A User-Friendly, Low-Cost, Real-Time Wheelchair Prototype Using Motor Imagery and Eye Blinking

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***Abstract*— EEG-based brain computer interfaces have been proposed as a method to facilitate the interaction of locked-in syndrome patients with the external world. In this paper, we present our design and implementation, including data acquisition, neurofeedback training, signal processing and machine learning algorithms of an EEG-based, OpenBCI wheelchair prototype. The wheelchair is controlled by motor imagery (MI) and eye blinking which generates four commands: forward, left, right, stop. Additionally, we developed a mobile app for caregivers to monitor the wheelchair and the user in real time, in conjunction with a heart rate-dependent brake system which together work to ensure the user's safety.**

I. INTRODUCTION

While patients with Locked-in syndrome lose complete control of the majority of voluntary muscles, their cognitive functions are usually unaffected. However, extraocular muscles often retain their function, allowing patients to potentially communicate through eye movements and blinking (1). In recent years, brain-computer interfaces (BCIs) have emerged as a method to enable patients with the locked-in syndrome to interact with the external world (2). Electroencephalography (EEG) is a technique to detect neural activity and has been widely used in conjunction with BCIs, due to its non-invasive nature, accessibility, affordability and fine temporal resolution (3).

EEG-based BCIs mainly use three signals: P300 wave, steady-state visually evoked potentials (SSVEPs) and motor imagery (MI). In particular, one does not require external stimulus to generate MI, allowing the users to control external devices at free will (4). When users execute real movements or imagine movements (during a motor imagery task), there will be suppression of the mu rhythm (7-13Hz) (5). In addition to the MI, eye blinking signals have been widely used in BCI-based wheelchair control (6). Eye blinking is relatively easy to detect, as it causes large electrooculogram (EOG) potentials in the 13-15Hz range, known as beta rhythm (6). (In this project, we mainly implement jaw clench, so need to introduce the jaw clench here.)

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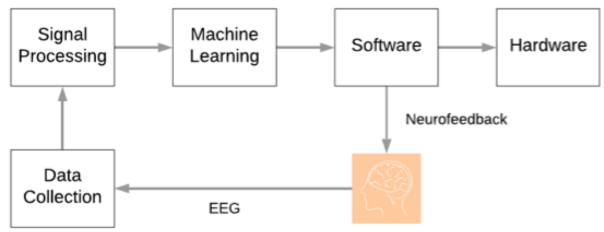

Fig. 1. Pipeline of the Study

Individuals with locked-in syndrome greatly rely on their caregivers for daily tasks. Caregivers are responsible for ensuring the well-being and the safety of these individuals (1). Thus, real-time communication between individuals with locked-in syndrome and their caregivers is crucial. To facilitate real-time communication, a caregiver mobile application was designed to be used alongside the BCI-controlled wheelchair. When individuals are in danger (i.e. collision), they undergo acute stress and their heart rate increases (7). To ensure the patients' safety, a heart rate dependent break system was implemented.

This paper presents an EEG-based OpenBCI design of a wheelchair controlled by motor imagery and eye blinking, with a break system applied through heart rate detection used as a safety measure along side our caregiver app. The paper is structured as follows: Section 2 describes our methods, which encompass data acquisition (2A), signal processing, neurofeedback (2C) software and hardware. Section 3 describes the software user interface, which includes user training dashboard, Caregiver Mobile APP, and emergency text notifications. Section 4 describes how we adapted the wheelchair to the BCI and the *Arduino* hardware. The results are further discussed in Section 5, and Section 6 concludes the study.

II. METHODS

A. Data Acquisition

Medical grade Ten20 EEG conductive paste was used to secure four OpenBCI passive gold cup electrodes directly onto the scalp of the participant. The four electrodes used to collect MI data were placed along the sensorimotor cortex

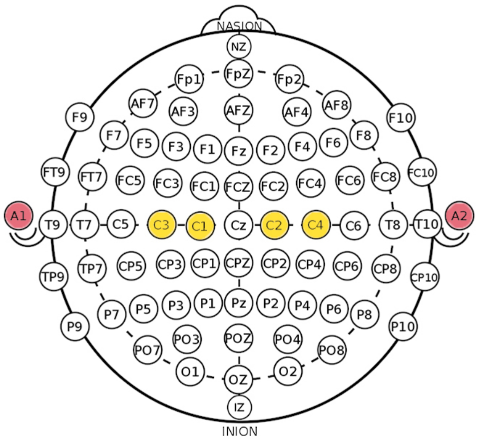

Fig. 2. International 10/20 electrodes configuration used to maximize -rhythm detection. Yellow are 7 Channels include C3, C1 for right hand motor imagery and C2, C4 for left hand motor imagery. Red are references electrodes.

