EOG (a frequent low frequency, amplitude artefact of the eye blink signal that may cause confusion in disease diagnosis) distortions with relation to earlobes. At 256 Hz, EEG data were captured. Based on PYTHON platform, the EEG data were processed using wavelet transform and examined. Data pre-processing was done before analysis. The raw EEG data were resampled from 1000 Hz–250 Hz and bandpass filtered from 1–30 Hz after being formatted.

The FFT is a mathematical algorithm that computes the Discrete Fourier Transform (DFT) efficiently. It converts time-domain EEG signals into the frequency domain, allowing for the identification of different frequency components within the signal, such as delta, theta, alpha and beta waves. The EEG signal x (t) in the time domain can be represented as:

$$X(f) = \int x(t)e^{-j2\pi ft}dt$$

The FFT approximates this by transforming discrete signals. The FFT result shows how much energy lies in each frequency band. However, one of the main limitations of

FFT is that it assumes stationary. For non-stationary signals like EEG, this could lead to a loss of temporal information. The wavelet transform in contrast to FFT provides both time and frequency information by decomposing the EEG signal into scaled and shifted versions of a mother wavelet. The continuous wavelet transform (CWT) is expressed as

$$W(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right) dt$$

Whereas ψ(t) is the mother wavelet, a is the scale(related to frequency)and b is the translation(related to time).The discrete wavelet transform(DWT)is more computationally efficient and breaks down the signal into a series of wavelet coefficients at various scales. The key advantage of wavelet transform over Fast Fourier Transform is its ability to capture both the time and frequency domain characteristics of EEG signals, making it suitable for non-stationary analysis.

2.3. Feature Extraction

Though there are so many features of EEG dataset but the most widely used features are power spectrum analyses. The Fast Fourier Transform yields the power spectrum and spectrogram signal over a time period (FFT). The bandwidths of the EEG power spectrum are referred as delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz) and gamma (over 30 Hz). Delta, theta, alpha and beta power are used as power features in our investigation. Theta waves associated with drowsiness, daydreaming and relaxed states. Beta waves linked to alertness, active thinking and cognitive processes. The theta/beta ratio is used as a measure of cognitive processing capacity, where a higher ratio might indicate more drowsiness or cognitive fatigue while a lower ratio suggests better focus and cognitive functioning. Alpha waves associated with relaxation and decreased attention or arousal. Beta/(alpha + theta) ratio helps measure cognitive performance and attentional resources. A higher value suggests greater cognitive performance and attention as beta reflects alertness and cognitive engagement while alpha and theta are linked to more relaxed or inattentive states. Cognitive parameters are measured for stressed subjects as cognitive processing capacity, cognitive Performance Attentional Resource Index, neural activity, vigilance index, arousal index, relative alpha energy and absolute alpha power. The brain's capacity for processing and analyzing information is referred to as cognitive processing capacity which incorporates number of cognitive processes including problem solving, perception, and memory attention though it depends on multitude of factors including age, educational attainment and cultural background is determined by theta/beta ratio. Cognitive Performance Attentional resource index (CPARI) parameter is to gauge an individual's capacity for sustained attention and long-term information processing even applied clinically to evaluate patients from different cognitive impairments as well as attention deficit hyperactivity disorder (ADHD) is determined by beta/(alpha + theta)) ratio.

3. Work Flow Chart

Neural activity is brain's continuous electrical transmission and current involves presynaptic potentials, postsynaptic potentials and neurotransmitter release measured by beta/theta ratio. Neurons are nerve cells that use electrical impulses known as action potentials to transmit signals throughout the body and passage of positively charged ions across the neural membrane produces these impulses. Vigilance index is an individual's level of awareness or alertness measured by the ratio of (alpha + theta)/beta. Arousal index is a time domain characteristics that measures a subjects mental states of relaxation, meditation and cognitive exertion is measured by the ratio of beta/alpha. Relative alpha energy is the amount of activity in the alpha frequency range (8–13 Hz) in relation to other frequency bands is measured. It indicates wakefulness, mental alertness and cognitive functions including perception and attention. An individual with higher relative alpha energy levels may be focused, aware and more capable of handling cognitive tasks. On the other hand changes in alpha energy levels may also be a sign of a number of neurological disorders, including Parkinson's disease, dementia and epilepsy. Finally the absolute alpha power is measured is the quantity of electrical activity in the brain's alpha frequency band linked to calmness, mental clarity and wakefulness. Increases in absolute alpha power are generally linked to a calmer, more concentrated mental state.

