Acute Mental Stress Measurement using Brain-IoT System

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***Abstract*—Every individual experience stress of varied intensity while performing daily tasks. Excessive stress can be harmful to human health. Hence, stress assessment is essential in preventing detrimental long-term effects. In this study, we investigate the feasibility of EEG for the measurement of acute mental stress. Also, the post-stress analysis with four distinct cases on stress-induced subjects is carried out. The experiments accomplished were conducted using an EEG headset, ThingSpeak database, and a mobile application. The subject is required to play a mobile game, which induces stress as the game level progresses. This raw EEG data is pre-processed and analyzed in MATLAB and sent over to the ThingSpeak database. When the acute level of stress is detected, the individual gets notified by the mobile application to prompt soothing music and closing eyes. Overall, the experiment concluded with reduced stress levels of the subject after closing eyes with and without music.**

Index Terms*— Electroencephalography (EEG), ThingSpeak Database, Galvanic Skin Response (GSR), Heart Rate Variability (HRV), Discrete Wavelet Transform (DWT)

I. Introduction

Stress at varied levels has an impact on human life. Chronic stress exposure is one of the reasons for unfavorable health and mental conditions. If adequately not treated, high levels of stress can lead to stroke, heart attack, increased fatigue, and headache [1]. Moderate stress vulnerability can be attributed to the secretion of glands in appropriate quantities, which results in a higher level of work performance, motivation, and more top push for action. Stress is psychologically classified into acute and chronic. Acute stress results due to recent work activities or hurdles expected in the future. Although acute stress arises for only a short period, it has the capability to impact the mental and physical health of the person undergoing such situations. It has been demonstrated that individuals experiencing frequent acute stress are vulnerable to high levels of chronic stress, which in turn leads to illness associated with the cardiovascular system, insensitivity towards the sugar level, and even various forms of cancer [2].

With the advancement of technology, a variety of stress measurement devices have been developed for medical professionals to aid individuals to detect stress levels. Electroencephalogram (EEG) and Electrocardiogram (ECG) based systems are measurement tools used and favored within clinical settings. These devices have electrodes which are in contact with the individual's skin, to monitor and record minute electrical activity that occurs on it.

Electroencephalography (EEG) provides data based on the activity of an individual's brain, in response to a quick change or at rest. When an individual thinks or acts, the neurons in the brain are fired, and EEG measures such voltage potentials across different areas of the brain. Invasive and non-invasive EEG practices are both used for clinical measurements. Invasive EEG requires to place electrodes on the brain surface while non-invasive devices today use a tight-fitting cluster of electrodes held collectively by a headpiece to collect data. Non-invasive EEG devices tend to provide data that might be not so accurate compared with the invasive methods, but using some augmenting techniques like Artificial intelligence and machine learning to analyze the signals outweigh the disadvantages which arise with invasive surgery. Processing EEG data in real-time allows users to send commands to control hands-free devices such as hands-free keyboards [3], robotic wheelchairs [4], and home automation [5].

In advancing technology with the sensors, Brain-IoT has become a major highlight for transmission of EEG data across the internet. The intention of this research is to capture a user's data through the signals acquired from a BCI headset. By integrating this form of technology into everyday life, individuals are able to expand their accessible within their households by transferring mental instructions to their household appliances.

In this research, an EEG is used to detect and measure the brain activity of an individual undergoing acute stress. The study involved measurement of differences in delta, alpha, beta and theta frequency from the human brain. Galvanic Skin Response (GSR) and Heart Rate Variability (HRV) sensors helped in providing a reference to data measured using EEG headset. The values obtained by the GSR sensor are processed using Neulog software. emWave Pro software is used to acquire the HRV data. EEG data is captured using g.Recorder software. The collected data is processed in the MATLAB and sent to the ThingSpeak database. A mobile application is used to keep track of the stress levels of the subject, and it triggers a notification as well as a music track to calm down the stressed individual. Overall, the goal of experiments was to detect stress and analyze the post-stress data for four cognitive cases such as Closed Eyes without Music, Closed Eyes with Music, Opened Eyes without

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Music, Opened Eyes with Music. Along with this, the aim was to develop a Stress monitoring and notification system that detects higher stress levels suggests the action required to reduce mental stress.

