Determining the Effects of Stimuli Frequencies and Periodicities as Patterned Distractions on a Student's Cognitive Ability

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Objective

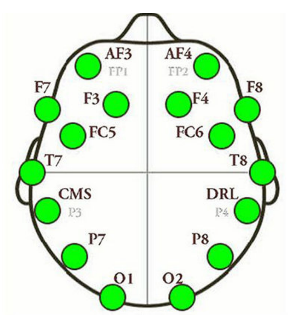
The goal of this project is to understand how users respond to different stimuli frequencies and periodicities as patterned auditive distractions. Data used from a previous research study reports the user's emotive, affective and cognitive information while being presented with different auditory distractions. After implementing regression models on this dataset to better understand the nature of the data, it helped indicate the patterns and frequencies of distractions and their corresponding effect on a person's cognitive ability.

Introduction

Measuring human cognitive ability is an important aspect in research regarding education. One such experiment explored the effects of presenting a high amount versus a low amount of information for a task and comparing the user's speed for each task (Lustig et al., 2006). This experiment tested how people's processing speed for information changed with certain distraction periodicities. However, it still falls under the umbrella of understanding human cognitive and affective ability. The basis for understanding how individuals learn is present in the Cognitive Load Theory which claims that only a limited amount of information can be processed at a given time (Sweller, 2011). This research project attempts to understand what factors have a real impact on this limited amount of information that humans can understand, especially considering the periodicities and frequencies of auditive distractions.

Recent developments in electroencephalography (EEG) technology have made it feasible to conduct research studies on students to improve current educational techniques. This makes the study more objective to the mental and emotional conditions imposed on the test subject that is difficult to detect from face-to-face instruction. EEG signals are divided into five wavebands that indicate activity from various parts of the brain, which include α, β, θ, δ, and γ waves (Liu et al., 2013). For this project, the dataset provided for the analysis (Paley, 2015) is reflective of the emotional constructs listed as follows: excitement, engagement, frustration, meditation, and boredom. The following images show the Emotive EPOC headset used in the prior study to collect responses from users and its respective spatial mapping.

Emotive EPOC Headset



Spatial Mapping of Electrodes

Research Question

What are the effects of stimuli frequencies and periodicities as patterned distractions on a student's cognitive ability?

Method

The process was divided into **three steps**:

1. Collection of data

- After thorough review of related studies, pre-existing data (Paley, 2015) for biometric sensor simulators were used to analyze different distraction stimuli and how they affect the emotional and affective state, and thus, the learning process of the study participants.

2. Pre-Processing of Data

- It is vital to pre-process the data so that the formatting and quality are appropriate for use in the classification and prediction models. Python libraries such as *pandas*, *numpy*, and *matplotlib* were used to pre-process the data shown in the following diagram.

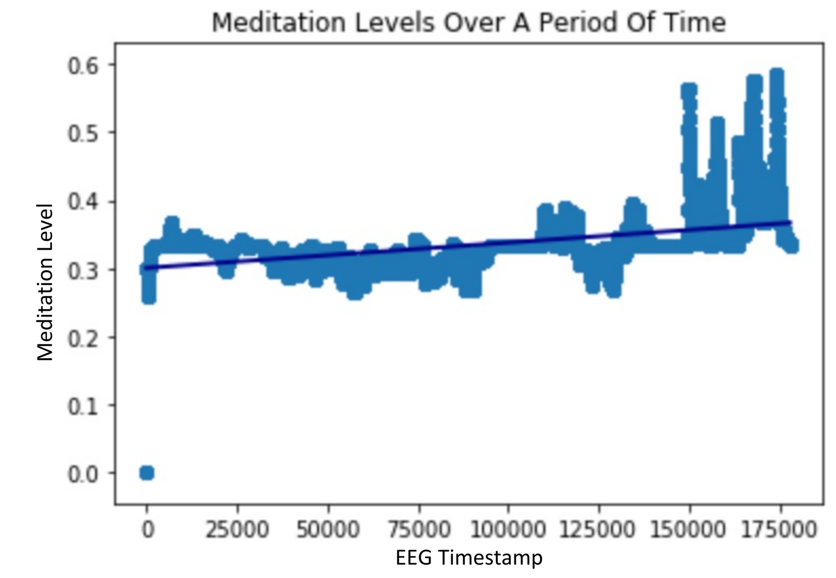
Define the values that will be omitted from the dataset in a list → Read in the data file, and drop the values that have matches with the values in the previously defined list → Create a data frame variable and specify the emotion response for which values need to be included → Create new lists for each each emotional response using the previously defined data frame

