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Advisor Name Mayank Goel Department Institute of Software Research

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Brain Board: A Context Based BCI keyboard

Jett Hays; Jaylem Brar; Ethan Todd

Part I. Abstract

As the world has become increasingly digitized, social relevance and economic viability have become dependent upon the ability to push buttons in a complex manner. Keyboards have become our link to vast amounts of information and computing power, but they have also restricted this access to those with the ability to express thought physically. Our project aims to sidestep this dependency through the development a mind-controlled keyboard that is 50% faster and 5% more accurate than those currently available. While brain computer interface (BCI) keyboards are not a new concept, current implementations suffer from excessive lag times and model inaccuracy. The blended method of direct sensing, machine learning, and text analytics we propose, is expected to increase the low signal to noise ratio characteristic of EEG data by providing autocomplete models and brainwave classifiers with the context of a user's neural activity. If successful, this context-based approach to BCI keyboards will grant the physically impaired increased access to the digital age, while simultaneously providing new ground upon which the BCI field can stand.

Part II: Research Question and Significance

While technology blazes a path into a digital future, those with physical disabilities are left with a present in which input systems remain reliant upon the complex movement of fingers. An alternative keyboard industry has attempted to establish a link between the disabled and computers, but current solutions on the market have focused on the ergonomics of a keyboard as opposed to attacking the concept of a keyboard itself (NIOSH).

A truly accessible keyboard will not merely make buttons bigger or reformat the QWERTY layout, but rather bypass a physical implementation of keys altogether; if you can think, then you can type. Research is being done in the area of BCI keyboards, however, previous attempts to bridge the divide between disabled humans and computers through noninvasive brain computer interfaces have resulted in only tenuous connections fraught with inaccuracies and excessive lag times. The current noninvasive standard is about 16 *letters* per minute (Nagel & Spüler, 2019). Invasive BCI implementations have fared better—achieving a 'typing' speed of 8-40 WPM—but the nature of an invasive process prevents these methods from being accessible alternatives to physical keyboards (Goldman, 2017). Our research objective is *to develop a noninvasive mind-controlled keyboard that is faster and more precise than those currently available through a context-based approach*. The software-based approach we propose, combined with readily available hardware, will decrease the economic and training burden associated with existing BCI approaches, while simultaneously providing a high performing model that can be incorporated within other virtual keyboard systems that are under development.

Part III: Project Design and Feasibility

A context-based approach— in which neurological signals provide additional features to a predictive text model— appears to be the most feasible with respect to our stated aim of increasing the accuracy and speed of noninvasive BCI keyboards. The separation of concerns inherent in Model View Controller (MVC) architecture will allow for this iterative testing process in which various aspects of the MVC can be evaluated and subsequently modified based on performance without demolishing the architecture as a whole. The proposed system will implement a MVC architecture in the following format:

Model: In order to reduce the lag between signal—in this case a user's brain waves— and system response, our model will have to reduce the false negative rate. While there is a necessary tradeoff between false negative and false positive rates, the context-based approach we propose, in which neurological and text cues reinforce one another, is expected to mitigate the decrease in accuracy associated with an increase in sensitivity.

The model will consist of two interacting components: a text analysis aspect that provides auto-complete functionality and an ensemble of classifiers for incoming EEG data. Our algorithm will need to classify event-related potentials (ERPs) triggered by the specific frequencies of items in our view (Siuly, Li, & Zhang, 2016). We expect a bagging method to be most appropriate for establishing a general model for ERP classification that avoids overfitting, and a boosted method to be most appropriate for user calibration (Aricò, Borghini, Di Flumeri, Sciaraffa, & Babiloni, 2018). Predictions of characters and/or words can then be fed into our text-analysis algorithm that, when combined with linguistic and emotional context, will provide auto-complete functionality. Word predictions will then be presented by the view for selection by the user. This interplay between a user's reaction to stimuli on the screen, background EEG processing, and text analysis presents a tractable area of exploration that has yet to be fully explored by traditional approaches (Aricò, Borghini, Di Flumeri, Sciaraffa, & Babiloni, 2018).

