Attention and Meditation Quantification Using Neural Networks

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***Abstract*— The advancements in dry-sensor technology have enabled easy brain activity data collection thorough a variety of portable brain computer interfaces based on electroencephalography (EEG) technology. This paper proposes a data analysis framework for evaluating the impact of various brainwave frequencies (delta, theta, alpha, beta, and gamma) on human attention. Multiple working scenarios have been created for the subjects targeting to enhance their level of attention. To properly evaluate the data by utilizing the artificial neural networks, several hypotheses have been defined. Their purpose is to group the brainwaves into low to medium frequency type and high-frequency type with the attention and meditation values and attempt to establish interconnections.**

Keywords-brain-computer interface; attention quantification.

I. INTRODUCTION

The study of the brain activity is a fascinating research topic, due to the inherent complexity of the human brain. The brain has remarkable and uncharted abilities to capture, integrate and process data. It can be seen as an enormous network of neurons that enables vast data processing potential. It also acts as a storage center and control, where information coming from senses merge and undergo several complex processes to help in the decision-making processes. Although the full extent of the brain's capacity it yet to be discovered, there are encouraging research avenues that advocate for life quality increase, recovery and rehabilitation for a plethora of medical conditions, such as stroke [1], paraplegia [2], Parkinson's disease [3], Alzheimer disease [4], etcetera. With the advent of dry sensor Brain Computer Interface (BCI) technology, capturing the brain's electrical activity can be done on a large scale. A BCI acts like a platform that detects and records small fluctuation in electricity generated by the cerebral cortex. The electrical activity of the brain is monitored in real-time using an array of electrodes, which are placed on the head skin in a process known as electroencephalography (EEG). The EEG readings represent the user's perception, and reaction to various stimuli from the surrounding environment. The brainwave frequencies depend upon the firing speed of the neurons and the number of neurons that fire simultaneously.

BCIs connect the brain with the computer by enabling the brain-waves raw data transmission, called neurofeedback. BCIs present new methods to enhance human-computer interaction, and opens new avenues for augmenting human abilities. One promising research direction evaluates brain functions via BCI and cures people with brain or spinal injuries via micro-grains implanted into the brain [5]. Analyzing the brainwave data, input-output patterns can be established with the aid of machine learning. The subject's intentions are correlated with specific outside actions.

Attention and meditation are internal underlying activities that occur continuously and are manifested either in a conscious or unconscious manner. Meditation does not have a rigid definition or live representation; however, the desired purpose through meditation is to reach the so-called "Zen" state of mind, to reduce pain or anxiety. Meditation aims to better the mindset and to train the mind in order to react properly in demanding situations. Attention is an internal process represented by an absolute mind state of full focus on a given action. Attention is the capability of concentrating exclusively on a specific task, while being able to ignore other external or internal triggers. The borderline between attention and meditation is shallow. One can be attentive while in meditation and vice versa.

In this article, a new method is proposed to evaluate and objectively quantify the attention and meditation levels of the subject with the aid of the NeuroSky BCI as a hardware device and the Neural Network software. The results are evidencing some patterns between the type of activity the subject is involved in and the brainwaves at that particular time. Based on the EEG data collection during various scenarios, the aim is to decipher a nuanced understanding of the brain during attentive and meditative stages.

Attention Levels:

- Arousal: Refers to our activation level and level of alertness, whether we are tired or energized.
- Focused Attention: Refers to our ability to focus attention on a stimulus.
- Sustained Attention: The ability to attend to a stimulus or activity over a long period.

Brain signals can be classified into five basic categories, Delta Waves (.5 - 3 Hz), Theta Waves (3 - 8 Hz), Alpha Waves (8 - 12 Hz), Beta Waves (12 - 38 Hz), Gamma Waves (38 - 42 Hz).

Rest of the paper is organized as follows. Section 2 presents an overview of the evolution of BCI and their applicability. Section 3 depicts the software and hardware components utilized, alongside the deployed methodology. Section 4 provides the hypotheses and scenarios of the experiments. Section 5 outlines the captured results for all hypotheses and scenarios.

