Real-time remote control of a car with an SSVEP-based BCI

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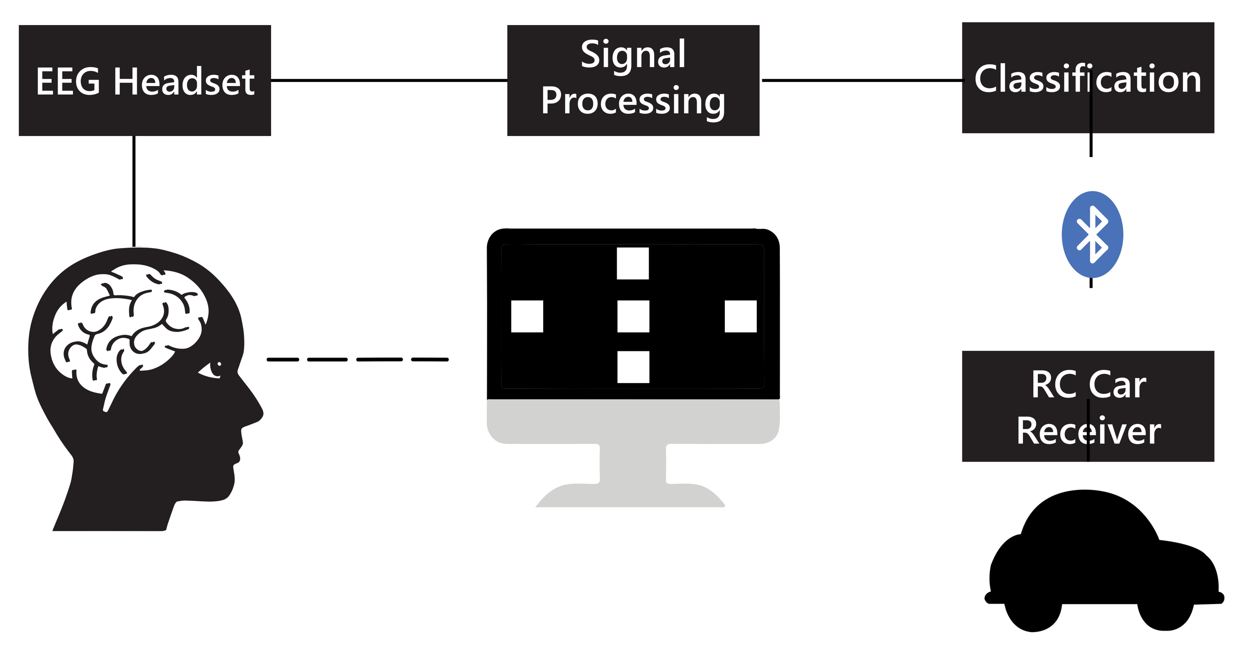
ABSTRACT

We aim to create an electroencephalography (EEG)-based brain-computer interface (BCI) to wirelessly and instantaneously control vehicle movement.

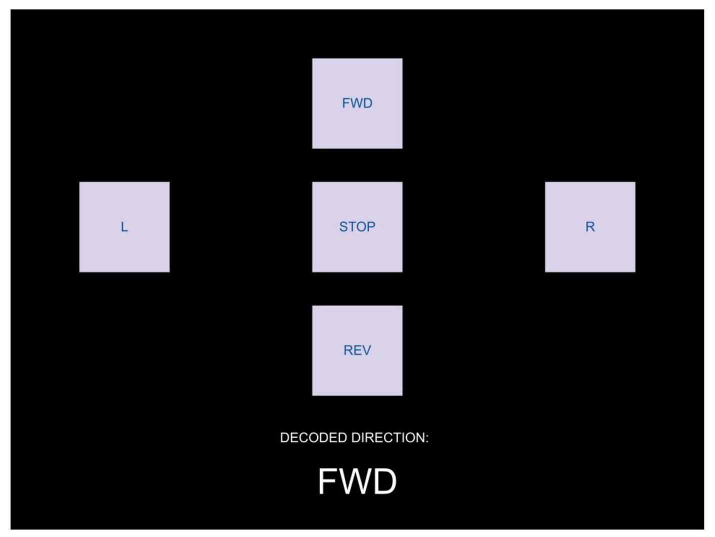
Through classifying steady-state visually evoked potentials (SSVEPs), we will control the movement of a model vehicle through a maze.

