Investigating Human Brain Waves in Shared Experiences

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Abstract

Artists desire to bring new experiences to viewers of their art. While modern technology, such as Neurosky Mindwave headset, allows artists to create such experiences, artists often strive to appropriately utilize such technologies. In other words, while the technology does exist, the techniques to utilize it does not. In this paper, we develop and demonstrate a technique that investigates similarity between the brain waves of two participants in a shared experience. Our results indicate that there exists multiple brain waves that offer a high similarity when subject to a given external stimuli. Based on our observations we make a case for artists to leverage our techniques and findings to better generate new experiences for all viewers of their art.

Keywords: EEG; external stimuli; data mining; covariance.

1 Introduction

Artists may desire to create aesthetically appealing interactive experiences. The advancements in Electroencephalogram (EEG) recording technology allow artists to create an interactive, multi-sensory experience. Using such technology allows capturing and utilizing peoples brain waves and alternate light and sound in a cinematic environment. EEG also empowers artists to create a closed feedback loop between light-emitting fiber optics and responsiveness of brain waveforms, in terms of changes in visual. Developing an adaptive environment that changes with regards to how different people’s brain waves change in response to visual and acoustic stimuli. However, to the best of our knowledge, mutual responses from pairs of participants have not been studied widely. Specifically, previous studies have mostly focused on how different brain waves of individual participants react to environmental changes, as opposed to shared reactions between pairs of participants.

Using EEG signals from multiple people, we perform an analysis of human brain waves to understand whether or not there exists certain environmental effects that stimulate a particular brain wave signal across multiple participants simultaneously. Our investigation comprises of visual and auditory experiments performed with 24 participants at Montana State University (MSU). Our analysis investigates covariance among changes in brain waves of multiple participants. We argue that utilization of similarity of brain waves allows artists to generate more responsive and appealing interactive experiences. Based on our analysis, we list our contributions as follows:
We design and develop techniques to carefully analyze human brain wave data obtained from Neurosky headsets [3]. Our techniques involve data imputation, noise reduction by smoothing the collected data, and investigating several metrics to identify similarities among brain waves of multiple participants.

With respect to the results, we discover that for audio-only and video-only experiments, the Gamma waves of two participants in shared experiences have highest covariance (similarity). Additionally, we identify that for the same experiments, the combination of Alpha and Beta waves offer high similarity. Finally, for experiments that involve both audio and video we identify that Beta waves and Alpha waves of two participants independently possess the most covariance (similarity).

Our analysis reveals that there exists brain waves that have a similar response to visual and auditory stimulus across multiple participants in shared experiences. Therefore, artists could potentially leverage our techniques to customize how light-emitting fiber optics can create a mutually enjoyable experience. For curious minds, our source code is available upon request at https://github.com/msu-netlab/brains.

The rest of the paper is organized as follows. In the next section, we provide a brief overview on the human brain waves and describe different wave channels. In Section 3, we discuss the data collection techniques employed by undergraduate students at MSU. In Section 4, we discuss several data analysis techniques we utilize for processing the brain wave data obtained from Neurosky headsets. In Section 5, we discuss the related work and offer a discussion on how our results complement previous results. Finally, we conclude in Section 6.

2 Overview of Human Brain Waves

The brain activity (measured as amplitude of electrical signals, in milli-volts) depends on a person’s alertness during any daily chore, varying from mediation to concentration. EEG waveforms are the most popular form of noninvasive brain recording in cognitive research and are widely used today to detect electrical activities in human brains. The current state of brain activity as well as many environmental factors influence how different waveforms dominate or are suppressed [9]. We refer to dominance of a wave as the continued presence of that wave with an amplitude higher than other waves during a measured time window. To illustrate dominance, notice in Figure 1 the separation of the different waves (2 through 6) from the EEG wave (1) based on frequency present during each time interval. At certain times, some waves have greater presence than others, leading them to be considered dominant.

Next, we categorize the human brain waves based on their frequencies and how they change based on the events that occur in real-time. Specifically, human brain waves are measured in Hertz (cycles per second) and divided into different frequency bands based on how fast they oscillate, described as follows:

• The Gamma waveforms have frequency ranging from 25 Hz to 100 Hz. Gamma waves have the highest frequency between all other brain waveforms [7, 12].
1. lowGamma with frequency ranging from 30 Hz to 50 Hz.
2. midGamma with frequency ranging from 50 Hz to 90 Hz.
3. hiGamma with frequency ranging from 60 Hz to 140 Hz.