This paper is organized in the following manner: Section II presents related work accomplished; Section III contains detailed information and implementations of the components used; Section IV includes the experimental setup; Section V consists of a detailed analysis of the results obtained from the study; Section VI provides a comprehensive conclusion of this paper, and Section VII explains future work to be conducted.

II. Related Work

The utilization of BCI headsets and the detection of acute mental stress using EEG signals have been extensively studied and researched. The use of EEG signals for determination of varying levels of stress is studied in [6], with a conclusion that there is a strong correlation between the alpha frequency power at the frontal temporal lobe and mental stress. As per [7, 8], more precise data to determine to relax and alert psychological states are provided by EEG than HRV or blood pressure. The research accomplished in [9] showed that variation in alpha and beta power is an indication of anxiety. The power of delta and theta frequencies is anticipated to go up while the power in alpha waves is expected to get suppressed [10]. Heart rate variability, Skin Conductance, blood pressure, and EEG collectively give the stress information with the accuracy of 91% using EEG signals and 95% using all physiological signals [11]. Various stress stimuli methods like videos, IQ or mathematical sums [12], Stroop color-word test [13], Public speaking [14], cold pressor [15], "Not Not" Mobile Game [16] and computer-related work [17] have been effectively utilized.

For the real-time usage of the EEG data, various systems based on the integration of EEG signals over the internet are being researched. A home automation system operated using EEG signals over IoT is studied in [18]. The experiments done in the same paper provided insights and concluded that Brain-IoT is a promising technique that offers comfortable home environments. In [19], an internet of brain things platform is used to perform analysis of human emotions. The study done in [20] showed that real-time monitoring of patients could be done remotely. This mechanism can be used to diagnose diseases with the help of correlated indicators. The research accomplished in [21] provided a deep learning framework for cognitive interactivity. In the same paper, authors have proposed two case studies, a brain typing system, and a cognitive robot in the IoT scenario.

III. Methodology

A. System Design

The stress detection system in this experiment is similar to that in [8]. However, a non-invasive EEG headset is substituted for the RFI frequency counter. GSR sensors were placed on the fingertips of the hand of the subject to reference data from the EEG headset. The subject then undergoes stress-induced activities while all devices record data in real-time. All data is recorded in their respective software, while EEG data will be analyzed using MATLAB and compared with data collected by GSR sensors. After this comparison, the EEG and GSR data will be sent to the ThingSpeak database to process if the subject was encountered acute stress. This stress will trigger an application to provide calming music in an attempt to sooth the subject's stress levels. This study will concentrate on alternating stress levels and linking communication between the brain and the computer.

A. Electroencephalography (EEG)

1) g.Nautilus EEG Headset: The headset used in this study used eight different electrode probes placed on a certain region of the brain. A subject will place the headset upon their scalp and properly secure the intended position of each electrode for an accurate reading. Once recording, the device will capture brain activity displayed on a monitor through a USB receiver as a voltage potential across all eight electrodes. Unfortunately, the reading may be slightly inaccurate due to the inference of the hair and high sensitivity to muscle movement.

2) g.Recorder Software: The g.Recorder software allows us to prescale the data before recording the data. The sample EEG is set at 250 Hz, notch filter at 58 Hz - 62 Hz, and the bandpass filter at 0.5 Hz - 60 Hz. The notch filter is set at this range to ensure no electric frequency interferes with the data. The bandpass filter range allows for readings of alpha, beta, delta, theta, and gamma waves ranging from 1 Hz - 60 Hz.

