Optimizing an assistive Brain Computer Interface that uses Auditory Attention as Input

By

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Abstract

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Brain Computer Interfaces (BCIs) allow individuals to operate technology using (typically consciously controllable) aspects of their brain activity. Auditory BCIs utilize principles of Auditory Event Related Potentials or Auditory Evoked Potentials as a reproducible controllable features that individuals can use to operate a BCI. These Auditory BCIs in their most basic format can allow users to answer yes or no questions by listening to either one auditory stimuli or the other. Current accuracy in intended response detection for these kinds of BCIs can be as good as mean accuracy of 77 % [5]. BCI research tends to optimize the computer side of the system however the ease of use for the human operating the system is an important point of consideration as well. This research project aimed to determine what factors make a human operator able to achieve the highest accuracy using a given previously successfully demonstrated classifier. This research project primarily sought to answer the questions; to what degree people can improve their accuracy in operating an Auditory BCI and what factors of the stimulus used can be altered to achieve this. The results of this project, obtained through the data collected from six individuals, found that slower stimuli speeds for eliciting Auditory Event Related Potentials were significantly better at achieving higher prediction accuracies compared to faster stimulus speeds. The amount of time spent using the system appeared to result in diminishing returns in accuracy regardless of condition however not before an initial spike in greater classifier prediction accuracy for the second condition run on each subject. Although further research is needed to gain more conclusive evidence for or against the hypothesis, the results of this research may be able suggest that individuals can improve their performance using Auditory BCIs with practice at optimal parameters albeit within a given time frame before experiencing diminishing returns. These findings would stand to provide benefit both to continued research in making optimal non-invasive alternative communication technologies as well as making progress in finding the potential ceiling in accuracy that an Auditory BCI can have in interpreting brain activity for the intended action of the user.

Keywords— Brain Computer Interface (BCI), Dichotic Listening, Operant Conditioning

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Terminology

- **Brain Computer Interface (BCI)** - A system which involves using some feature of (*typically real-time*) brain activity as the input for some application.
- **Auditory BCI** - A Brain Computer Interface where the brain activity used to drive the system is related to some aspect of the auditory perception systems in the human brain.
- **Operant Conditioning** - conditioning in which the desired behavior or increasingly closer approximations to it are encouraged or discouraged via positive or negative reinforcing stimulus respectively.
- **Electrolencephalography (EEG)** - A measure of the electrical activity in the brain as recorded via electrodes placed on the scalp. This is a form of non-invasive quantification of brain activity.
- **Evoked Potential / Event Related Potential (ERP)** - An electrical potential with a specific pattern elicited by some sort of stimuli.
- **Dichotic Listening Task** - A method in neuroscience and neurology research where a participant is presented with two, typically competing, sound sequences / auditory stimuli, one per ear and at the same time.

1 Introduction and Background

Since first appearing in the 1970s, BCIs have experienced rapid advancement, particularly due to research in machine learning and artificial intelligence that enhances understanding of brain activity [15]. Emerging research in BCIs largely revolves around computational components, however consideration of the human brain component of a Brain Computer Interface is also crucial. Different BCI designs require users to perform known, reproducible cognitive tasks to operate real-time brain activity interpretation systems. This study evaluated the features of an Auditory BCI aiming to optimize user operation and experience, keeping the classifier translating brain activity to output as a constant factor. Within the broader scope of enhancing BCIs as assistive communication technologies, these interfaces serve as vital aids for those with communication difficulties, providing a level of autonomy. Typically, users consciously select characters or messages via functioning sensory systems, and their intentions are interpreted through real-time brain activity analysis. Even though some BCIs use implants in motor control brain areas, capable of conveying up to 90 text characters per minute with 94% accuracy [16], this study focused on minimally invasive technologies. These non-invasive technologies, not necessitating any surgical procedures like brain surgery, offer feasible options for BCIs, particularly for individuals considering invasive brain surgery as a last resort for communication.

1.1 Locked-In Syndrome

Locked-in syndrome (LIS) is a complex medical condition presenting with quadriplegia, bulbar palsy, and whole-body sensory loss due to damage in the brain stem, most commonly the anterior pons. Cognition, vertical eye movement, blinking, and hearing are classically preserved in patients suffering from the condition. The diagnosis of the locked-in syndrome is often challenging due to its similarity with conditions such as akinetic mutism and coma. It may take weeks to diagnose, and family members at the bedside are usually the first to notice the decreased motor functions of the patient [12]. Notably, due to the often preserved cognitive and sensory functions, systems such as Brain Computer Interfaces (BCIs) provide a promising avenue for communication and control for individuals with LIS. BCIs can both be utilized to as research methods for gaining further insight into LIS as well as therapeutic interventions for potential practical systems for communicating with those afflicted by LIS [3].

1.2 Brain Computer Interfaces

A Brain Computer Interface (BCI) encompasses three fundamental components. The first is the source, which collects real-time brain activity and transmits it to the second component, the signal processing module. This module can either be third-party software or integrated software that performs real-time calculations on the actively streaming brain activity to extract the features required to operate the BCI [13]. The third and final component is the user application, which can essentially be any application capable of receiving its input from the output of the signal processing component.For instance, in technologies designed for assistive communication, the user application usually resembles some form of message creation program, such as a speller application. This standard implementation is exemplified