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II. RELATED WORK

A BCI is a non-invasive approach of retrieving and monitoring cerebral activity (EEG recordings), and its methodology is seamless; as a result it has a wide range of applications. BCI's and their associated data are used in neuroscience, cognitive science [6], psychology [7], psychiatric branch [8]. BCI's area of application has extended over the years to neuro-management [9], neuro-marketing [10], human interactions, and engagement.

An impressive research effort has been conducted towards improving life in many aspects by utilizing brain-controlled techniques, including the alleviation of comorbid psychological disorders. The employment of specific neurofeedback protocols serves as a remedial treatment for Attention Deficit Hyperactivity Disorder (ADHD) [11] and Autism Spectrum Disorder (ASD) sufferers [12], normalizing irregular neural activity that occurs during high anxiety episodes. Therefore, in some cases neurofeedback is considered an alternative for the pharmaceutical treatment.

Other groundbreaking applications of neurofeedback include prosthetic and robotic arms, human gait [13], emotion detection, and classification [14]. Newer approaches suggest significant advantages in employing EEG interfaces in workplace optimization [15] through stress recognition [16], in neuro-marketing [17], decision factors, and hyper scanning [18] that follows the brain processing, sustaining synchronization of actions. With the fast growing horizon in life quality improvement, a plentitude of EEG based palliative remedies occurred. Among those, BCIs are employed both invasively via MEA (microelectrode array)/ via brain micro implants and non-invasively via electrodes placed on the head, i.e., dry/wet biosensor technology. The biosensors detect minuscule amounts of electricity generated by the brain and drive various protocols quantifying the meditation and attention levels (e.g., for the Attention Deficit Hyperactivity Disorder and Autism Spectrum Disorder cases). Meditation has benefits in subsiding the severity of ADHD [19], ASD [12], depression, stress, anxiety, Obsessive Compulsive Disorder (OCD), personal disorders [20].

Although many studies focused on exploring the brainwave feedback via EEG in the sphere of neuroscience, its application realm broadened and so did the discipline fields as shown in Figure 1.

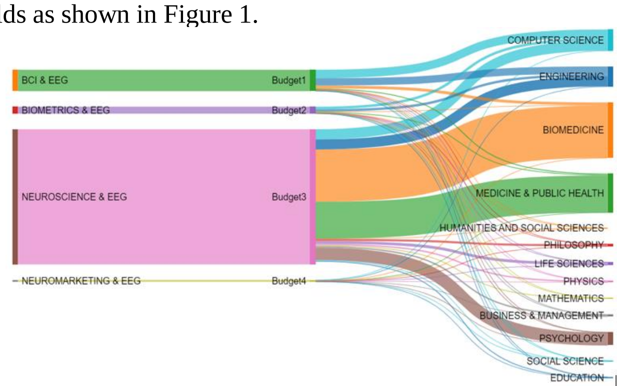

Figure 1. Systematic mapping of EEG applications based on disciplines.

The systematic mapping depicted in Figure 1 was carried out on the Springer database by using the search strings indicated on the left, the results were filtered on their release date between 2000-2022.

Over the last two decades, the interest in the BCI research topic has exponentially grown. The top five activity fields that are tightly connected to the BCI are computer science, engineering, biomedicine, medicine and public health and philosophy refer to Figure 2.

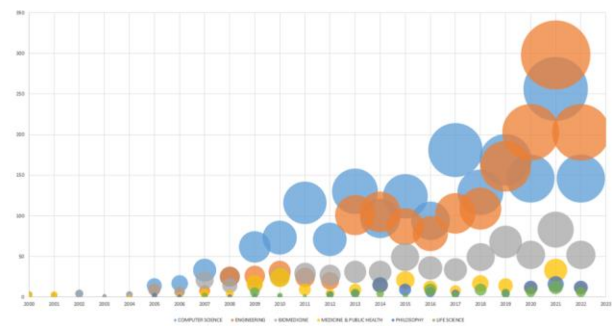

Figure 2. Time evolution of BCI interest based on the research topic.