- The Beta waveforms have frequency ranging from 12 Hz to 40 Hz [1, 4]. Beta waveforms are dominant when humans pay attention to a stimulus, are engaged in a problem solving task, or are involved in making a decision. Beta waveforms are further divided into three groups based on the frequency:
  1. lowBeta with frequency ranging from 12 Hz to 15 Hz
  2. midBeta with frequency ranging from 15 Hz to 20 Hz
  3. hiBeta with frequency ranging from 18 Hz to 40 Hz

- The Alpha waveforms occur due to the resting state of the brain. The frequencies of the Alpha waveforms range from 7 Hz to 13 Hz [2].
  1. lowAlpha with frequency ranging from 7 Hz to 9 Hz
  2. Frequency ranging from 10 Hz to 13 Hz correspond to midAlpha and highAlpha

- The Theta brain waves activate during sleep but are dominant in deep meditation as well. The frequencies of the Theta waveforms range from 3 Hz to 8 Hz [4].

- The Delta waveforms are generated in deep sleep and meditation and their frequencies range from 0.5 Hz to 3 Hz [4].

- Finally, the infra-low waveforms or slow cortical potentials are difficult to study and very little is currently known about them due to the fact that these waves are difficult to detect accurately. These waves have frequencies less than 0.5 Hz [4].
3 Data Collection Methodology

The data available for this work was collected by several undergraduate students at Montana State University (MSU) prior to our analysis and involvement in this work. To the best of our knowledge, we will describe how experiments were conducted as well as the data collection process. The experiments were conducted with the help of multiple volunteer participants that agreed to be in a room together and were instructed before the experiment as to how the experiment will be conducted. Once the headset was placed on the participant and had been initialized, one of the three experiment conditions, audio-only, visual-only, or both audio and video, was selected and played in front of the participants. Next, the brain activity was recorded as the experiment progressed, in terms of the electrical signals that correspond to different brain waves (as described in Section 2). The electrical signals recorded by the headset for different brain waves were collected at every seconds. Our total data comprises of magnitudes of electrical signals of different brain waves along with the timestamps collected from 12 experiments performed with the help of 24 participants.

4 Data Analysis

With respect to the experimental evaluation of the collected human brain wave data, we investigate whether there exists any covariance between the different brain waves of two participants throughout an experiment. Such an approach allows us to understand if there exists a similarity between specific brain waves of participants in a shared experience. However, before we perform analysis of the collected data, we perform data imputation by filling in blanks using prior data entries. This approach is based on the assumption that prior values will be similar to the next value. Specifically, the number of missing values we synthesize across all of our experiments has a mean of one with a standard deviation of four. The maximum number of missing data points we synthesis for an experiment is 29 out of 180 samples.

We first calculate the unscaled magnitude of brain waves in milli-volts squared (covariance) that indicates how the brain waves of participants switch from varying together (positive covariance) to independent (zero covariance) to inversely varying together (negative covariance). In our investigation, we look at the data with sliding window intervals, ranging from 5 seconds to 30 seconds in increments of 5 seconds. This approach allows us to control how much of the prior data impacts the covariance at the time that we are analyzing as well as how ”smoothed” the data becomes. Specifically, a larger sliding window will smooth the covariance over time more than a smaller window.

Given that each experiment requires two participants, we calculate the covariance between every combination of these two participants’ brain waves and analyse how the covariance fluctuates at various sliding window durations during the experiment. With all of these covariance distributions calculated throughout the experiment, we next determine which brain waves show high covariance. In order to determine high covariance, we first divide each covariant distribution into sub-graphs, where each sub-graph is a positively covariant stretch of the original distribution. Next, for each sub-graph we calculate the following three metrics:
The fraction of each sub-graph’s duration out of the total experiment duration.
2. The fraction of each sub-graph’s average height during the duration compared to the total experiment maximum height.
3. The fraction of each sub-graph’s area under the curve out of the total positive area throughout the experiment.