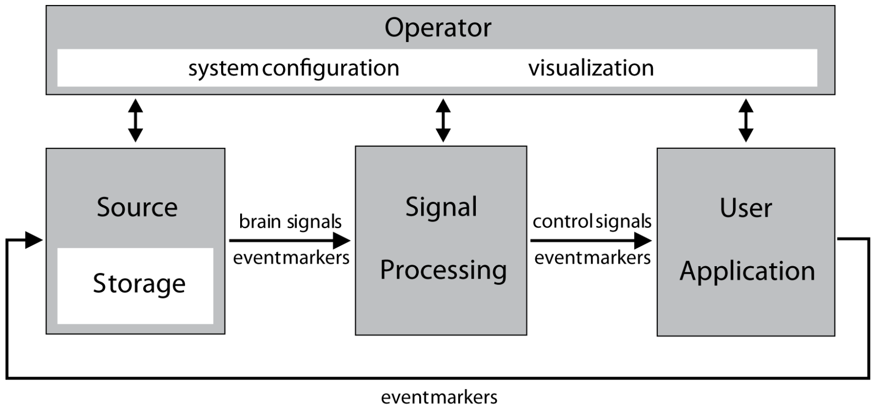

Figure 1: The standard system configuration for any system designed using BCI2000. BCI2000 allows for the creation of efficient and modular BCIs.

in BCI2000, a software application specifically designed for crafting BCIs (Figure 1). The source of brain activity can differ, but methods that provide real-time data like EEG are typically preferred. EEG is particularly effective due to its high temporal resolution and minimally invasive nature [14]. While there is flexibility in the specific features of brain activity and the conversion of that activity into actions, these fundamental components remain the gold standard for designing and operating BCIs.

These three components also form the basis of Auditory Brain-Computer Interfaces. Auditory BCIs involve the usage of auditory stimuli or the processing of auditory information as the user-modulated input for BCI systems. The brain's responses to auditory attention tasks are known as Event Related Potentials (ERPs), which can be observed in data that has been processed by the signal processing stage of these types of BCIs [11]. There are a variety of known Auditory Event Related Potentials, many of which have been used for various applications in the design and implementation of BCIs [8]. Systems such as the Auditory BCI described in this study stand to improve our understanding of making BCIs that work such that further applications can be explored into utilizing these types of systems for practical communication with individuals such as those afflicted by LIS [5].

2 Hypothesis and Goals

The primary hypothesis for this research project was that **classifier accuracy will be positively correlated with usage time and slower stimulus speeds**. The primary questions being asked in assessing this hypothesis were as follows: what stimulus speeds result in the highest classification accuracy for an Auditory BCI, and does that accuracy improve over time? Some other goals of this project were understanding more about the upper limits of stimulus speeds for Auditory BCI.

Naturally, although high speed stimulus will result in obvious difficulty in operation of the system, prior research in Auditory BCIs suggests potential benefits of the optimal high-speed stimulus configuration. In the context of this study, *stimulus speed* refers to stimuli presented per second. As proposed in Lopez-Gordo et al. (2012) [10] and Hill et al. (2014) [5], Auditory BCIs may benefit from higher stimuli presentation speeds by enabling a user to communicate intention at a faster rate hence more information can be communicated in less time. Thus far research in Auditory BCIs has demonstrated functional and practical solutions to using the human brain's auditory processing abilities alone as a means for communication in a BCI. Based off of the success of prior results which are represented in this study as the *slow* condition.

3 Methods

3.1 Auditory BCI Design and Setup

3.1.1 Hardware

The Auditory BCI this project used involved streaming real time brain activity as collected from a DSI24 dry-electrode EEG device [1]. This dry electrode array is capable of both wired and wireless communication of EEG, however a wired configuration was used so as to ensure a higher sampling rate. The stimulus used for this study was synchronized with the real time EEG using a hardware based synchronization widget capable of rapidly delivering an event marker into the EEG data stream in real time [7]. The hardware synchronization widget used in this study used the same design described in Hill et al. (2021) [7].

The DSI24 was wired into a PC running **Windows 10** with a **micro-USB to USB-A cable**. The hardware synchronization widget, was connected to the PC using a builtin USB-A male connector, and an **8-channel sound card** of the experimenter's choice its USB-A male connector. Over-ear headphones were utilized for stimulus delivery to participants. The headphones utilized required volume control for either ear piece in order to allow for the adjustment of audio on a case by case basis for each participant. The headphones for this study required a single 3.5mm stereo audio connector in order to plug them into the the 8-channel sound card. The additional 3.5mm stereo cable was used to connect another channel from the sound card to the hardware synchronization widget. This experimental hardware setup can be visualized in Figure 2.

3.1.2 Software

This study relied on the utilization of several essential software components: a developer build of BCI2000, available at www.bci2000.org, along with an Auditory BCI software that had previously been employed in prior research endeavors using BCI2000 [5]. The software utilized differed from prior research primarily through a modification to accommodate the dry-electrode EEG hardware utilized for this research project.