The brain produces five types of waves (Delta, Theta, Alpha, Beta, and Gamma) continuously and for each BCI recording, only one of the brainwaves will be dominant having the greatest intensity. In case of a single BCI dry sensor, its placement is significant in the securing the best neurofeedback. For instance, the prefrontal region of the brain is in charge of problem solving, generating multiple prosaic/routine like judgments, planning, behavior and emotions. The Pre-Frontal Cortex (PFC) functions are complex cognitive functions as well as shortsighted behavior, to be able to act with a goal in mind, and self-control. It receives the sensory information, plans resources based upon that, and keeps close communication with other regions of the brain to enact a reaction. The reactions have a broad range, and most importantly, they include redirection of attention.

Five types of brain signals are scrutinized, each of them epitomizing special features, such as frequency, amplitude, shape, activation stimuli, as well as illustrating their own peculiarities related to the physiological facet. The EEG records the brain activity in employing the operating principles of a differential amplifier, which collects two electrical inputs and displays the output as the difference between inputs. Extremely beneficial while addressing very small electrical signals, such as the ones that appear in the brain.

Initially, the literature sustained the idea that the low-frequency brainwaves directly influence the meditation level, and the high-frequency brainwaves are associated with high attention levels. As the research interest in brainwave activity grew, studies have shown that high-frequency brainwaves are also developed while meditating.

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III. SYSTEM COMPONENTS

The systematic sequence of processes employed in the paper encompass both a hardware (NeuroSky Headset) and a software component (MindWave of NeuroSky and NeuronalNetwork Tool of MatLab). The initial phase is the raw brainwave signal acquisition, followed by an intrinsic pre-processing step to for feature/pattern extraction.

A. Hardware Component

The project employed the Neurosky BCI (link), to collect EEG data. As depicted in Figure 3, the NeuroSky's headset fundamental elements are the sensor (electrode) that records the EEG data, supported by the ear clip that acts as a ground and reference. The electrode and the ear clip of the Neurosky BCI record the brain activity by using the operating principles of a differential amplifier, which collects two electrical inputs and displays the output as the difference between them.

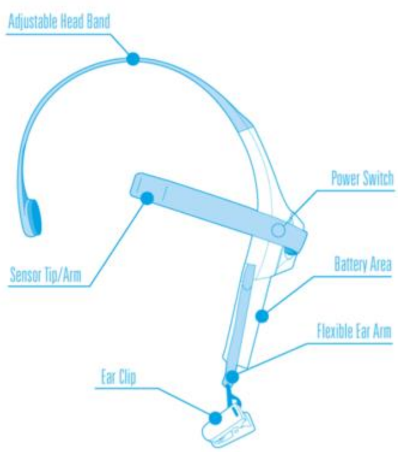

Figure 3. NeuroSky HeadSet.

The placement of the dry electrode on the Pre-Frontal Cortex (PFC) region of the frontal lobe is due to the fact that the frontal lobe serves the executive function, making decisions and delegating the output supported by the motor nerves to the entire body.

B. Pattern Extraction Neural Network Design

The process diagram shown in Figure 4 portrays the three significant steps followed in pursuance of attaining ready-to-use data for the neural network procedure.

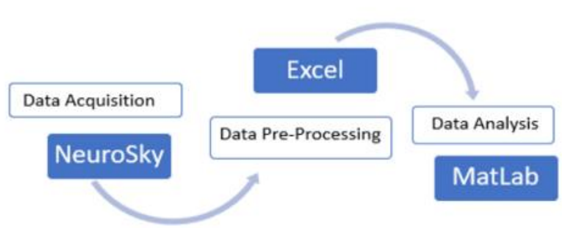

Figure 4. Process diagram.

For pattern extraction we employed the Neural Network application (NNstart) of the MatLab environment. This tool is designed to mimic the human neuronal system by artificially creating a neuronal network, modeled by multiple layers of neurons. There are three types of neural layers: input, hidden and output layer, as illustrated in Figure 5. Within the NNstart, neurons' pairing is illustrated by connection weights of neurons, each neuron has its own weight and bias, which is associated with storage of information and is fed into the transfer function that serves as a liaise model and translates the input variables to output variables.