of the subject, rear to the frontal lobe and just before the central sulcus that separates the frontal lobe from the parietal lobe (8). Two reference electrodes were placed on the subject's two ears. C1, C2, C3, and C4 channels were used, as recommend for the detection of the optimal μ-rhythm (4). For eye blinking and heart-rate data, two gold cup electrodes were placed beside the left eye and left wrist of the participants respectively. To acquire raw EEG data, a computer device configured to OpenBCI's Cyton Biosensing 32-bit board would be used.

To simulate an indoor environment, the experiment would be conducted in a room with ambient noise level. The participants would be seated comfortably on a chair or wheelchair facing a laptop screen. Before they are connected to the electrodes, the participants would be asked to remove any earrings, necklaces, glasses and/or to untie their hair to reduce noise during EEG data collection.

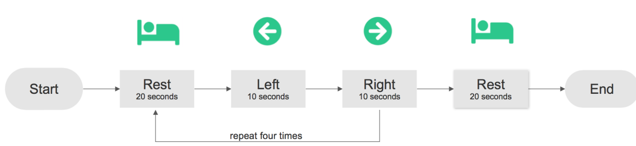

Fig. 3. Visual cue-based experimental paradigm

To obtain optimal data, we designed a visual cue-based experimental paradigm with three MI tasks. The custom-built software interface prompts the participant to imagine a certain state using visual cues (left arrow, right arrow, and sleep for rest) (Fig.2). EEG data labelling is done synchronously with the collection process; the software has the ability to recognize EEG patterns as originating from the left, right or resting task and labels the results accordingly.

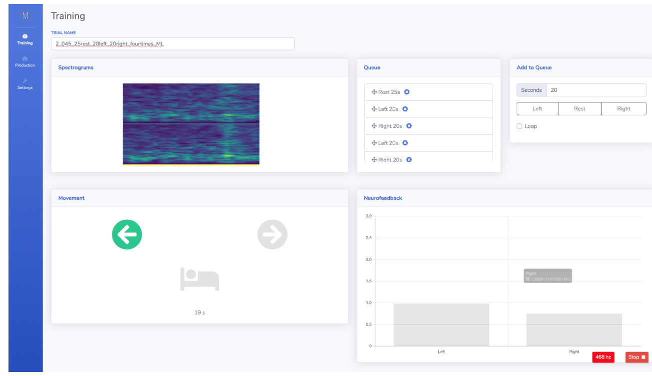

Fig. 4. Dashboard

B. Neurofeedback

Generation of robust motor imagery can be a difficult task for most individuals without prior training, as people tend to imagine visual images of related movements intead of kinesthetic feelings of actions (4). Thus, various MI neurofeedback training methods have been proposed (4).

The MI neurofeedback training is performed on the production tab of our user dashboard. (Description of the dashboard)

C. Signal Processing

Our targeted frequency range is the mu rhythm (8-12Hz) when the subjects are at rest and beta rhythm (13-36Hz) when the subjects blink their eyes. To process real-time data, we sampled at 250 Hz with a time window of two seconds, which is a standardized protocol on EEG data (ref needed).

The signal was first notched-filtered at 60 Hz and 120 Hz to remove the power-line noise across all eight electrodes (9). In order to determine the optimal filter method for the targeted frequency range (mu band (8Hz-12Hz) and beta band (13-36Hz)), five filter designs were compared. Among *Butterworth*, elliptic, *Chebyshev Type I, Chebyshev Type II,* and the Window Method of the FIR filter, the frequency spectra showed that *Chebyshev Type I* filter performed the best. In particular, the performance of the filter improves marginally for mu and beta rhythm detection when *Chebyshev Type I* filter was used.

After the data pre-processing, we used Power Spectral Density (PSD) to extract the power of the mu band (8-12Hz) and the beta band (13-36 Hz) with respect to frequency. We compared the periodogram method and Welchs averaging method, and found that Welchs method gave us a cleaner signal.

$$E = \int_{-\infty}^{\infty} |x(t)|^2 dt$$

where $x(t)$ represents the time series data of the signal and E, the energy of a signal.