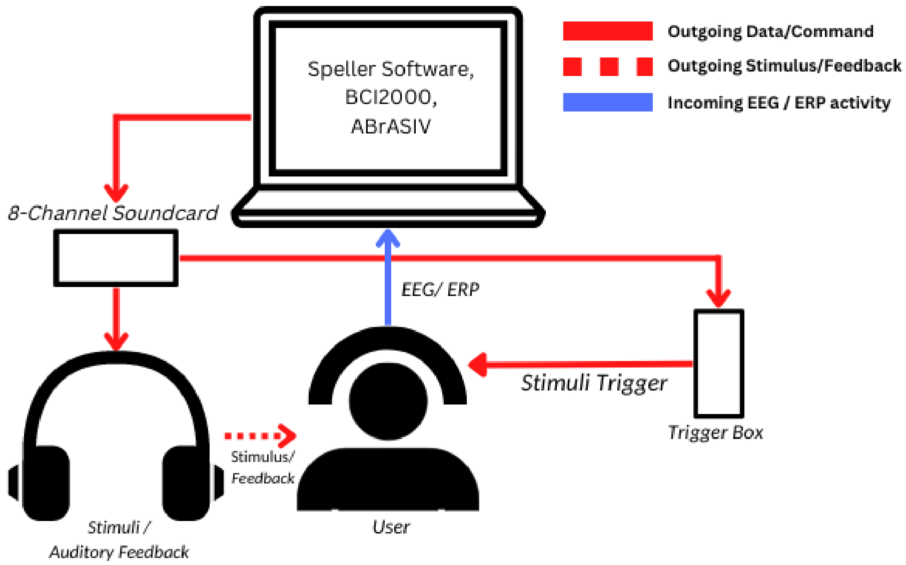

Figure 2: Hardware experimental setup: Stimuli and Commands are sent to the *DSI24* recording device and the brain's evoked response is sent to back to the system. The system interprets the incoming data in realtime and delivers feedback accordingly before presenting stimuli again. This is the fundamental concept of a BCI: *A system that takes brain activity as an input and delivers sensory feedback to the user*.

The signal processing on incoming data was conducted in real-time, adhering strictly to the methods laid out by Hill et al. (2012) [6] and Hill et al. (2014) [5]. The incoming EEG data was subjected to a band-pass filter between 0.1 and 8 Hz, facilitated by a Butterworth filter of the sixth order. Various methods were adopted to extract features from the incoming data, such as calculating the right-left difference of each within trial average, implementing spatial whitening, and adopting the recommendations put forth by Farquhar and Hill (2012) [2].

Crucially, the classifier used to identify the attended stimuli after each trial was not a new development; rather, it precisely made usage of the methodology outlined in Hill et al. (2014) [5], using BCpy2000, a Python framework tailored for BCI2000. This re-usage was intentional; no element of the classifier was altered for this study, as the focal point of the investigation lay in discerning the variance in accuracy when the stimulus was manipulated. In alignment with Hill et al. (2014) [5], the classifier weights were determined by applying L2-regularized linear logistic regression for each experimental run. Following the computation of the initial weights from the first run, the classifier then began to generate estimations for the most likely attended stimuli for each subsequent trial with both the classifier predictions and prompted stimuli saved following each run to allow for further analysis of results. The software essential for running this experiment is a custom suite designed with BCpy2000 and is available through the National Center for Adapative Neurotechnologies (https://www.neurotechcenter.org/).

3.2 Experimental Procedure

3.2.1 Stimulus Design

The stimulus for the Auditory BCI in this study builds off of research utilizing a dichotic listening task in conjunction with a participant's ability to consciously isolate one of many stimuli in order to operate the system [10]. The fundamental paradigm involves an initial calibration of a classifier for each subject, followed by the subsequent classification and evaluation of auditory attention tasks (Figure 3).

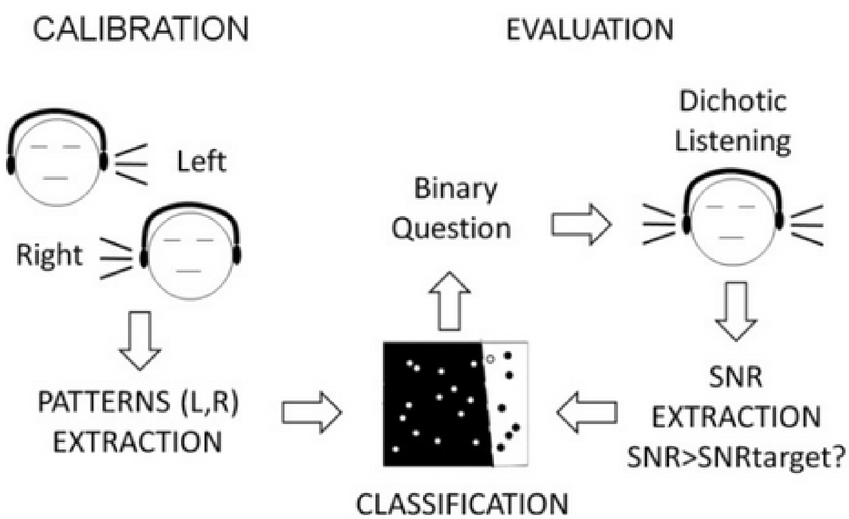

Figure 3: This diagram illustrates the general paradigm that all the Auditory BCIs this research builds off use. A dichotic auditory stimuli are played to the user who can select one of two options by consciously directing their attention towards one stimuli over the other

Like research performed in prior iterations of the BCI, the stimulus utilized was natural language synthesized audio of the words "Yes" and "No". The auditory stimulus was fitted with additional qualities to make them as salient from each other as possible such as the utilization of two different synthesized voices for stimulus presentation as well as the incorporation of a counting task for salient "Yup" and "Nope" stimuli in the "Yes" and "No" auditory stimulus streams respectively. All of these additional qualities were incorporated in accordance with results from prior research so as to make either auditory stimulus as easy to consciously isolate as possible [5].

In contrast to prior adaptations of the Auditory BCI used for this study, the stimulus presented per second was altered for three different conditions of slow, medium, and fast presentation speeds. These stimuli were determined precisely using a consideration of the ERPs that are of primary interest to Auditory ERPs such as the N100, P200 and P300, just as stimuli in prior evaluation of this Auditory BCI had been selected. The stimulus per second for each condition was determined using an internal toolkit for visualizing the ERPs generated by both an attended and unat-