Figure 1: Data Flowchart



A user focuses on controlling remote buttons on a monitor, inducing SSVEPs. Such signals are captured by an EEG headset, processed, and translated into different movement commands. These are then sent via Bluetooth to the model vehicle.

Figure 2: Graphical User Interface



Directional buttons labeled FORWARD, BACKWARD, LEFT, RIGHT, and STOP on the graphical user interface (GUI) flicker at different frequencies to induce SSVEPs. Focusing on a directional "button" will induce a unique SSVEP for the button.

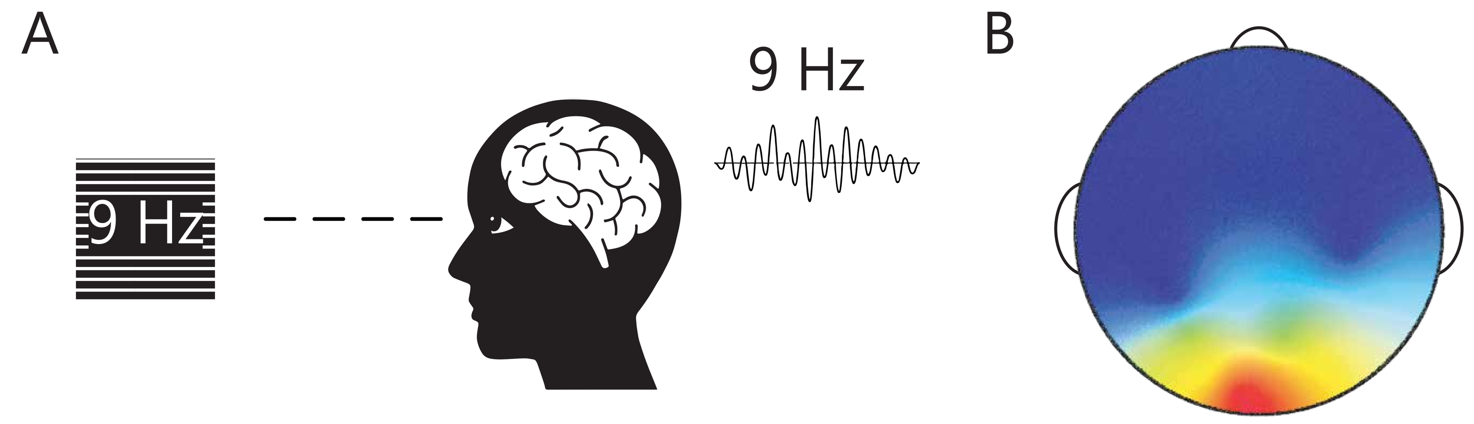
SIGNIFICANCE

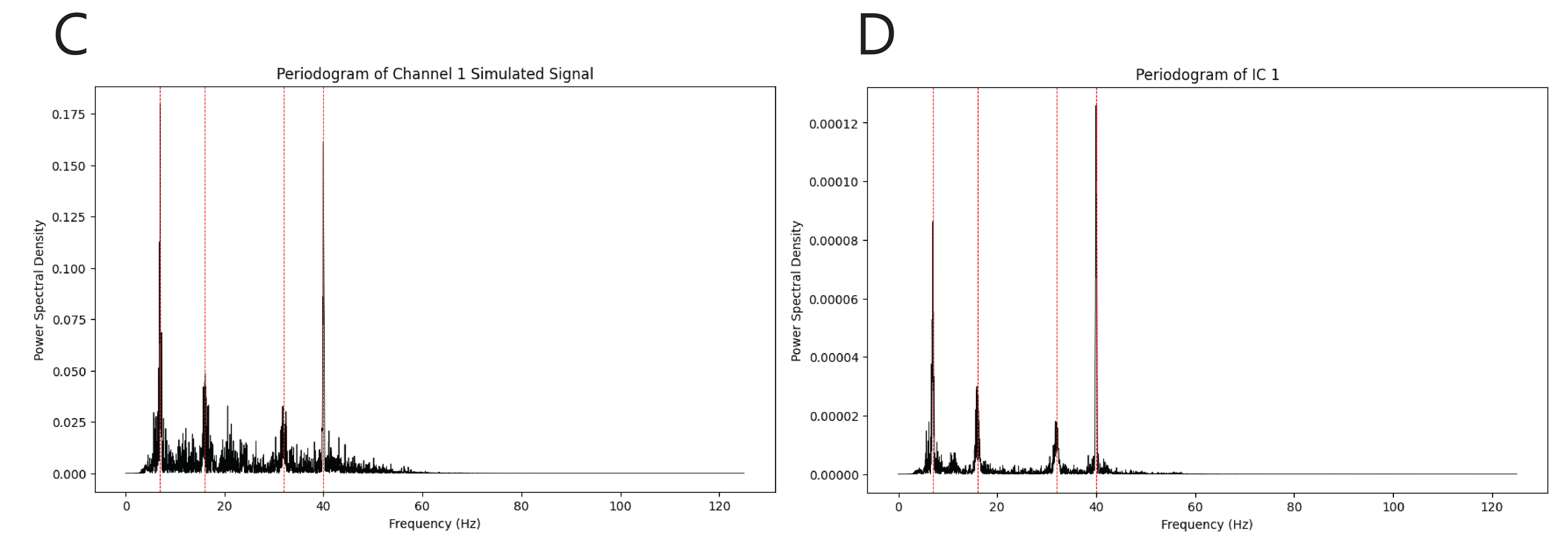
Approximately 1.7% of Americans are paraplegic and require assistance for mobility. Several BCIs have been developed to