D. Machine Learning

The paradigm used to move, turn, and stop the wheelchair consists of alternating between three states: Rest, Stop, Intermediate. Motor imagery classification takes place within the intermediate state, which outputs either a full stop, or a command to turn the wheelchair in the appropriate direction. To switch from one state to another, artifacts, such as jaw-clenches, are used. A sustained artifact signal of X sec will command[needsyn] the wheelchair to move to the next state.

A linear regression is used to classify, in real-time, the motor imagery state of the wheelchair user. The feature used in the regression is the average mu band power, given as the average of the frequencies of interests (8-12Hz) for all time points. The linear regression then gives a motor imagery state for every given time point. The direction with the most occurrence within a 3 second time-window is the final decision output and is fed to the wheelchair. [need parameters of linear reg] If no motor imagery signals are detected and jaw-clenches are sustained, the wheelchair will go into a stop. Sustaining jaw clenches again will bring the wheelchair to move forward.

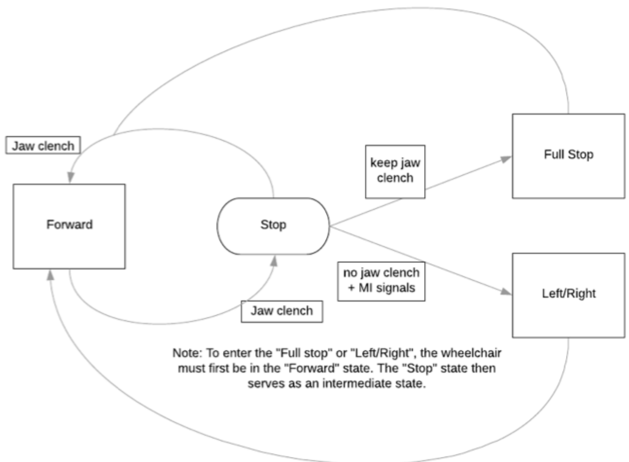

Fig. 5. Wheelchair state commands

E. Hardware

The commercially available *Orthofab Oasis 2008* wheelchair was modified and customized to fit the needs of the project. The motor controller of the wheelchair was replaced with two commercial-grade 40A, 12V PWM controller connected to an Arduino Uno. Furthermore, the seat of the wheelchair was reupholstered and custom-built footrests were installed. Four motion sensors were installed around the circumference of the footrest for the implementation of the self-driving feature.

III. Software Features

A. Caregiver APP

An application capable of sending the wheelchair's location to the caregiver in real-time was designed as a safety measure for wheelchair users. A notification feature is implemented so that the caregiver receives a text via Twilio, a cloud communication platform, when the user of the wheelchair experiences trouble or distress (i.e. obstacles,