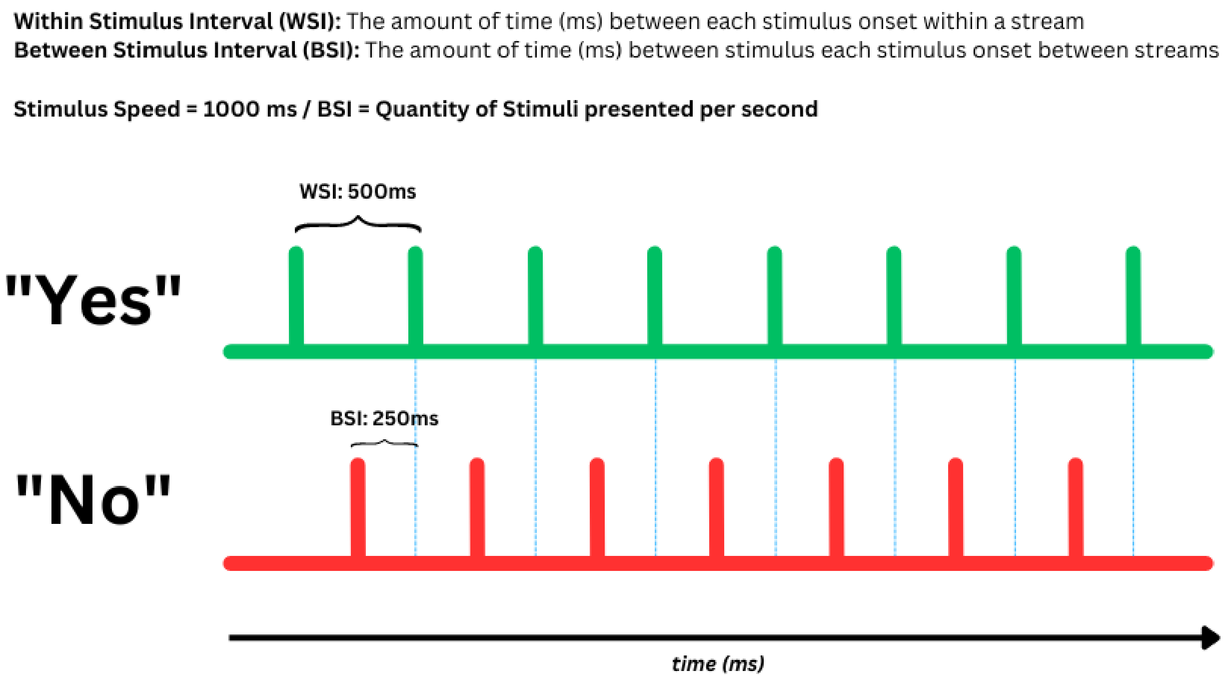

Figure 4: A visual representation of the parameters defining the *slow* condition with a presentation speed of exactly 4 stimuli per second. Each spike in a stimulus stream indicates a stimulus presented as audio to the research participant. Additional terminology such as the *Within Stimulus Interval* and *Between Stimulus Interval* were important components in determining the optimal stimulus speeds.

tended stimulus, ensuring that their overlap would not result in the loss of prominence for the attended stimuli. The slow stimulus was selected to be identical to the stimulus used in prior research with the Auditory BCI [5]. Figure 5 shows an example visualization of the ERPs expected from any given participants brain activity in response to auditory stimulus. The primary interest in evaluating faster stimulus speeds (more stimuli per second) was in evaluating upper limits in stimulus-per-second before the participant is no longer able to reliably operate the system using their auditory attention. Prior research has suggested that faster stimulus presentation speeds may be capable of improving the amount of information a participant would be able to communicate using the same Auditory BCI paradigm [10] [9].

Table 1: Parameters for each of the three conditions evaluated in this study

Trial Condition	**Between-Stimulus Period**	**Within-Stimulus Period**	**Stimuli-Per-Second**
Stimulus Speed: Slow	250 ms	500 ms	4.00
Stimulus Speed: Medium	150 ms	300 ms	6.66
Stimulus Speed: Fast	100 ms	200 ms	10.00

Through the usage visualized ERPs, three different stimulus-per-second values (stimulus speeds) were determined as three different conditions to evaluate experimentally. These three conditions serve to evaluate the first portion of the hypothesis that slower stimulus speeds (fewer stimuli-per-second) would result in higher classifier accuracy as a direct

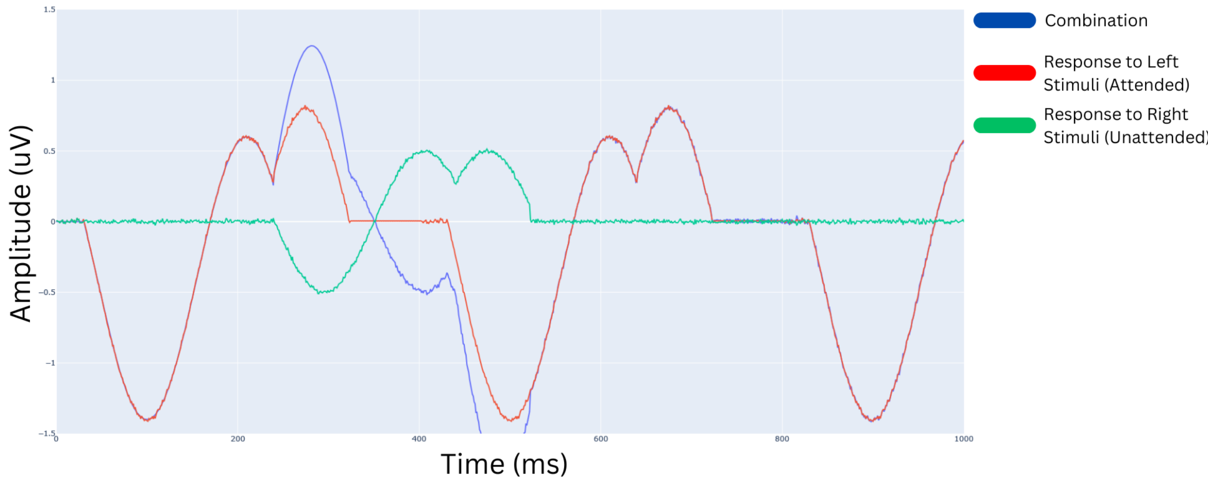

Figure 5: The visualized ERPs of a sample of stimulus with a speed of 5 stimulus per second. Shown in red is the sample dominant ERP. Shown in green is the sample non-dominant ERP. The blue waveform represents the combination of these two wave forms interfering. This visualizer served as a tool for determining which stimulus parameters have a better chance of being classified properly by the complete Auditory BCI.