3. Processing of Data

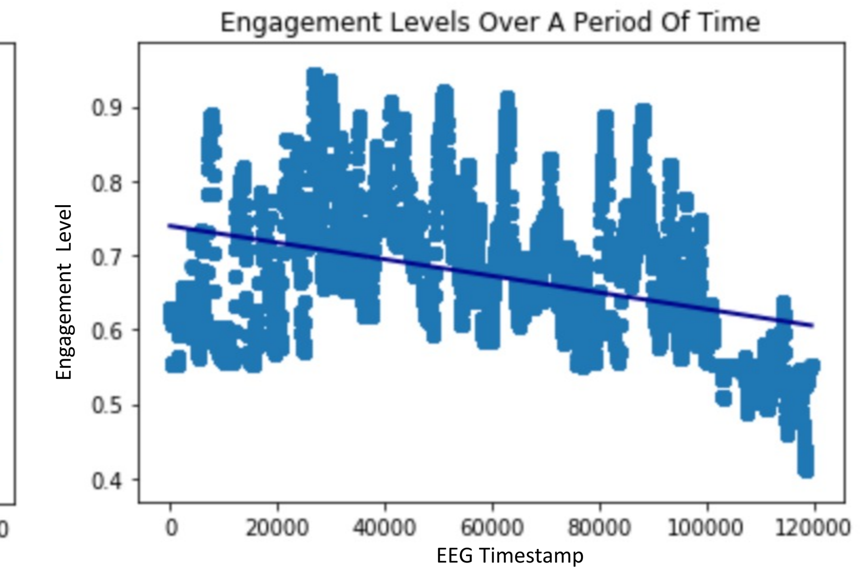
- After collection of results, various prediction models such as linear regressions need to be performed to analyze the data using Python scripts. Statistical data such as the p-value, t-statistic, and R are to be collected to determine linear correlations.

Results and Findings

- This research was centered towards cleaning the pre-collected data within the meditation and engagement constructs and performing linear regression models.
    - **Meditation:** As the timestamp progressed in the dataset used to analyze emotional responses, the meditation value steadily approaches 1, indicating an increased state of mindfulness over time. Through several data, given a 95% confidence interval (α = 0.05), the p-value conducted under a linear regression was significantly lower than the α. The average p-value for meditation was 0.0080. This indicates that meditation levels are linearly correlated with the time that the subject is exposed to a certain distractive stimuli such as the classical music genre, as presented in the sample data.
    - **Engagement:** As the timestamp progressed in the dataset used to analyze emotional responses, the engagement value remains steady but relatively high, indicating a strongly engaged learning pattern over time. Through several data, given a 95% confidence interval (α = 0.05), the p-value conducted under a linear regression was significantly lower than the α. The average p-value for engagement was 0. This indicates that engagement levels are also linearly correlated with the time that the test participant is exposed to the classical music genre, as presented in the sample data.
- The findings differed from the original study as it determined there was a linear correspondence for engagement and meditation, whereas the original study was unable to find a linearized correlation through a one-way ANOVA. A limitation with linear regression model is that there is not always a linear correlation between the data and as a result linear regression may not be an ideal fit.



Sample Regression Model for Meditation



Sample Regression Model for Engagement

Conclusion

The objective of this research was to investigate the emotional responses elicited from auditory stimuli and to understand the relationship between the frequencies at which these distractions are presented from pre-collected data. This was calculated by performing data analysis on the respective linear regression models of certain emotional responses such as meditation and engagement. However, the original study was not able to determine a linearized correspondence after running a one-way ANOVA for both meditation and engagement. The findings of this research indicate that relaxing stimuli like classical music better engage the learner over time, which increases cognitive ability when performing tasks requiring critical thinking. Additionally, being in a meditative state also calms the learner to strengthen neural networks in the hippocampus, which controls learning, thus increasing focus levels. The nature of the data helped the subject's meditative and engagement response to auditory stimuli. The subjects had a positive response to auditory stimuli like classical music as evidenced by the high levels of engagement and meditation throughout their assessment. This leads to the conclusion that classical music may have a positive impact on subject's cognitive ability in similar learning environments. However, it is important to note that a linear model might not be the most accurate prediction model. For example, a k-means cluster that aggregates data through centroid-based similarities can improve the analysis by increasing similarity relevancies.

Acknowledgements and References

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