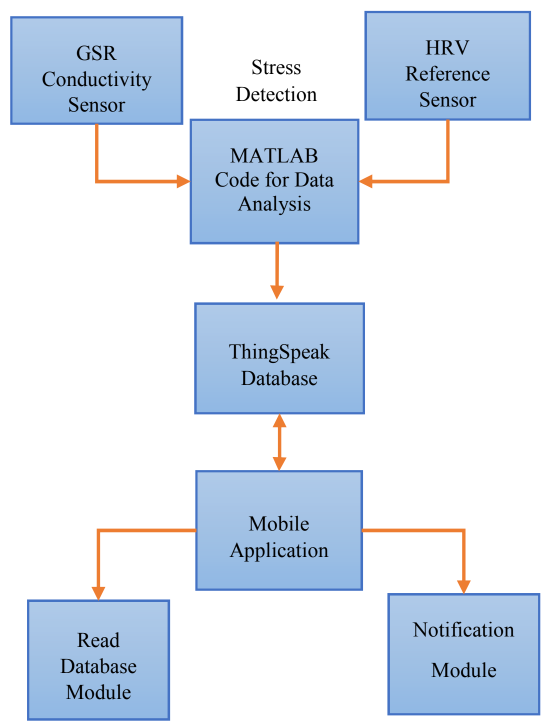
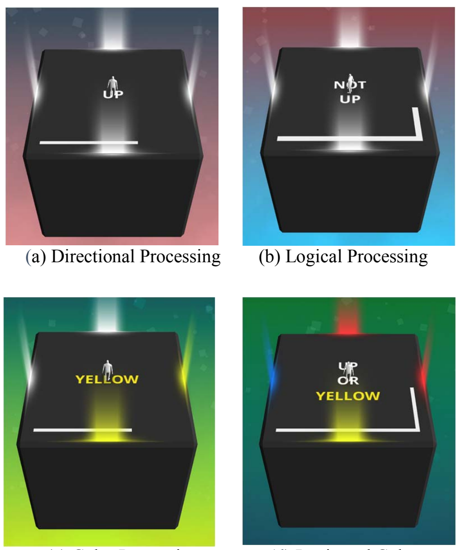


Fig. 1. System Block Diagram

B. Stress Stimulation

Stress is usually caused by a subject's experience with certain tasks and reaction to their environment. During our testing, we will present a mobile brain-teaser game to simulate a task to the user. This will induce acute stress to see certain periods when the user undergoes stress to complete the task presented.

The game is known as “Not Not,” previously used in [16], is a mobile brain-teaser video game requiring the user to have fast reactions to each task that must be followed to advance between each level. As per [16], the “Not Not” game is more effective way for induction of mental stress than traditional Stroop test. Hence it was selected as stress stimuli method. The game has a player move a character on a cubic platform and provided five options of moving their character up, down, left, right, or not at all. A text will appear on the surface of the 3D shape, and the user must follow it to progress the game. The game slowly becomes more difficult as the user adapts as later levels require the user to follow a direction, color, or both.



(a) Directional Processing (b) Logical Processing

(c) Color Processing (d) Logic and Color Processing

Fig. 2. “Not Not” Mobile Game

“Not Not” is played on an Android emulator known as Nox App Player which carries out the same function as an Android device, but instead use arrow keys as input commands for directional swiping.

(e) Level 2 Difficulty (f) Level 3 Difficulty (g) Game Loss

Fig. 3. “Not Not” Mobile Game Level Difficulties and Game Loss

In addition to the game’s increasing difficulty, there is a time frame that each command requiring the user to gradually make faster decisions, the higher that the level becomes. The means behind this game is to produce stress when the user is progressing through the game or fails to accomplish a task.

C. *Wavelet Transform*

The wavelet transform (WT) is a tool that provides a representation of a function in the time-frequency domain. Usually, in engineering, the type of WT used is a Discrete Wavelet Transform (DWT), which is used to simplify signals to orthogonal wavelet basis functions.