effect of said stimulus being easier to maintain attention towards. Stimulus were presented in chunks of four runs each consisting of twenty trials that each involved a single prompt to attend to one of the two stimuli, followed by a dichotic listening task, then classification and evaluation. The division of conditions into chunks of four runs was to allow for the first quarter of each condition to be utilized to calibrate the classifier to that particular participant. The subsequent runs two through four involved the same task design, but now accompanied with auditory feedback if and only if the classifier's predicted intended response and the prompted attended stimulus match.

3.2.2 Test Subjects and Procedure

The test subject population for this research project were healthy adults within the age range of 30 ± 10. Participants were acquired from within the National Center for Adaptive Neurotechnologies and from Union College through the assistance of an SRG Grant submitted Fall 2022 from transporting up to 15 Union College Faculty and Students to and from the VA. All subjects were compensated with $25 USD for one hour of data collection.This project ended up utilizing data from 6 healthy participants, each joining for data collection within for a single one - hour long session consisting of a total of three conditions, each composed of 4 runs of 20 trials per run for a total of 80 trials per condition and 240 trials for the full duration of the experiment.

A collection of **20 trials** is referred to as a single **Run**. This study evaluated **4 runs** for each of **3 conditions**. A total of **12 runs** were conducted for each participant with a single run lasting roughly 5 minutes and the total experiment taking roughly **1 hour** not including setup time. **Figure 6** shows a diagram referring to the trial structure. The conditions of the within-groups experimental were designed for evaluating optimal BCI configuration across all participants.

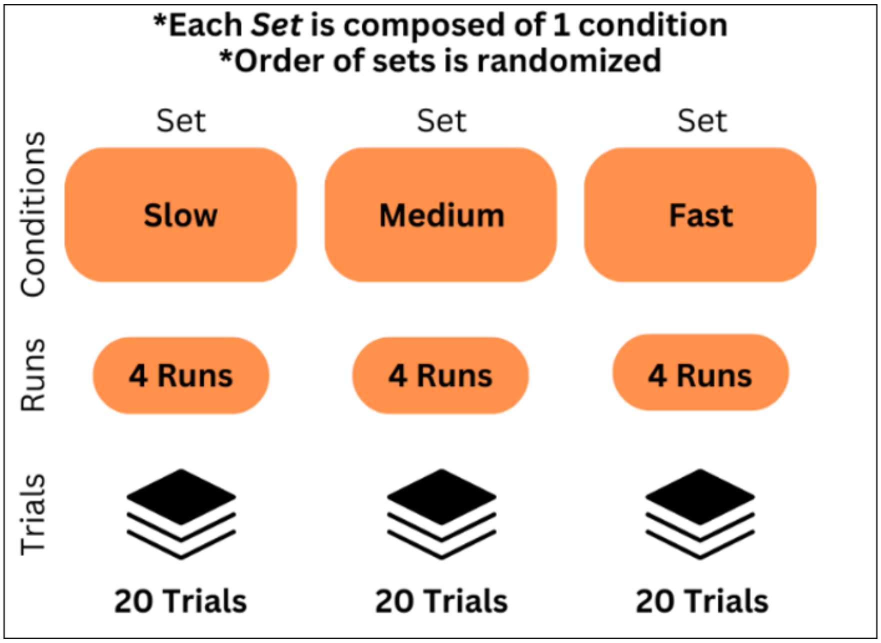

Figure 6: Diagram depicting the Trial Structure in the format of three sets.

Stimulus speed was quantified with each stimulus **within-stream period** referring to the duration in milliseconds between stimulus onset for each stream (i.e. The duration of time between the first ”Yes” and the next ”Yes”) and **between-stream period** referring to the duration in milliseconds between stimuli from each stream (i.e. The duration between the first ”Yes” and the following ”No”).

3.3 Data Analysis and Quality Validation

3.3.1 Retrieving Data for Analysis

The data was analyzed in evaluation of experimental results for or against hypothesis of this research project were retrieved from classifier prediction outputs following the second, third and forth runs for each condition for each participant. In order to evaluate classifier prediction accuracy for different conditions, the predicted attended audio was compared with the recorded prompted stimulus and an accuracy for each run was evaluated and analyzed further. The storage of the classifier predicition data was an already incorporated feature to the custom BCI2000 build that this research project utilized.

3.3.2 Signal Quality Validation

Signal quality for this study was evalutated using **ABRASIV**, a custom complex analysis tool developed for this project for conducting efficient comparative analysis on data for BCIs. This software toolkit was designed as a wrapper over several existing signal processing frameworks for the Python programming language such as BCpy2000, matplotlib, numpy and pandas. The fundamental contribution of ABRASIV was the seamless and rapid automation of the analysis of large data sets. This was validated first on data from Hill et al. (2014) [5] and Hill et al. (2012) [6] before being utilized to analyze the data collected in this study. For this project, ABRASIV primarily served as a toolkit for validating the quality of the data being collected to ensure that the results were reliable. In addition, ABRASIV's reliability as a software toolkit was evaluated by conducting analyses identical to that performed on data from Hill et al. (2014) [5].