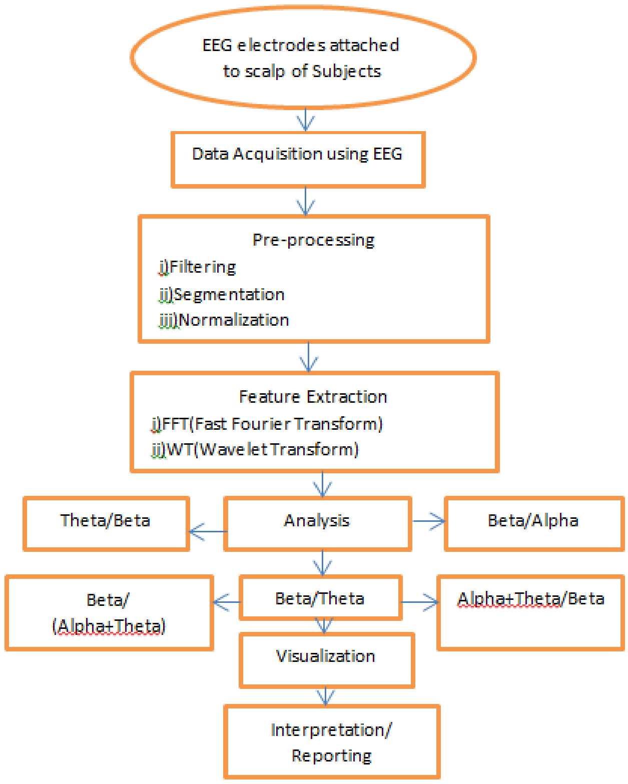

Figure 2. Flow chart of the EEG identification method.

4. Results and Discussion

Figure 3 shows original EEG signal acquired by our experimental setup. The plot consists of 4000 samples in terms of time with amplitude. For our work 45 samples were taken for the analysis.

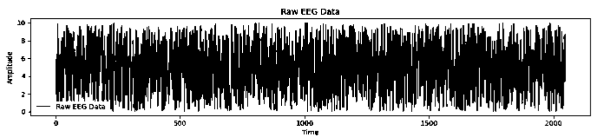

Figure 3. Graphical representation of acquired raw EEG data.

Further the feature extraction and power ratio computation revealed the stress pattern and meditated pattern in the values of the cognitive processing capacity, cognitive performance attentional resource index, neural activity, vigilance index, arousal index, relative alpha energy and absolute alpha power. fig.(a) shows higher theta/beta ratio reflecting increased cognitive processing capacity and vice versa.

Figure 4 shows the relative power of stressed subjects. It indicates that alpha and beta frequency is dominating in stressful state of human being.

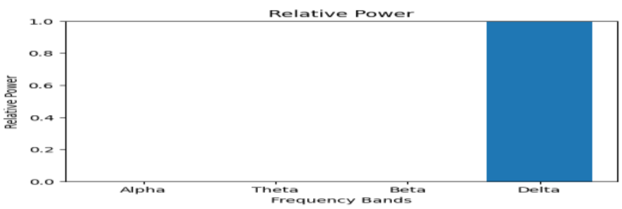

Figure 4. Relative power of regular six month meditated subject.

Similar cases for arousal index and vigilance index whereas opposite is the case of cognitive performance attentional resource index, neural activity, relative alpha energy and absolute alpha power.

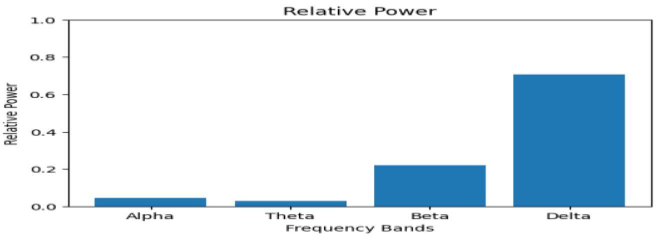

Figure 5. Relative power of a stressed subject.

Table 1. Parameter comparison of Meditated and stressed subject.

Parameter	Meditated Subject	Stressed Subject
theta/beta: cognitive processing capacity	2.679879529016447	0.6914774017755025
Beta/(Alpha+Theta): Cognitive Performance Attentional Resource Index	0.316705399622247	3.4477972690623653
Beta/Theta–Neural Activity	0.37315110219413994	1.4461788591099374
(Alpha + Theta)/Beta–Vigilance Index	3.1575085274604047	0.2900402552589618
Beta/Alpha–Arousal Index	2.0936752233592366	2.491049990459207
Relative Alpha Energy	0.010283879348809394	0.00890083696033333
Absolute Alpha Power	0.008403217464981586	0.009128117934638072

5. Conclusions

The consequences of human stress are profound and multifaceted, affecting both physical and psychological well-being. The growing body of literature survey suggests that managing stress should be a public health priority, with interventions targeted at reducing chronic stress exposure and mitigating negative effects. This study validated that the proposed method of cognitive parameter for the identification of stress for a normal human subject and stressed state for the subject. Future research will involve determining whether the characteristics derived utilized to classify stress levels.

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Data Availability Statement:

Conflicts of Interest:

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