The signal for the eight channels in the EEG recording is decimated by two to acquire the detail coefficients and approximation coefficient placed at level 1(A1 and D1). After this, the approximation coefficients are sent to level 2 to repeat the process, while the wavelet decomposition level was set to level 5 [24]. The calculation by averaging these coefficients aids in finding the power of each band.

D. *ThingSpeak Database & Mobile Application*

ThingSpeak is an open-source application developed for IoT. It uses the HTTP protocol to send and receive data to the database. In this research, a channel with four distinct fields to store a mean absolute power for an alpha, beta, delta, and theta frequency components were created. The data obtained from the MATLAB code was sent to the ThingSpeak Database. A mobile application for IOS was developed to trigger the music. The platform used to create this application was Thunkable.

IV. Experimental Setup

The experiment consisted of a single task separated into four different trials. Each subject was tested by having each one plays the mobile game, “Not Not” and exposed to silence or music after a certain interval of gameplay. Data were collected while the subjects were at rest, playing the mobile game, and during an idle period of time. The arrangement of the experiment had subjects play the game while having three different measuring devices placed on them. The experimental setup is shown in Fig. 4.

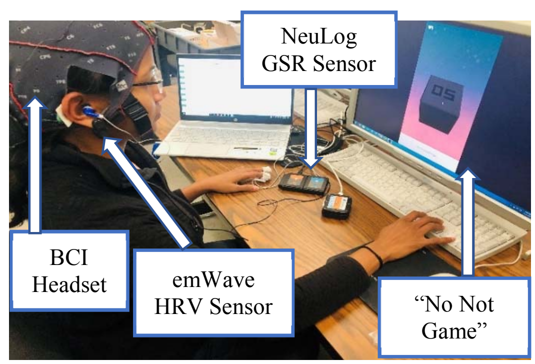


Fig. 4. Experimental Setup

It required two laptops, having one laptop record the data while the subject was playing and the other for the subject to play the game. The laptop documenting the data was connected to the three recording devices: g.nautilus EGG electrode cap, NeuLog GSR sensor, and emWave HRV Sensor. Each device was used to measure the subject’s EEG, heart rate, and skin conductance, respectively, while the subject concentrates on playing the game.

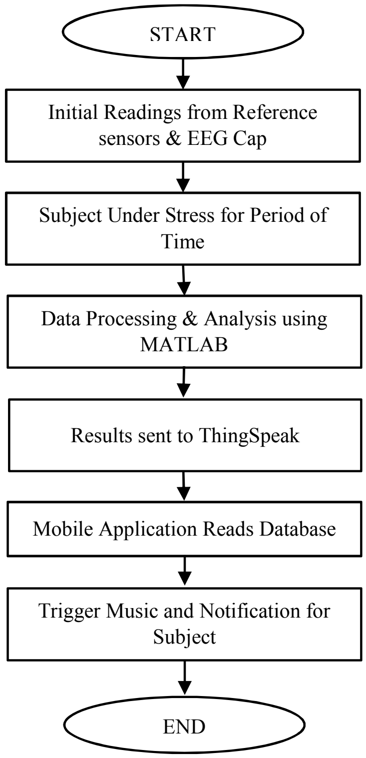


Fig. 5. Experimental Process

In addition, every instance the player loses, the game is marked as an event within the g.recorder. After the period of gameplay, the subject will either listen to music or be given silence while having their eyes open or closed. In total, four trials were conducted for each subject. All EEG data from each trial recorded and analyzed in MATLAB. The processing was used to determine the absolute frequency power of each subject's trial to observe if the stress level had decreased.

V. RESULTS & ANALYSIS

The experiment for this research required four different trials to be conducted. Each trial had the same initial process of having the subject play the game and recording each time the subject lost. The only distinction between each trial was the post-game activity in which the user must listen to a piece of music while closing and opening their eyes. And in other trials, the music was kept off, and readings were taken with eyes closed and open. In total, four subjects were tested during this experiment to see instances of decreased stress.