assist paraplegic individuals with tasks such as limb control or vehicle operation, but remain limited by their accuracy, speed, and accessibility.

SSVEP classification is a growing area of research, focusing on accuracy and speed.

We hope our findings may spur further development of quick, accurate, and accessible BCIs designed to aid physically disabled individuals.

Figure 3: Example SSVEP

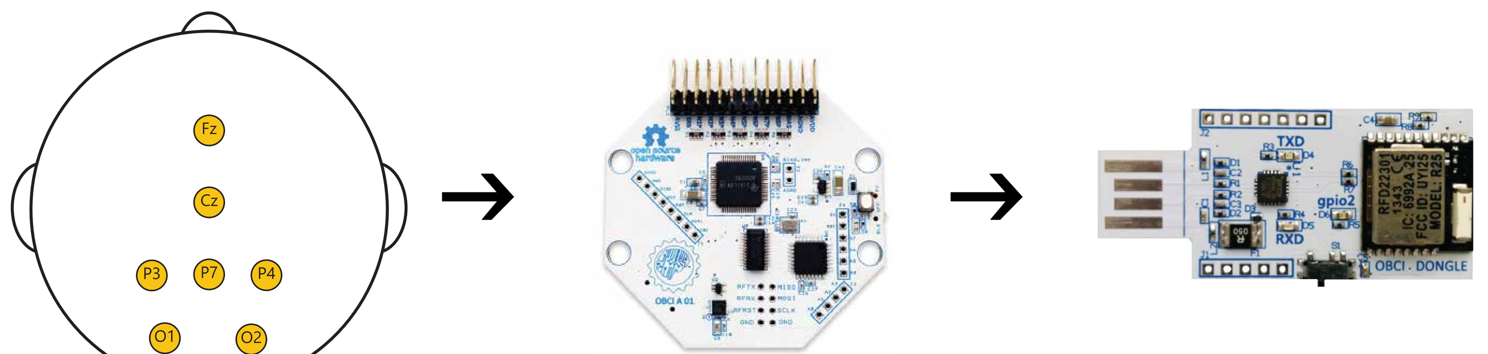




A) SSVEPs are electrical signals in the brain induced by visual stimulation. We will use these signals in particular due to their high information transfer rate, superior performance compared to P300 and motor imagery-based BCIs, and minimal training requirement. B) Simulated EEG topographic map of an induced SSVEP.

