Validating Koalacademy, a neuro-guided language learning platform

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ABSTRACT

Koalacademy is a language learning tool predicated on the subsequent memory effect (SME), which differentiates the brain activity between the successful or unsuccessful encoding of a studied word to memory, relaying this information back to the user in real-time. We take advantage of the SME in confirming or denying the encoding of words during the process of studying them, allowing for selective repetition of poorly studied words, thus improving the success-rate of learning. The present study is focussed on validating the underlying framework of Koalacademy, a scalable Brain Computer Interface (BCI) platform that is able to present stimuli and stream brain data in a timely fashion comparable to other traditionally validated means of obtaining electroencephalography (EEG) data from BCI headsets. The present study utilizes a comparison oddball task. We have two conditions, including a control condition using a single board computer—which brain data is streamed to and is triggered via a light sensor at the onset of stimulus on the Koalacademy platform—, and an experimental condition consisting of brain data streaming and triggered through Koalacademy. The present study is the first of two, while the latter aims to validate whether a cloud trained machine learning model based on data collected through Koalacademy is able to successfully predict subsequent recall in real-time.

INTRODUCTION

The efficacy of learning is often disturbed by fluctuation in encoding information to our memory. Although we are capable of storing nearly infinite amounts of visual information, our ability to encode new information differs across individuals and situations (Fukuda & Woodman, 2015). What if we could predict the likelihood of remembering a studied item during the process of studying, and use that information to improve the efficiency and success-rate of learning?

Our research attempts to explore this question through the use of Koalacademy, a language learning platform intended to optimize the learning of a language.

To this end, the present study focuses on validating a scalable BCI platform through participants completing two conditions where their brain data is obtained through an EEG headset, and an oddball task.

Before we can start testing a computer program's ability to predict learning with the use of EEG brain data, we need to test the equipment's ability to acquisition brain data aligned with discrete events. An oddball paradigm will be used to reliably elicit a clear event related potential (ERP), or the voltages generated in the brain in response to the oddball stimuli. The standard visual stimuli will be presented to participants in green flashes, whereas the oddball stimuli will be the one presented intermittently in red flashes. ERPs will then be compared across both conditions.

The oddball paradigm is useful for validation of our study, because it gives a clear indication of a change in brain activity. Thus, we can clearly analyze when and to what extent a person's brain is reacting to a stimulus. (Kuziek et al., 2018).

Once this methodology is established, our group’s next steps are to integrate the present study’s methods into the next study, replacing the use of light flashes as stimuli in the oddball tasks used to analyze encoding with Mandarin words, aiming for cross-language acquisition. The next study involves the Koalacademy framework using OpenBCI EEG headsets and deep neural networks (DNN) to analyze brain data, predict the SME, and provide feedback to users on the likelihood of subsequently remembering “items” of Mandarin during the studying process, to help them learn the language more efficiently. Predicting the SME via EEG is a valid approach, as supported by Arora et al. (2018) receiving nearly 75% accuracy in using DNNs, and Hohne et al.(2016)’s 65% accuracy in doing so with EEG recordings derived from the hippocampus. In simplest terms, Koalacademy is a platform using low-cost EEG to deliver neuro-guided learning.

METHODS

Participants

We will recruit 10 adult participants for the study. They must have corrected to normal vision. Each participant will go through 5 blocks of 50 trials for both conditions. The study should take approximately one hour to complete, including setup. Prospective participants must contact the laboratory’s email. After signing a consent form approved by the Alberta Research Information Services, University of Alberta participants will be fitted with an EEG cap by a lab assistant, and impedance will be checked and reduced to below the conventional 5000 ohms.

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Materials and Procedure

The BCI application will be hosted on a serverless web platform and will use hardware including 16-Channel Cyton-Daisy EEG headsets developed by OpenBCI in various sizes (small, medium, and large), all with 16 integrated ThinkPulse™ Active Electrodes. A Cyton+Daisy 16-Channel Biosensing Board [OpenBCI] will output signals from the OpenBCI. In addition, we will use a 8GB RAM Raspberry Pi 4 (RPi4), a low-cost single board linux computer that can work with EEG. Alongside hardware, a combination of React, JavaScript, Firebase, and the OpenBCI node module will be used to create the Koalacademy web application, so it can run independently on client systems. React is used to combine front end development through HTML and CSS with dynamic, interactive JavaScript elements.