There are several ways of evaluating the quality of an electrophysiological signal, however to remain consistent with methods from prior Auditory BCI research, the quality of a signal can be observed as a result of calculating a signal to noise ratio (SNR) [10] [5] [4]. ABRASIV was designed with many ways of calculating the SNR from a provided dataset however the quality validation used the same SNR method as Hill et al. (2014) [5], a D-prime analysis. Through the usage of identical SNR calculations, ABRASIV was able to demonstrate its reliability as a research tool for this study and in addition validated the quality of the data we were collecting.

3.3.3 Data Analysis

Using methods adopted from Hill et al. (2014) [5] and Hill et al. (2012) [6] to interpret the results of this research and assess whether the hypothesis posited held, the resulting prediction accuracy for each condition, run, and set were analyzed as a function of the percentage of hits per metric. In this context, hits refers to a instance where the classifier determined that the user attended stimulus and the prompted stimulus were equivalent. The results of these data were saved in a predictions data file for each subject following each run that began with a classifier trained, in this case runs 2,3,and 4. On the resulting data, statistical tests were conducted to evaluate significance. Primarily, a one-way analysis of variance was conducted on condition vs. prediction accuracy, run numbers vs. prediction accuracy, and set number vs prediction accuracy. Significant results were further analyzed with an all-pairs Tukey test.

4 Results

The results all measured metrics against prediction accuracy. The prediction accuracy (as mentioned in methods) was equal to the number of correct predictions (quantified by the amount of prompted stimuli that matched predicted stimuli) out of all stimuli. This can be thought of as a hit or miss ratio. (For example: a run where the classifier identified that the participant correctly attended to prompted stimuli 16 / 20 times would have a prediction accuracy of 80% for that run).

The means of all conditions representing stimulus presentation speeds of 4 stimuli per second (slow), 6.66 stimuli per second (medium) and 10 stimuli per second (fast) were calculated and their associated averaged prediction accuracy were compared. A oneway ANOVA determined that the results of the condition against accuracy were statistically significant (F Ratio: 7.4757, P-Value: 0.0016*). The R-Squared value of a best fit line was found to be 0.249391. An all-