A) Simulated EEG signals from 8 channels. Signals are bandpass filtered from 5-50 Hz. SSVEPs induced at 1000, 2000, 4000, 5000, 5500 ms. Artifacts induced at 500 and 3000 ms. B) Decomposed signals from independent components analysis (ICA). Artifacts are successfully identified in IC 2. C) Periodogram of channel 1 signal. SSVEP frequencies (7, 16, 32, 40 Hz) are identified with red vertical lines. D) Periodogram of IC 1.

Figure 4: EEG Configuration



The electrodes in use are as follows: P3, P7, P4 (parietal lobe), O1, O2 (occipital lobe), Cz (ground), and Fz (reference). Signals will be recorded with an OpenBCI EEG headset (left), connected to the Cyton (middle), and sent to the Bluetooth dongle.

Figure 5: Signal Acquisition and Processing

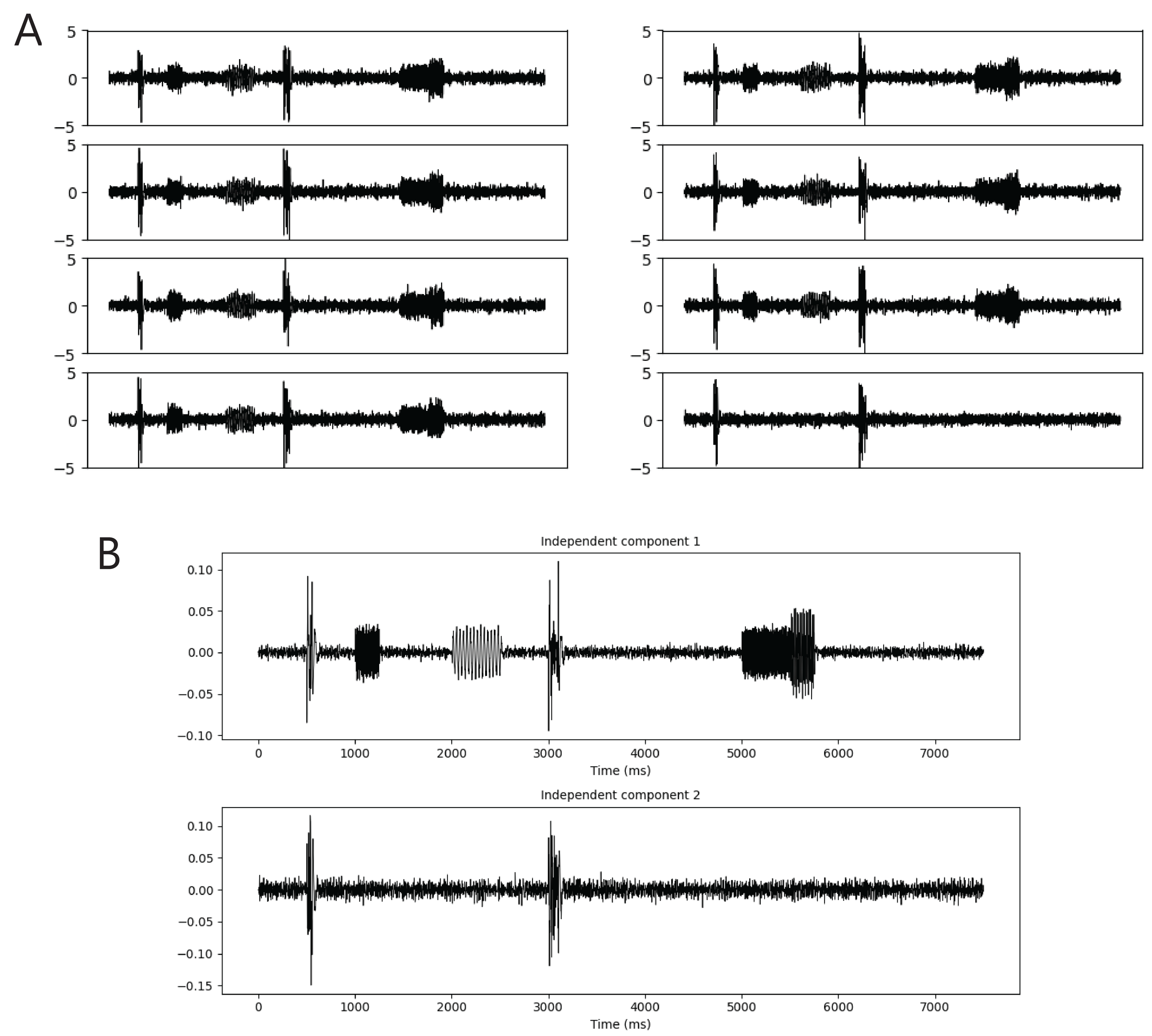


Figure 6: Classification Algorithm

A

$$\rho = \frac{a^T \sum_{XY} b}{\sqrt{a^T \sum_{XX} a}\sqrt{b^T \sum_{YY} b}}$$

B

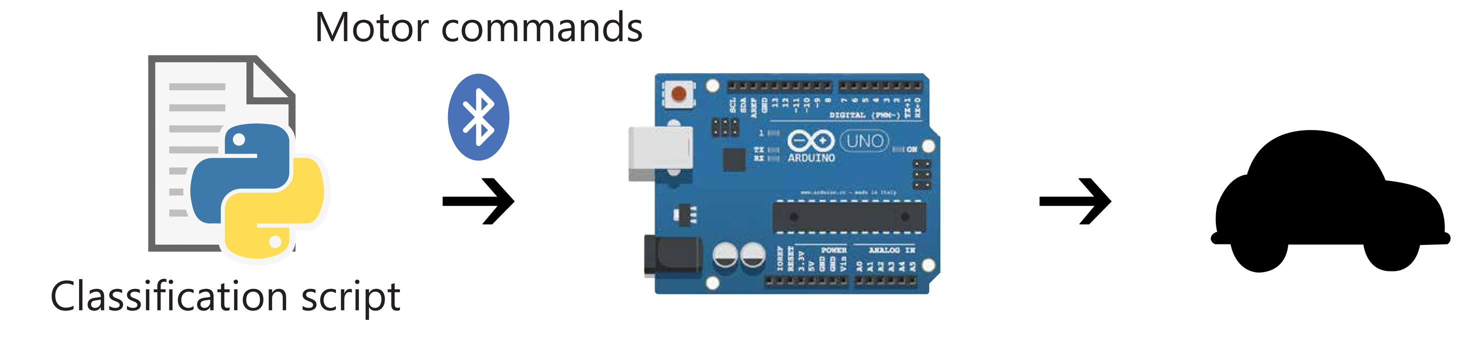
$$T(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^* \frac{(t-b)}{a} dt$$

C

$$\frac{1}{2}w^T w + C\sum_{i=1}^{l}\xi$$

A) Canonical correlation analysis (CCA) coefficient formula. EEG matrix will be correlated with a template frequency matrix. B) Continuous wavelet transform (CWT). Output of transform and CCA coefficients will be used as features. C) Support-vector machine (SVM) objective function. A design matrix will contain the features from CCA and CWT and will be passed into the SVM. The SVM will be trained on labeled data to classify different SSVEP frequencies as direction commands.

Figure 7: Remote Control Vehicle Schematic



CONCLUSIONS

Based on our research, this design is a robust proof-of-concept of a remote control BCI vehicle. Software and hardware adjustments will be made to even further maximize the usability of the BCI. Navigation of the vehicle through a maze will demonstrate success for this project; its completion will hopefully encourage further research and development in the field of assistive BCIs.

ACKNOWLEDGEMENTS

We would like to thank CruX UCLA, Dr. William Speier, and CruX academic and research sponsors for their funding and support toward this project.