The control condition involves OpenBCI data streaming to an RPi4 triggered by an array of light dependent photoresistors. The RPi4 connects to the monitor with a mini HDMI to detect light stimuli presented through the Koalacademy browser. A green flash means there are standard stimuli, and a red flash is indicative of oddball stimuli, as received by the GPIO pins of the RPi4. The RPi4 marks a rising edge (where the trigger goes from 0 to 1) depending on the intensity of the flash which marks the trigger of each sample. Encoding is based on the intensity of the light. Kuziek et al. (2018) successfully used an oddball paradigm to test the effectiveness of Raspberry Pi 2 hardware. The experiment did use an earlier model of the computer, but we anticipate similar accuracy.

The experimental condition involves OpenBCI data being triggered by the React component and streaming to the PC. The Cyton-Daisy BCI connects to web browsers through a port extension, and OpenBCI data is collected. Once users are on Koalacademy's Oddball page and select the OpenBCI headset option, a requestport() programming function causes the user to select which USB device they choose. Once they select the OpenBCI, there is then a SerialPort object which can be read and written from. We will have to send a start signal before the Cyton 16-Channel Biosensing board can output sample signals from the OpenBCI. The output is given in binary format.

The BCI's data is collected through the following code in a custom React component: When the first trial in the first block starts, an array with 16 empty subarrays is created to store the samples for each of the 16 electrodes. The way the OpenBCI is currently set up requires passing in the time it takes for a trial, but since we are recording from the first block to the last block consecutively, we pass in a maximum value. We also pass in an empty array to store triggers, the triggers are stored as [code, sample#].

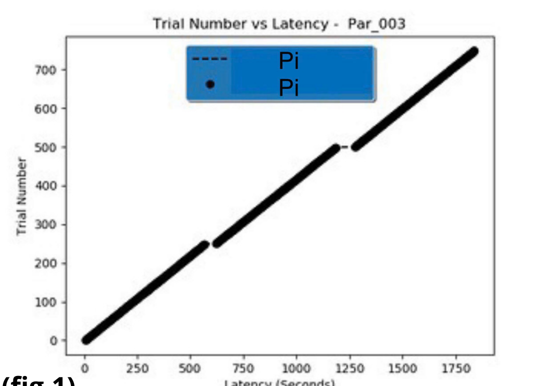
Whenever a sample is returned from the OpenBCI, each of the electrode values is appended into the subarrays. When the last trial in the last block is finished the OpenBCI is stopped and disconnected, the array is then stored in a comma separated values (CSV) file where each row is a sample and each column is an electrode. If a sample is associated with a trigger, then it will show up on the 17th column. We will add a timestamp at the end of each sample in the CSV as well. In real time, the OpenBCI data is specifically streamed to the PC through the COM3 port, which relays hardware data to the PC to the processor.

For each participant, Condition I's event related potential (ERP) will be compared to that of Condition II's through participants completing a visual oddball task while they complete the conditions. Data will be streamed to the Koalacademy webpage and triggers will be embedded in the website. For the oddball task, the program will produce white triggers that are detected by the light dependent resistors attached to the RPi4.

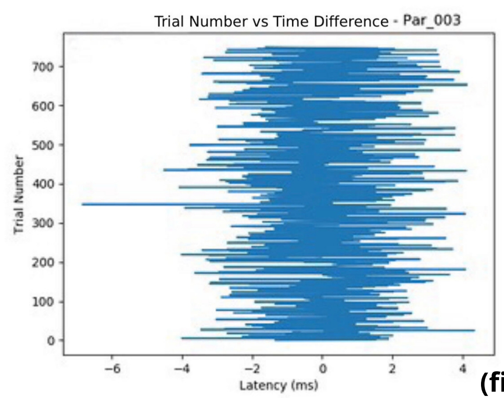
EEG Analysis Techniques

No pre-processing will be done for the present study. All EEG data will be aligned with the Raspberry Pi and PC. 1000 millisecond epoch times are locked to the onset of standard and target stimuli with the average voltage in the first 200 milliseconds of the baseline period. We will use a 100 millisecond baseline period prior to trigger onset to avoid ERP activity influence on the root mean square (RMS). Additionally, we will plot and compare P300 stats across both conditions, as well as standardize analysis across both conditions, so they have the same epoch slicing,

PROJECTED RESULTS



(fig.1)



(fig..2)

The figures above display the timing of the Raspberry Pi triggers versus the Koalacademy triggers.