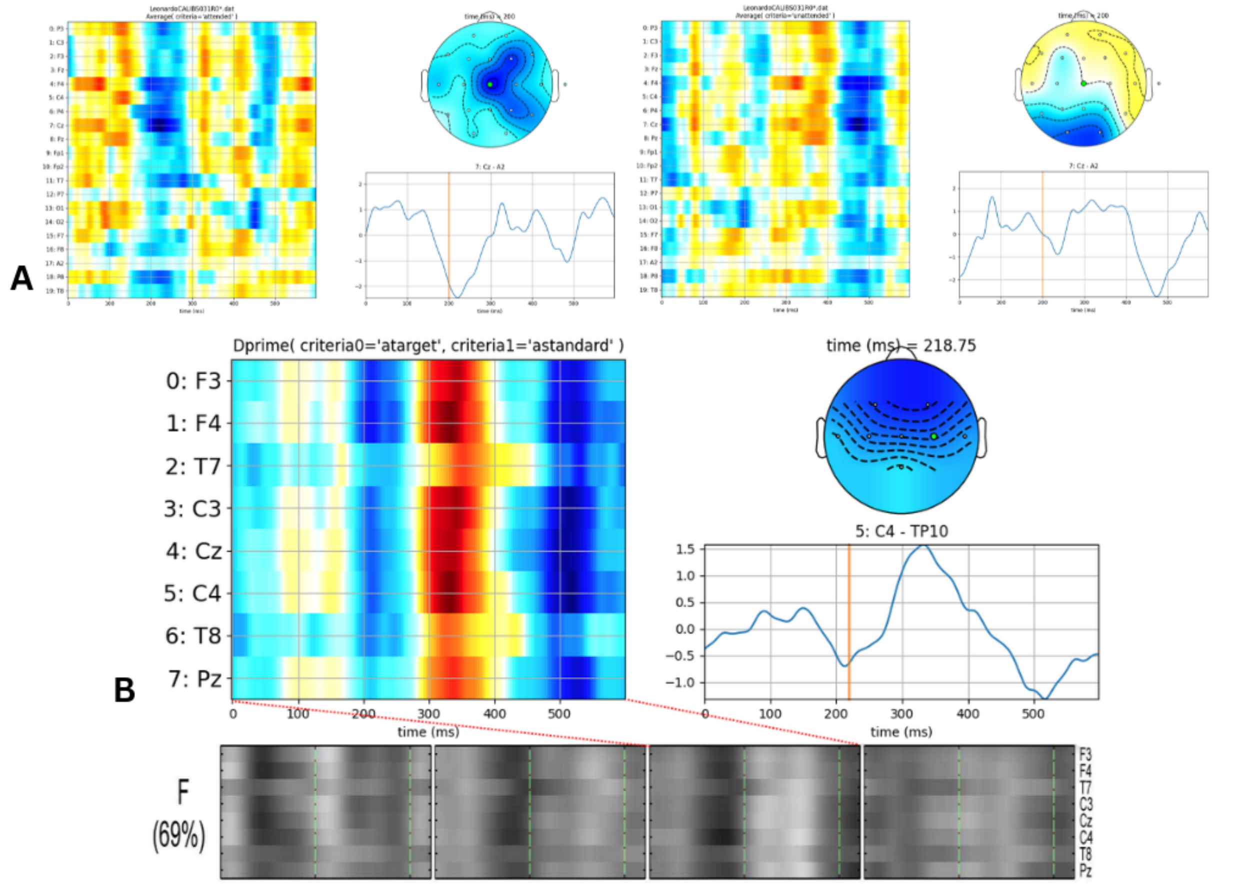

Figure 7: Shown here are different outputs of the ABRSAIV during the signal quality and validation component of this research in the form of raster plots visualizing the shape of averaged EEG for the evaluation of ERPs within data.
A: ERPs evaluating the Auditory BCI for this study. The two raster plots show brain activity for **attended** and **unattended** stimuli. Notice how for attended stimuli, a very prominent negative at 200ms. The unattended stimuli has no trough at 200ms but does have one around 450ms. This is actually because in this paradigm stimuli are played exactly 250ms apart. Hence, after 250ms pass from unattended stimuli playing, the stimuli to attend to plays again resulting in an Evoked Potential 200ms after and thus showing it at 450ms for unattended. Note that depending on the manner through which the raster plot is generated, the ERP may be inverted indicating that the trough at 200ms may actually be a peak indicating a prominent P200 ERP. **B**: A rasterplot generated off of data from Hill et al. (2014) [5] depicting the **D-prime** analysis of attended target stimuli versus attended standard stimuli for **Subject F** in Hill et al. (2014) [5]. This comparison of ABRASIV's output against the results reported in prior research served to confirm ABRASIV's reliability as a data analysis tool.

pairs Tukey Test further found that the Slow Condition was significantly different from Fast (P-Value: 0.0015*), and was also significantly different from Medium (P-Value: 0.0331*), however Medium and Fast were not significantly different from one another (P-Value: 0.5285).The calculated means of all conditions as shown in Figure 8, demonstrate that, in line with the hypothesis, the slowest condition consisting of a between stimuli period of 500ms and a within stimuli period of 250ms, performed significantly better than the other two conditions.

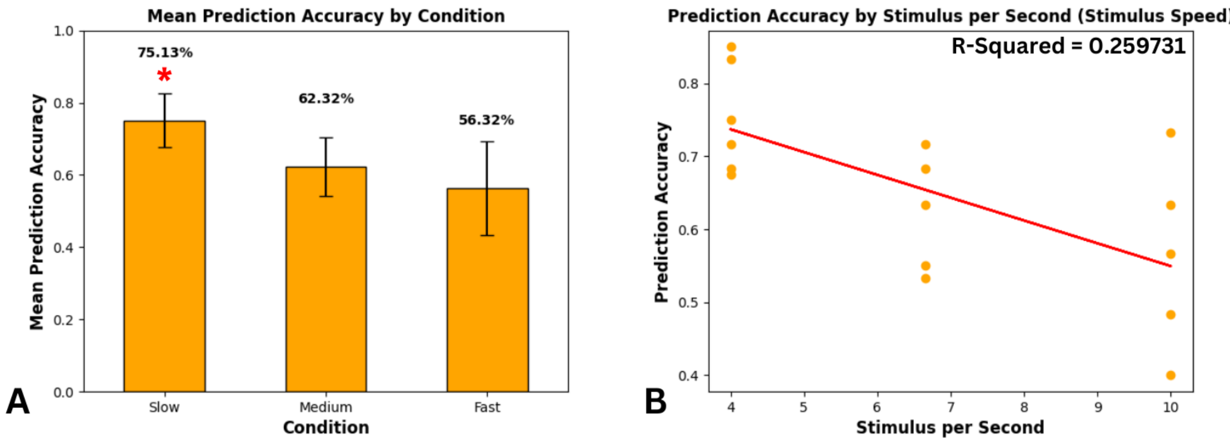

Figure 8: The calculated mean accuracy for condition and associated stimulus per second.
A: The calculated means of each condition as averaged from the six subjects whose performance metrics were quantified by the system's integrated classifier. **B**: A linear regression analysis on the condition data as quantified by stimulus per second vs prediction accuracy. The significance probability was equal to **p** < **0.0005***

In terms of change in prediction accuracy over time in terms the classifier's accuracy across runs, a oneway ANOVA determined that none of the the runs were statistically significant from each other hence across all runs regardless of set number or condition there was no statistically significant changes in performance across runs (F Ratio: 1.7559, P-Value: 0.1844). The experiment was conducted over multiple runs, and the accuracy measurements were consistent throughout (Figure 9). This means that there was no increase in accuracy over time, hence the hypothesis didn't hold for this specific case of accuracy over time. The consistency in prediction accuracy across runs regardless of condition order suggests that the experimental conditions were effectively controlled, minimizing the influence of confounding factors on the results.

Expanding the analysis of change in classifier accuracy over time to the overall trend across all sets - an interesting pattern was found. The number of sets experienced by the participant, which can be considered analogous with the amount of time spent in the experiment overall resulted initially, in a statistically significant increase in prediction accuracy, independent of condition, from Set 1 to Set 3 (F Ratio: 3.7851, P-Value: 0.0302*) as determined by a oneway ANOVA (Figure 10). Initially there was a noticeable increase in accuracy, however by the third set for all subjects there followed a statistically significant drop in accuracy by the third set. This finding indicates that the participants' performance improved initially but then declined, suggesting the presence of a learning effect or some other factors affecting their cognitive processing. An all-pairs Tukey Test found a statistical significance between the second set and the third set (P-Value: 0.0229*). There was no statistically significant difference between the first set and second set (P-Value: 0.2780), or the first set and third set (P-Value: 0.3912). A linear regression analysis found no statistically significant trend from the first set to the third (R-Squared: 0.027211, F Ratio: 1.2867, P-Value: 0.2625).