Before the game, the subject was asked to have a minute of inactivity to have initial data for the EEG, HRV, and GSR to collect. The subject was asked to do 4 minutes of total gameplay with the "Not Not" mobile game. This mobile game becomes increasingly difficult as the subject progresses through the game. The subject's heart rate and EEG signals are collected and mark each time the player loses as an event to see if the subject is developing stress during the 4-minute duration. Four sets of trials were conducted, having four differences being the four 2-minute post-game activities. By order of games, Games 1 and 2 had the subject exposed to silence while the difference is that they had their eyes opened and closed, respectively. Game 3 and 4 followed the same process of having their eyes opened and closed; however, the music was played to soothe the subject.

Fig. 6. ThingSpeak Database Mean Absolute Power for Alpha

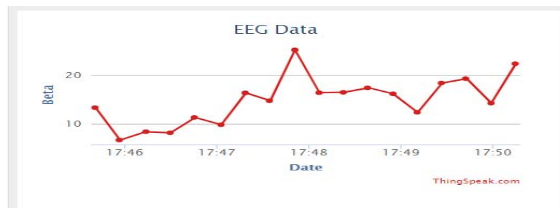


Fig. 7. ThingSpeak Database Mean Absolute Power for Beta

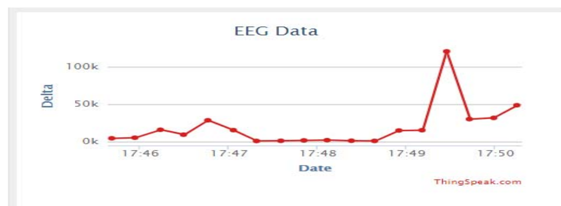


Fig. 8. ThingSpeak Database Mean Absolute Power for Delta

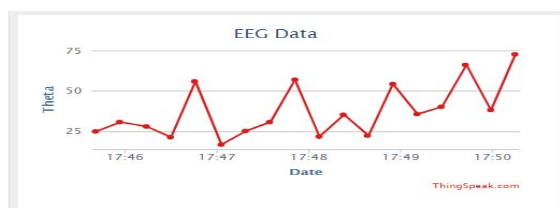


Fig. 9. ThingSpeak Database Mean Absolute Power for Theta

The mean absolute power for an alpha, beta, delta, and theta were computed after the trials and sent to the ThingSpeak database. The readings for the initial game and the other four trials were sent. So, there are six values per subject and 18 values in total in the graphs shown in Fig. 6,7,8,9. These values were used by Mobile application for triggering the music.

The graphs shown below are the readings of three subjects. Fig. 10 shows the initial and game alpha and theta mean absolute power. The initial readings were taken before the stress was induced, and the other readings in Fig. 10 are during the gameplay. Fig. 11 displays alpha and theta mean absolute power results after the higher stress level is detected and four different cognitive state conditions were tested. Both alpha and theta mean absolute powers were observed to determine if whether the subject was exposed to stress and calmed down. Out of the four subjected tested, three had shown significant results in following the intentions soothing the subject. The other result had been disregarded due to inaccurate data collection and mistakes occurring during the procedure of the experiment. The EEG data of the three subjects displayed a decrease in alpha waves and an increase in theta waves coinciding with theories explained in [10].

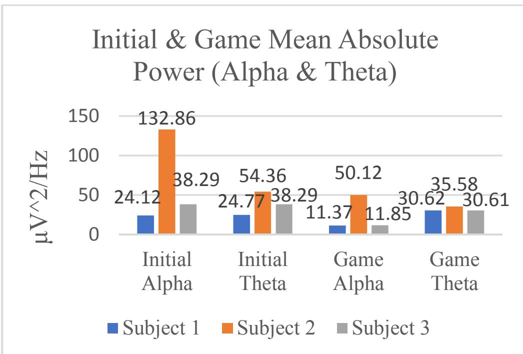


Fig. 10. EEG Initial & Game Mean Absolute Power (Alpha & Theta)