DISCUSSION

The projected results show that timing is consistent across both conditions. Thus, they demonstrate that Koalacademy can embed time synchronized triggers that align with brain data comparably to that of a traditional objective measure, such a light sensor being activated. Due to conflicting time arrangements, the ERP results were not analyzed. Improvement could be made to the present study by deriving the grand average ERPs from the oddballs and standards for both conditions. Then, we could conduct a point-wise subtraction of the oddball ERP from the standard ERP for each condition. Finally, the resultant difference waves could be compared across the control and experimental conditions. The results, along with the ERPs and their comparison across conditions, provide the basis of confirming that the platform has a valid way of collecting data. Both for the data that will be used to generate the machine learning model as well as implementing live neurofeedback in future research.

In future research after the validation of Koalacademy, we hope to involve the framework using OpenBCI headsets in conjunction with deep neural networks (DNN) which perform live classifications of whether a word will be subsequently remembered, to provide the user with feedback, in real time, on whether the word is to be encoded or not. Accordingly, words are repeated based on the quality of study, as analyzed by the DNN. To attempt forecasting successful encoding of a studied item, our research continues to utilize the subsequent memory effect (SME). Brain activity in select region(s) is higher while individuals study items they will later remember (indicative of successful encoding), and lower brain activity towards items they will later forget. According to the spectral analysis research conducted by Kang et al. (2020), successful encoding can be observed in higher alpha and theta band frequencies, and lower gamma frequencies. Friese et al. (2013) supports Kang et al. (2020)'s spectral analysis with similar results, and also relates remembered items to the right frontal cortex's increased theta-band activity, the parietal-occipital regions' higher gamma-band activity, and the prefrontal and occipital cortex's decreased alpha-band activity. Our research aims to make use of contemporary research on the SME to create an efficient language learning platform.

There is flexibility for the Koalacademy framework to connect to other OpenBCI hardware aside from the Cyton-Daisy, such as the Ganglion (4-channel). The cost-effectiveness and portability of the headsets demonstrate the accessibility and power of commercial BCIs. It would allow a company to scale up the distribution of these headsets for use with Koalacademy on a commercial scale.

Overall, Koalacademy's interactive, web-based platform, its independence of computer specifications, and its usage of commercial Brain Computer Interface (BCI) EEG headsets, renders it an accessible, low-cost alternative to traditional modes of optimizing language learning. It can be modified to provide endless options for both assessment and treatment of speech or learning language disabilities, as well as to fit the needs of everyday language learners in increasing the efficiency of learning. The platform transforms traditional laboratory late analyses to the instant processing of live user brain data into actionable information, in real time.

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LITERATURE CITED

Arora A., Lin J., Gasperian A., Maldjian J., Stein J., Kahana M., Lega B. (2018) Comparison of logistic regression, support vector machines, and deep learning classifiers for predicting memory encoding success using human intracranial EEG recordings. *Journal of Neural Engineering* 15.

Friese, U., Köster, M., Hassler, U., Martens, U., Trujillo-Barreto, N., & Gruber, T. (2013). Successful memory encoding is associated with increased cross-frequency coupling between frontal theta and posterior gamma oscillations in human scalp-recorded EEG. *NeuroImage*, 66, 642–647. https://doi.org/10.1016/j.neuroimage.2012.11.002

Fukuda, K., & Woodman, G. F. (2015). Predicting and improving recognition memory using multiple electrophysiological signals in real time. *Psychological Science*, 26(7), 1026–1037.

Höhne M., Jahanbekam A., Bauckhage C., Axmacher N., Fell J. (2016) Prediction of successful memory encoding based on single-trial rhinal and hippocampal phase information. *Neuroimage* 139:127-135.

Kang, T., Chen, Y., Fazli, S., & Wallraven, C. (2020). EEG-Based prediction of SUCCESSFUL memory formation During vocabulary learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(11), 2377–2389.

Kuziek, J. W. P., Redman, E. X., Splinter, G. D., & Mathewson, K. E. (2018). Increasing the mobility of EEG data collection using a Latte Panda computer. *Journal of Neuroscience Methods*, 308, 34–47.