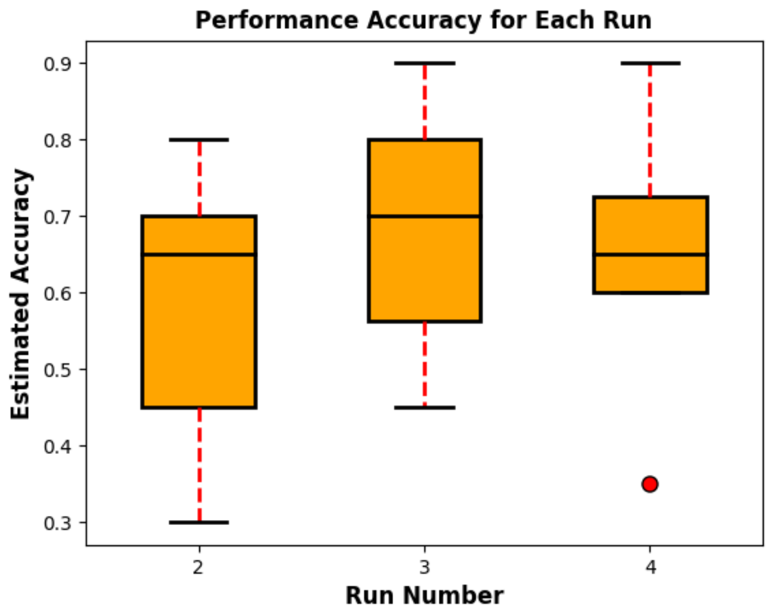

Figure 9: Change in classifier prediction accuracy over runs. Runs start from Run #2 as Run #1 is always spent calibrating the classifier weights to the participant before it can begin classifying their data as described in the Methods.

Despite the lack of statistical significance in some aspects of these results, the observed trends in the data and the significance in certain analyses suggest potential patterns and differences that warrant further investigation. It is important to consider that the effect size and power of the statistical tests may influence the significance levels obtained. Additionally, other factors not accounted for in this study, such as individual differences or external variables, may contribute to the observed fluctuations in accuracy.

5 Conclusion

This study aimed to evaluate the effectiveness of different stimulus speeds and usage time on prediction accuracy while keeping the methods for generating predictions identical to prior research in Auditory BCIs. This was performed to find features of an Auditory BCI that make it optimal for the user to operate. The results indicated a notable trend; as hypothesized - slower stimulus speeds composed of 4 stimuli per second were associated with higher mean accuracy compared to medium (6.66 stimuli per second) and fast (10 stimuli per second) conditions. Although statistical significance, as well as sample size were modest - further exploration with more participants could reveal a more pronounced and significant difference between slow conditions and other conditions. Additional future work in analyzing the results of study's such as this should also consider utilzing metrics such as Signal-to-Noise Ration to assess the

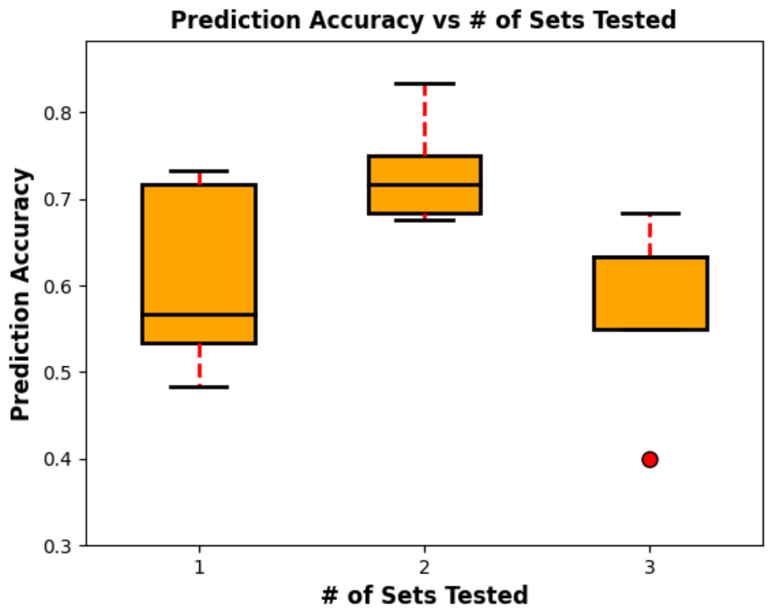

Figure 10: Change in classifier prediction accuracy over runs

prominence of ERPs under different conditions.

While the hypothesis regarding optimal stimuli held true, the prediction that classifier accuracy would improve over time did not necessarily hold. The decline in accuracy after a certain period may be attributed to cognitive fatigue, as the task of directing auditory attention was observed to be tiring over time as was verbally indicated by all individuals who participated in this study. This finding may prove crucial, especially considering that Auditory BCIs are intended to assist individuals with limited communication alternatives. Understanding the diminishing returns in classifier accuracy over time is essential for developing effective and practical BCIs.

Future research continuing the concepts of this study would likely involve a larger sample size of at least 15 participants within the same age range. Keeping the results of this study in mind, future data collection should be conducted during shorter sessions spread out across several days to potentially observe improvements in classifier accuracy due to participant adaptation. Furthermore, additional future work in this area could explore different classifiers and compare their performance to the one utilized in this study. Evaluating various classifiers can provide insights into their suitability for Auditory BCIs and potentially enhance prediction accuracy as has been evaluated in prior research BCIs.

In conclusion, we found that with a reasonable certainty, slower stimulus speeds result in greater prediction accuracy than medium or fast, at least for the provided parameters. This is observable regardless of condition order. In terms of how the classifier prediction accuracy changes over time, there are still many more features to consider, primarily whether or not a cognitive fatigue is a contributing factor to the decline in accuracy after an increase in accuracy.

This study contributes to the existing literature on stimulus speed and prediction accuracy by providing a starting point for generating more empirical evidence for designing BCIs that are as good as their ease of use is. However, further research is needed to explore the underlying mechanisms and factors that influence the temporal dynamics of accuracy. Moreover, the applicability of the findings in this research to both more Auditory BCI work as well as other domains of computational neuroscience should be evaluated in future studies.

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