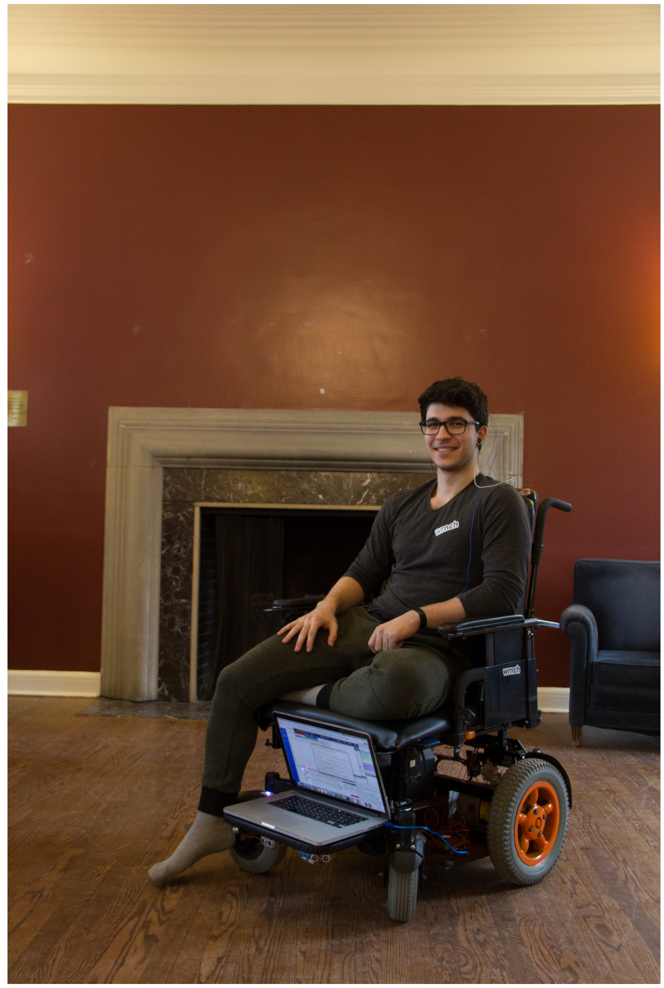

Fig. 6. Wheelchair

trauma, high stress, malfunction, etc.). The location information is received through the location services of the user's smartphone. The measure of stress dictating whether to send an alert or not is currently based on heart rate monitoring information. Once the heart rate exceeds a pre-established threshold customized to the users resting heart rate, the caregiver is alerted that the user might require assistance.

B. Assisted-Driving

Relying on motor imagery for finer navigation is challenging if not impossible. We therefore created an assisted-driving model which serves to refine the finer detail movements involved in straight navigation.

The model has two primary functions: wall following and object avoidance.

In order to detect whether the user is following a wall, two ultrasonic sensors one on the left and one on the right are used to continuously monitor the wheelchairs position relative to a potential wall. In order to determine if a wall is present, a linear regression model is fit to the last 5 seconds of sensor data collected from each side. A threshold on the standard error determines whether the wheelchair is approaching a wall from the side or is parallel to a wall. If a wall is detected, the optimal distance to the wall is calculated as the median of the data from 5 seconds ago to 1 second ago. If the difference between the current and optimal distances to the wall is large, a slight turn is executed to correct it.

The second function of the assisted-driving paradigm is obstacle avoidance. The two sensors used in wall following are combined with a frontward facing sensor and a sensor pointing at 45 from the vertical towards the ground. As the wheelchair approaches a small obstacle, using information about the chairs distance from the obstacle, the algorithm determines if there is room to navigate around it. Once the obstacle has been cleared, the wheelchair continues on the straight path that it had initially set out on. If there isnt room to navigate around the obstacle, the wheelchair comes to a complete stop and the user decides what subsequent action they wish to execute. The system uses the 45 ultrasonic sensor to detect the presence of stairs or steep hills in its upcoming path and stops if the former are detected.

IV. Discussion

Here, we have provided an outline of a user-friendly, low-cost, real-time wheelchair prototype that utilizes motor imagery signals and eye blinking to assist the user. We have introduced our data acquisition, neurofeedback, signal processing, and machine learning methods. Furthermore, we have also discussed additional features that we have added to a wheelchair - such as the caregiver mobile app and assisted-driving.

Our current methodology uses jaw-clench as a mean to navigate by allowing the user to toggle between different states. This was the most robust signal we could acquire and proved to work quite well, but this is far from ideal considering locked-in patients cannot produce jaw clenches. An obvious next direction will be to chose a signal that can be produced by the targeted patient populations. The small amount of electrodes used in the current experiment prevents us from attaining high temporal and spatial sensitivity, which subsequently affects the sensitivity of the signals we can pick up and work with.

To prevent the wheelchair from changing the states too quickly, we set the minimum time for each state to be four seconds, which means that the wheelchair has to stay in a state for at least four seconds before it can change to another state. However, the four-second period also makes it less flexible to control the wheelchair. For example, if the wheelchair is moving forward, it cannot stop within four seconds even if it will collide with an obstacle in four seconds. To solve this problem in the future, we will integrate our self-driving feature into the states command, which did not do in this paper. In order to be able to change the state more flexibly, we will also try to process the signals in smaller time windows to increase the real-time sensitivity to the brain signals.

3. How the wheelchair can be developed to apply to more than just locked-in syndrome patients 4. Significance of devices software features; 5. The cost of the product is low

We are currently developing a doorway detection and navigation algorithm which would enable autonomous navigation through doorways. This feature is developed as doorways are a major hindrance to wheelchair users wishing to gain autonomy. Our current model uses an X-Box Kinect sensor for doorway mapping, planning and navigation as outlined in CoPilot (Panzarella T., Schwesinger D., Spletzer J. (2016) CoPilot: Autonomous Doorway Detection and Traversal for Electric Powered Wheelchairs. In: Wettergreen D., Barfoot T. (eds) Field and Service Robotics. Springer Tracts in Advanced Robotics, vol 113. Springer, Cham).

V. Public Availability of Data

github link?

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