View: The view controls the interface between the user and ERP inducing stimuli. Numerous methods of display have been produced by prior studies including hexagonal, circular, and Rapid Serial Visual presentations, but a matrix solution in which characters flash at different frequencies appears to be the most tenable (Kumar, 2014). This method takes advantage of the Steady-State Visual-Evoked Potential (SSVEP) paradigm, which will provide our model with a relatively high signal to noise ratio (İşcan & Nikulin, 2018). Once enough context has been established, the view will provide the user with an array of autocomplete options that will significantly increase typing speed.

Controller: The controller will act as the bridge between the stimulus inducing display and stimulus classification. In addition, the controller will ensure data collection and stimulus production stay in sync, while also preselecting a classifier.

Performance will be measured on a words per minute basis, with this data collected from a variety of users to ensure the extensibility of our system. We also intend on using chance performance to compare our model's performance to that of a random classifier; this will provide valuable feedback while limiting the amount of data we must collect.

Weeks	Hours	Anticipated Benchmarks and Tasks to Complete

Pre-project	N/A	Review relevant literature and open source EEG data sets. Reach out to professors with domain specific knowledge.
0-1	12	Setup sensor and associated software.
1-3	20	Complete construction of view/ controller. Design SSVEP paradigm.
3-5	20	Collect data in conjunction with view and controller.
5-8	30	Clean data. Time allowed for additional/revisional data collection. Continue research EEG feature supplemented text analysis.
8-15	70	Construct model in accordance with typical ML pipeline. Continuously evaluate classifier performance with respect to previously developed systems.
15-18	30	Model experimentation and evaluation. Complete working prototype with context-based cues.
18-22	40	Continue to refine system. Gather performance statistics.
Post-project	N/A	Compile summary/ paper. Reach out to publications. Disseminate.

Part IV. Background

Development of a BCI based keyboard requires the complex integration of data analysis, machine learning, signal processing, and programming. A plethora of projects have honed my abilities in these fields and provided me with a firm grasp of Python (including ML focused libraries such as SciKit and OpenCv), C, and SQL databases. A complete listing of these projects can be found on my GitHub: https://github.com/jettblu. I am currently taking a course on data science, which has furthered my understanding of statistical models, and a course on machine learning and sensing—taught by my faculty mentor— which has provided me with the tools to implement all aspects of a machine learning pipeline. Jaylem Brar of Berkeley will be responsible for data analysis, the co-development of classifiers, and model evaluation, while I will be responsible for the construction/implementation of our MVC. Ethan Todd will be responsible for sensor setup and data collection.

Part V. Feedback and Evaluation

Our advisor, Mayank Goel, will provide verbal feedback on a weekly basis and review collected EEG data for potential patterns our models may have missed. Performance will be evaluated with respect to our stated objective of boosting the accuracy/ speed of existing BCI keyboards.

Part VI. Dissemination of Knowledge

All avenues of official dissemination will be explored including, but not limited to, the Meeting of the Minds, the International Conference on Brain Computer Interfaces, the 10th International Winter Conference on Brain-Computer Interface, and Google's Distill. We also intend to make our results accessible to a wider audience through the publication of articles on popular websites such as Medium and Towards Data Science and through videos on platforms such as YouTube. In summary, the results of our research will take the form of a working prototype, a formal paper, accessible articles, and short videos; all code will be made open source on GitHub.

Part VII. Budget:

Item	Description	Cost
Ultracortex "Mark IV" EEG Headset	3D-printable headset capable of recording research-grade EEG signals. Includes dry EEG sensors.	$449.99
Cyton Biosensing Board (8-channels)	Board samples EEG data which is then transmitted wirelessly to computer.	$499.99
Dry EEG Comb Electrodes (Pack of 30)	Enhance wearability and Ag-AgCl signal quality of headset.	$29.99
Total Direct Cost:	*sum of above items (all purchased through **OpenBCI**)*	**$979.97**

When combined into one headset, the above items will allow for the recording and transmission of research-grade EEG signals. As our proposal centers around real-time EEG data, it is imperative that our sensing apparatus is capable of the high-quality sampling rates (250 HZ across 8 channels) that the above headset enables. All components are sourced from OpenBCI, a company known for producing open-source, low-cost, and research-grade biosensing hardware. OpenBCI also includes a free GUI with their hardware that will be useful when analyzing live data. Any portion of the budget that is not met by SURG, will be covered with independent funds. The EEG headset can be printed in CMU's SMASH lab.

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