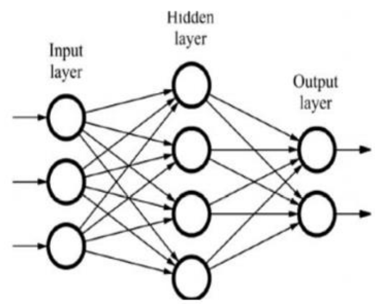

Figure 5. Multi layered neural network.

The pre-processed EEG recordings (input data) are randomly segregated as follows:

- Training - used for training purposes; these are presented to the network during the training and the network is amended in accordance with its error.
- Validation - used to validate that the network is generalizing and stop training before overfitting. The validation data are used to measure network generalization, and to cease training when generalization stops improving.
- Testing - used as a completely independent test of network generalization. These have no effect on the training itself, however they supply an independent measure of network performance during and after the training.

The input data causes the internal state of the neurons to change in accordance to the nature of the input and triggers neural activation. The target is the desired output for a given input. The output is as close as possible to the target by adapting the weights of each node in the network. The output of the node is the weighted sum of all inputs and is processed by using an activation function that determines the behavior of a node.

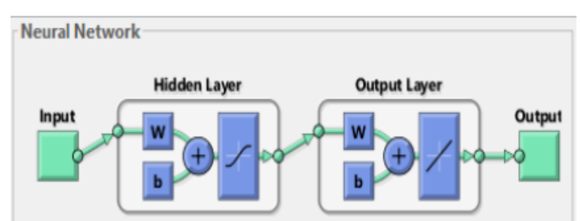

Figure 6. Artificial Neural Network Structure MatLab.

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Figure 6 epitomizes the structure of the neural network in MatLab; additionally it presents the input-output connection scheme.

The first part of the functional diagram is represented by the NeuroSky headset for raw brainwave data acquisition; Followed by the NeuroSky's embedded pre-filtering, improving the quality of the raw data gathered from neuronal activity (weak electrical signals), eye blinking (identified as a skin stretch response).

The pre-processed data is subjected to multiple algorithms to be analyzed (feature extraction included) and properly interfaced for the user. The result is a document containing data values for each brainwave defined by the headset's protocol (Delta, Theta, Alpha1, Alpha2, Beta1, Beta2, Gamma1, and Gamma2).

A proprietary algorithm within the Neurosky's software called NeuroExperimenter computes the levels of attention and meditation. For each recorded dataset, there is a time stamp, and the sample rate is 1Hz. The second step is to pre-process the data and prepare it for the actual analysis in MatLab software. The pre-processing is represented by engaging the data feature engineering technique, which aids the prediction percentage in machine learning algorithms, handling null values, adequate data import into the NNstart, and dataset split into subsets. The third phase achieves the pattern extraction with the aid of the NNstart of MatLab.

C. *Parameters Configuration*

To effectively analyze the NeuroSky recordings, input and target variables need to be correctly defined within MatLab NNstart for each experiment. The operating scheme of NNstart MatLab is the following:

- Initialize the weights
- Compute the error (difference between output and desired output)
- Re-compute the weights
- Adjust the updated weights
- Repeat the process for all training data until the error reaches an acceptable level

An epoch represents one training iteration of the data though the network, this procedure is repeated until a satisfying outcome is obtained. A result that is labeled as satisfying entails an error that is below the threshold value or the minimum error (difference between the desired output and the achieved output). The type of network (feed-forward), the number of neurons on the hidden layer, the training algorithm and inputs and targets vectors must be defined. After uploading the data vectors, the program divides it into three data categories: training, validation and testing, each associated with a percentage.

The methodology featured in Figure 7 represents a graphical illustration of the pathway pursued in order to reach the appointed results.

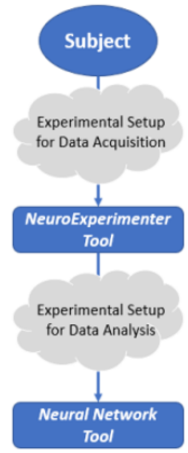

Figure 7. Working methodology.