We then give equal weight to these three metrics and calculate which wave pairs offer the most dominant stability. In Figure 2 we illustrate the importance of these metrics when participants undergo an experiment comprising both audio and video stimuli. The x-axis represents the relative timestamps during the experiment. The y-axis represents the average covariance between the \textit{hiBeta} waves of the participants involved. We observe from the figure that although during the interval 65 to 80, the curve achieves maximum height, however, the area covered during the interval is smaller than the area covered by the curve during the interval 100 to 140. Further, the height of the curve during the interval 65 to 80 is likely to be a result of sudden noise, while the height of the curve during the interval 100 to 140 is relatively stable. We argue that the combination of duration, height, and the area under the curve of the sub-graph assists in identifying the stability of the covariance.

In Table 1, we summarize our results demonstrating the brain waves that respond the most to audio-only, video-only, and both audio and video experiment conditions. Specifically, we consider length, average height, and area as equal contributors when selecting which wave pairs respond similarity the most to changes in video and auditory stimuli. For example, for audio-only experiments, the collective response with the length, average height, and area considered together, the combination of \textit{lowBeta} and \textit{lowAlpha} waves have higher covariance (similarity) than the combination of \textit{hiBeta} and \textit{lowAlpha} waves. Additionally, for video-only experiments, the \textit{midGamma} waves of two participants in shared experiences have highest covariance (similarity). Finally, for both audio and video experiments, \textit{hiBeta} waves have the highest covariance (similarity). Note that \textit{hiBeta} appears as the two highest covariance measurements at two difference sliding window widths.
<table>
<thead>
<tr>
<th>Experience</th>
<th>Wave One</th>
<th>Wave Two</th>
<th>Sliding Window Width (sec)</th>
<th>Length (%)</th>
<th>Average Height (%)</th>
<th>Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audio-only</td>
<td>lowBeta</td>
<td>lowAlpha</td>
<td>30</td>
<td>21.5</td>
<td>57.0</td>
<td>63.5</td>
</tr>
<tr>
<td></td>
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<td>lowAlpha</td>
<td>30</td>
<td>20.0</td>
<td>53.0</td>
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</tr>
<tr>
<td></td>
<td>lowGamma</td>
<td>lowGamma</td>
<td>30</td>
<td>22.0</td>
<td>45.0</td>
<td>62.0</td>
</tr>
<tr>
<td>Video-only</td>
<td>midGamma</td>
<td>midGamma</td>
<td>30</td>
<td>16.0</td>
<td>56.0</td>
<td>62.0</td>
</tr>
<tr>
<td></td>
<td>lowGamma</td>
<td>lowGamma</td>
<td>30</td>
<td>17.0</td>
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<td>62.0</td>
</tr>
<tr>
<td></td>
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<td>theta</td>
<td>30</td>
<td>15.5</td>
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<tr>
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<td>hiBeta</td>
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<tr>
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<td>20.0</td>
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</tr>
</tbody>
</table>

Table 1: Results showing the top three brain waves that possess high similarity across audio-only, video-only, and both audio and video experiments.

5 Related Work and Discussion

There have been a number of research studies that investigate collaboration between pairs of subjects by recording brain activities when these subjects are involved in talking [10, 13, 14]. However, these studies do not require participants to share a common visual or auditory experience.

A few studies identify domination of Gamma waveform’s oscillation is related to the enhancement of attention to either visual or acoustic stimulus [8]. Other studies report suppression of Alpha waveform while subject is attending to visual or auditory information [6, 11]. Although there is still an ongoing debate on having a different Alpha power modulation in auditory attention [16], however audio stimulus can have similar effect on Alpha modulation same as a visual stimulus[15]; For example, when a participant is trying to discriminate a pitch in an audio stimulus, Alpha waveforms are showing a decrease in oscillation [15]. Although, we observe that Alpha waveforms are actively alternating during our experiments, we can only conclude that participants were listening (paying attention) to the audio stimulus. Further, more interpretation of attending or filtering noise to discriminate for each changes of pitch require more detailed event recording setup.

6 Conclusions

In this study, we investigate similarities in different brain waves when two people participate in a shared visual and auditory experience. Using the brain wave data collected by volunteered participants at MSU, we identify that Gamma waves and combination of Alpha and Beta waves respond the most to audio-only and video-only stimuli, whereas Beta waves respond the most when both audio and video stimuli are present. Based on our results we make a case for artists to utilize our data analysis techniques to customize environmental changes based on how participants interact to the audio and visual stimuli.
Acknowledgments

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References


