Mathematics Senior Showcase 2020 Mathematics Senior Showcase

12-1-2020

Morse-Code Encoded Eye Blinking as a Source of Biometric Authentication via EEG

Ben Adams

Meghan Edgerton
Boise State University

Gabe Miles
Boise State University

Callum Young
Boise State University

Morse Code Encoded Eye Blinking as a Source of Biometric Authentication via EEG

Callum Young, Gabriel Miles, Ben Adams, Meghan Edgerton

BOISE STATE UNIVERSITY

INTRODUCTION

As technology evolves, it has slowly become more integrated into our everyday lives, with some devices even becoming a physical part of us. A brain-computer interface (BCI) seeks to bridge the gap between man and machine by creating an artificial link between the two. BCI's cover a wide range of applications, from reading brainwaves to help those with paralysis speak, sending electrical impulses into the brain to treat diseases like Parkinson's, to the Neuralink created by Elon Musk to connect our brains to our smartphones. With new machine learning models, it may be possible to collect data transmitted by these devices and reproduce it, which could have disastrous consequences if that information is used for device authentication [1, 2, 3].

EEG

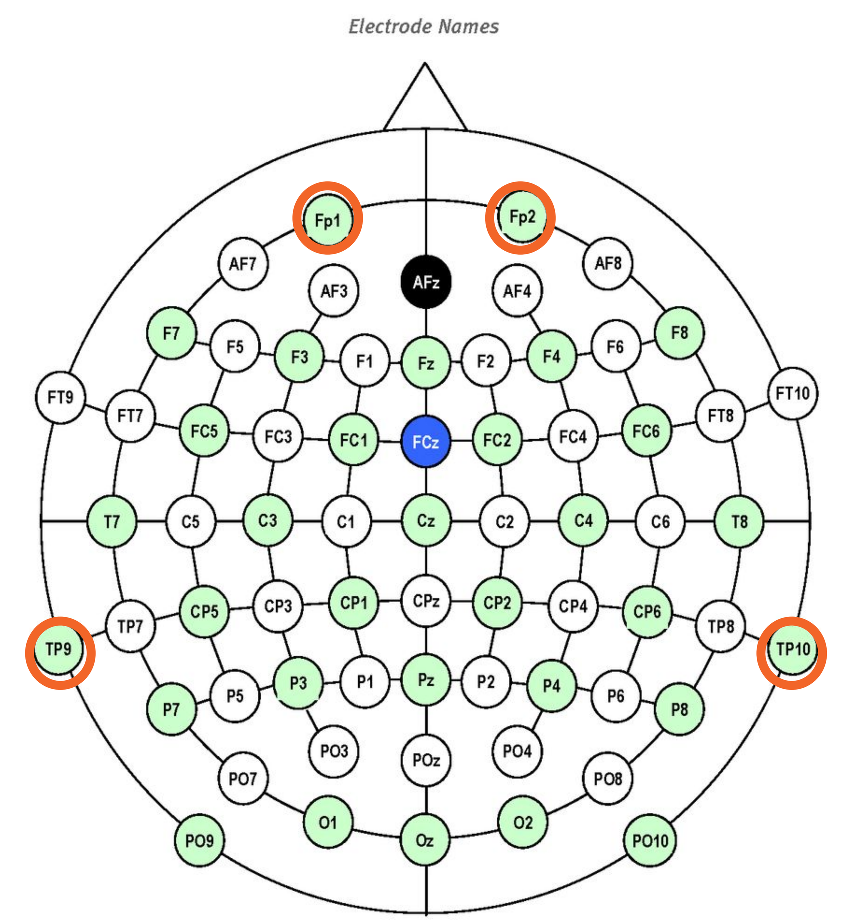
The electroencephalogram (EEG) uses electrodes placed on specific locations on the cranium to pick up trace amounts of electrical activity. This activity falls into two categories - neural electrical activity called brain waves, and non-brain electrical activity called artifacts. For our project, we focused primarily on three of these present on the EEG:

- Alpha brain waves: shorter frequency, larger amplitude
- Beta brain waves: longer frequency, lower amplitude
- Eye blink artifacts: increases in potential from movement of eyeball during blinking