IV. EXPERIMANTAL SETUP

The following hypotheses are considered:

- H0 Both meditation and attention levels are equally affected by all eight types of brainwaves defined by the NeuroSky headset protocol (Delta, Theta, Alpha1, Alpha2, Beta1, Beta2, Gamma1, Gamma2).
- H1 The meditation level is equally affected by the low to middle frequency brainwaves (Delta, Theta, Alpha1, and Alpha2).
- H2 The attention level is equally affected by the high frequency brainwaves (Beta1, Beta2, Gamma1, Gamma2).
- H3 contrasting the H2 hypothesis, the meditation level is equally affected by the low to middle frequency brainwaves (Beta1, Beta2, Gamma1, and Gamma2).
- H4 contrasting the H1 hypothesis, the attention level is equally affected by the high frequency brainwaves (Delta, Theta, Alpha1, and Alpha2).

By employing the hypotheses approach, there is a sense of inclusiveness, which might open new research avenues. In order to complete the cycle, two datasets have been gathered. Certain scenarios establish the data acquisition phase:

Dataset 1:

- Scenario 1 - Coding - spent 11 minutes working at coding a math game.
- Scenario 2 - Simple math - spent 2 minutes doing simple math.
- Scenario 3 - Reading - spent 2 minutes spent on reading the article When Biking and Bears Don't Mix (Random article on NY times).
- Scenario 4 - Social Media - spent 1 minute looking at social media on the phone.

Dataset 2:

- Scenario 1 - Baseline experiment for 5 minutes in a quiet room. The subject is required to remain silent,

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stare straight forward at a stationary wall, do not move.

- Scenario 2 - Simple math for 2 minutes obeying the baseline requirements, except the fact that the subject must look at the computer's screen and solve math exercises that consist of addition of two numbers, both being under 100. The math exercises must be taken in the subjects' head and the solutions must not be said out loud.
- Scenario 3 - Visual experiment for 2 minutes that respect all the criteria mentioned into the baseline scenario, except the fact that now the subject will be looking at different GIFs or animated pictures.
- Scenario 4 - Audio experiment contains three sub-scenarios that are wrapped into one; the subject will listen to three different audio files at different times, each audio listening performed by the subject must be followed by the brief two-minute baseline break. The audio files are very distinct from one another, the first and second files contain contrasting music genre and aim to determine a personal taste or a yes/no reaction. The third audio file is consisting of white noise and it is used to observe the subjects' reactions to it. The duration for the first audio experiment is five minutes, the second one lasts six minutes and the third one four minutes.

V. EXPERIMENTAL RESULTS

The main parameter that has been closely investigated in the experimental analysis is the regression of the artificial neural network for all of the hypotheses, scenarios and subjects. Regression illustrates the connection between the output variables and input variables. The regression values were acquired after training the neural network for each of the cases.

The first dataset represents the data from a single subject, that performed four scenarios, coding, reading, simple math and social media browsing. For this particular case, Figure 8 portrays some trends and patterns, that can be identified with the assumption that the data is influenced by the physical and emotional state of the subject and their disposition at the time of the recording. The overall score for all the scenarios is the highest for hypothesis 0, which states that all brainwaves impact the levels of both the attention and meditation. One can notice that the highest reading was registered by employing hypothesis 0, for the reading scenario and the lowest regression score for the reading experiment is when employing hypothesis 2.

Dataset 2 is comprised of the data gathered from two subjects that performed exactly the same activities. One pattern that arises is that in case of H0, all of the regression recordings associated to the scenarios have the highest values, indicating a better fit.