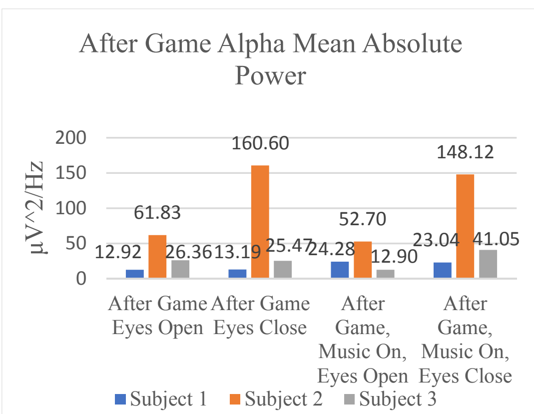


Fig. 11. After Game Alpha Mean Absolute Power

Along with EEG data, the heart rate and skin conductivity were also recorded and analyzed in Fig. 12, and Fig. 13 Observing the data, the heart rate of each individual seemed to be nearly the same level, which may show that stress has little relation to heart rate rising or decreasing. This also could have been due to the conditions of the experiment such as the environment or how the subjects perceive the activity. Opposite to this hypothesis, skin conductivity results showed a steady rise throughout each trial, indicating some induced stress.

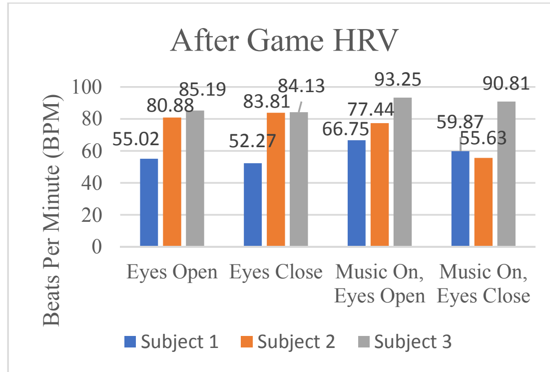


Fig. 12. HRV Experimental Data

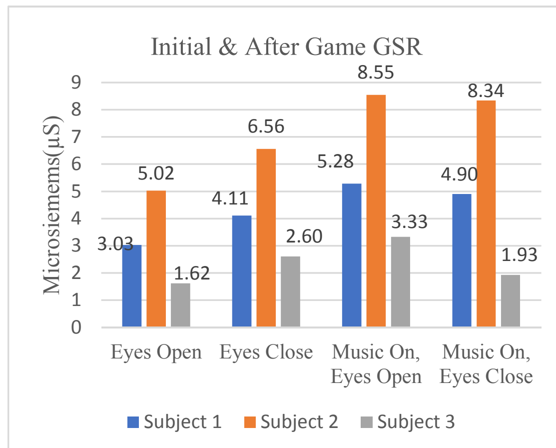


Fig. 13. GSR Experimental Data

Overall, the results gathered were consistently observing the frequency patterns on each chart presented for each specific measurement.

VI. Conclusion

In this paper, four different scenarios for stress reduction were tested. The testing required three subjects to undergo 2-minute of "Not-Not" gameplay, and then post-game readings with eyes open/close and music on/off were acquired. Comprehensive data collected from EEG displayed increases in theta mean absolute power alongside decreases in alpha wave Mean Absolute Power. Hence, analysis of the EEG alpha and theta frequency components alongside the HRV and GSR sensor data allowed research investigators to conclude that the closing eyes is an effective way to pacify an individual's acute mental stress.

VII. Future Work

In the future, the goal is to conduct more testing and developing a real-time stress monitoring system. This system will provide a quick and non-invasive solution for individuals to diagnose and cope with their stress levels. Besides this provides individuals with a cost-efficient alternative to treating their stress rather than having the reliance on medication or consulting a professional.

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