Morse Code

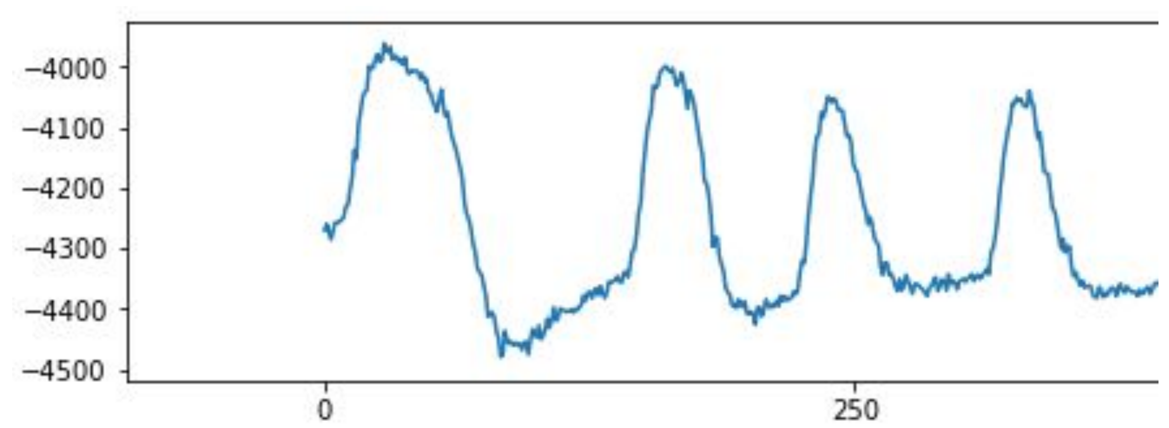
A	• —	U	• • —
B	— • • •	V	• • • —
C	— • — •	W	• — —
D	— • •	X	— • • —
E	•	Y	— • — —
F	• • — •	Z	— — • •
G	— — •		
H	• • • •		
I	• •		
J	• — — —		
K	— • —	1	• — — — —
L	• — • •	2	• • — — —
M	— —	3	• • • — —
N	— •	4	• • • • —
O	— — —	5	• • • • •
P	• — — •	6	— • • • •
Q	— — • —	7	— — • • •
R	• — •	8	— — — • •
S	• • •	9	— — — — •
T	—	0	— — — — —

Electrode Map



Electrode locations during tests: Fp1, Fp2, TP7, TP8 [4]

EEG Recording for "B"



OpenBCI

We used a 4 channel EEG headband purchased from OpenBCI for data collection. OpenBCI is a company that provides open source biosensing software that is used to operate the EEG and collect attributed data. It also automatically cleans the data, filtering out most of the interference from several sources - including electrical activity of facial muscles, slight head movement, and ambient electromagnetic radiation.