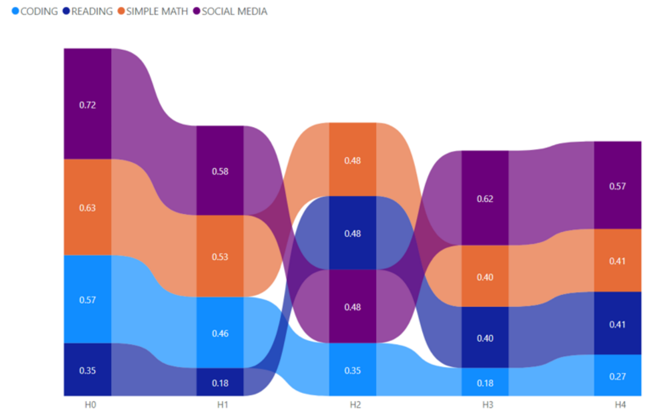

Figure 8. Dataset 1 Experimental Data Comparison Based on Hypotheses and Scenarios.

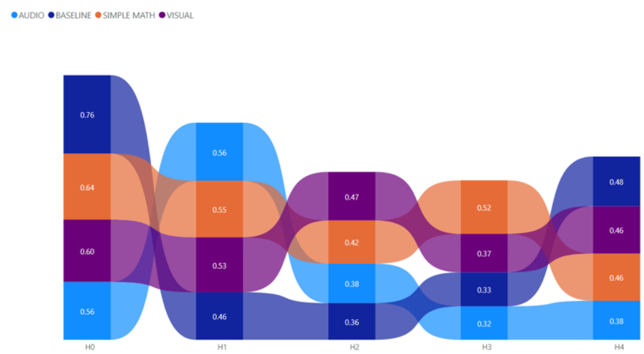

Figure 9. Dataset2 - Subject 1 Experimental Data Comparison Based on Hypotheses and Scenarios.

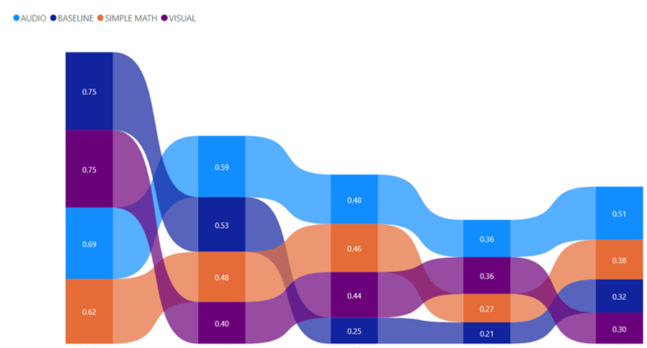

Figure 10. Dataset2 - Subject 2 Experimental Data Comparison Based on Hypotheses and Scenarios.

Based on the results featured in Figure 9 and Figure 10, an appealing parallel ensues. The Baseline activity developed a significant regression value for both participants when considering hypothesis 0 and a low regression value for the rest of the hypotheses. The Audio scenario employing H0 establishes that the second subject has an improved response to audio stimuli in regards to attention level, scoring a higher regression result in comparison to the first subject; The results for the rest of the hypotheses in the Audio scenario for both participants are similar. Hypothesis 0 in the Math scenario is still as effective as before, both subjects scoring a high regression value for it in contract to the other hypotheses. A dichotomy is present when H3 is inspected for the Math experiment, the second subject's regression value exhibits a mismatch, scoring a low regression level, juxtaposing with the first subject's regression score. The Visual result reiterates the hypothesis 0 as being advantageous in the case of these two participants. The methodology engaged throughout the paper is an enabler. By enlarging the pool of subjects, the diversity of the scenarios and by utilizing the presented method of monitoring attention and meditation levels can provide instructional designers with knowledge for better designing the learning mix, evaluating required cognitive efforts to foster attentional processes and ensure better training results.

VI. CONCLUSION

Objective attention quantification is a complex task. However, attention is an important ingredient of learning. BCI provide a noninvasive way to collect brain activity in real time and may be employed in user attention quantification. In this paper, we evaluate several learners as they perform different tasks and discuss various methods to analyze and compare brainwave data. We observe common patterns for all users, despite the limitations faced in data interpretation. The goal is to expand and increase the experiments user base to detect patterns in user attention based on the audio-visual content presented. We believe that BCI can be employed successfully in improving the learning outcomes and fine tuning learning materials for adult learning.

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