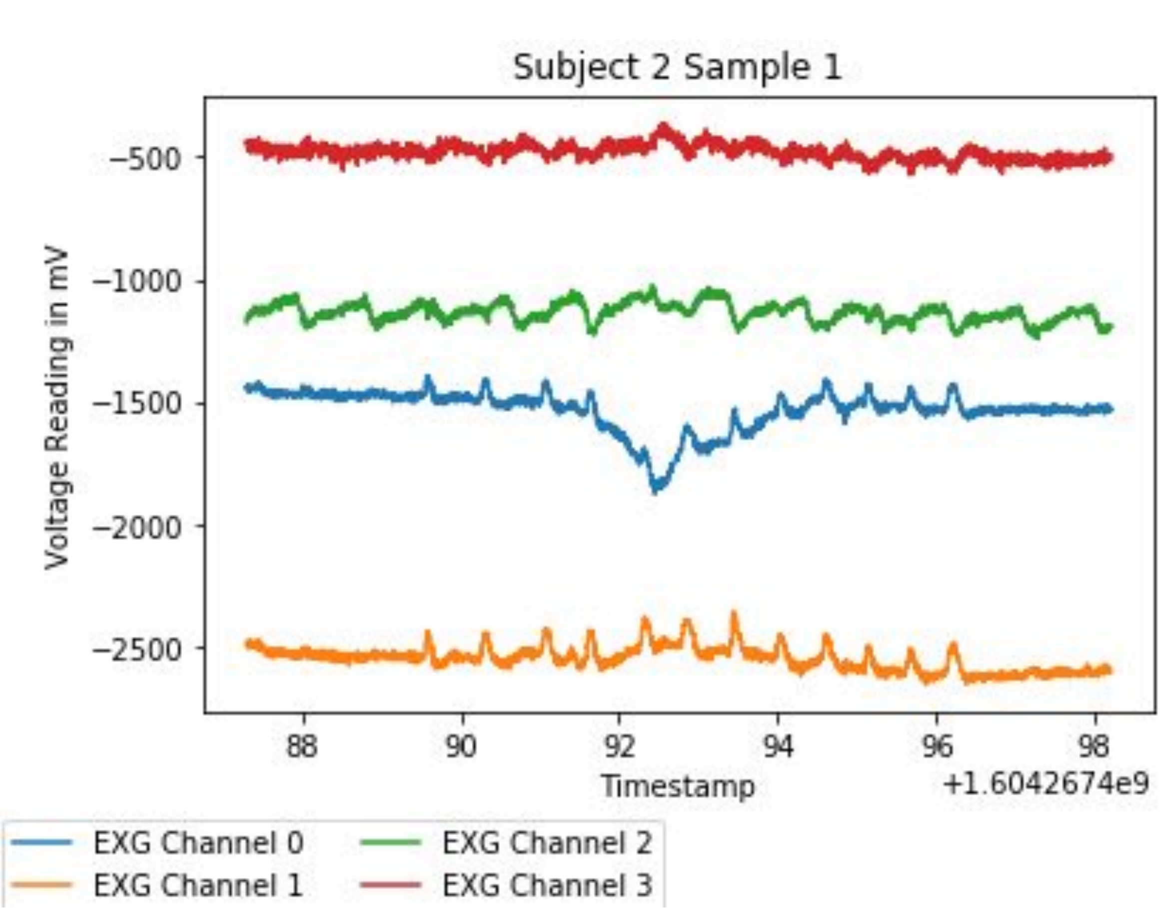
Methods

The first step after data collection was to trim the data and visualize it. In order to do so, we analyzed the data using Python to figure out the intervals in which the EEG picked up on when the test subject was blinking at varied speeds. The plots display the voltage readings from the four different channels over the time in which the samples were taken for each test subject.

Data

- 4 electrodes, one stream of data per electrode
- Each stream reports the voltage for the respective electrode
- Amplitude of waves represent change in voltage
- "Events" are characterized by larger spikes in the graph

EEG Electrode Data



Conclusion

We have shown that biometric devices such as EEG's and other implantable sensors such as Brain Computer Interfaces (BCI) are prime candidates for biometric authentication. These devices are able to measure passwords relayed by the individual both through electrical and mechanical movement, and are consistent enough in order to reliably send an encoded password to a device for authentication.

Artifacts occur because of the movement and activities of the subject, so outlier handling and methods to ignore irrelevant data are necessary, as these artifacts occur even in more controlled environments.

Future Work

EEG data is provided as a stream of biometric information, and common practices to interpret temporal data such as Recurrent Neural Networks also show promise in this line. Basic assumptions can be made about the format of the data, but an RNN can be used to learn the patterns of the individual and extract meaningful information from such streams of data from devices.

References

[1] Nishimoto, T., Higashi, H., Morioka, H., & Ishii, S. (2020). EEG-based personal identification method using unsupervised feature extraction and its robustness against intra-subject variability. *Journal of Neural Engineering, 17*(2). doi: 10.1088/1741-2552

[2] Chan, H. L., Kuo, P. C., Cheng, C. Y., & Chen, Y. S. (2018). Challenges and future perspectives on electroencephalogram-based biometrics in person recognition. *Frontiers in Neuroinformatics.* doi: 10.3389/fninf.2018.00066

[3] Wu, Q., Zeng, Y., Zhang, C., Tong, L., & Yan, B. (2018). An EEG-based person authentication system with open-set capability combining eye blinking signals. *Sensors (Basel), 18*(2), 335. doi: 10.3390/s18020335

[4] Rupasov, V., Lebedev, M., Erlichman, J., & Lee, S. (2012). Time-dependent statistical and correlation properties of neural signals during handwriting. *PLoS ONE, 7*(9). doi: 10.1371/journal.pone.0043945

Acknowledgments

We thank the Boise State College of Innovation and Design for their support of the project, as well as our mentors Dr. Liljana Babinkostova, Robert Erbes (Idaho National Laboratory), Jay Radcliffe (Thermal Fisher Tech), Dr. Marion Scheepers and Dr. Edoardo Serra.