A PLATFORM TO ASSESS BRAIN DYNAMICS REFLECTIVE OF COGNITIVE LOAD DURING PROSTHESIS USE

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ABSTRACT

Prosthetic hand operation often results in high levels of cognitive burden on the user which can lead to fatigue, frustration and device rejection. Some previous work that quantified this cognitive load relied on subjective questionnaires or distraction tasks. We have adapted a protocol capable of real-time, objective, non-distracting assessment of cognitive load for use with individuals controlling a prosthesis. Here we present this platform to assess cortical dynamics during prosthesis use. We describe a custom-built lightweight prosthesis simulator and an electroencephalography (EEG) assessment. We also present pilot work that shows how alpha inhibitory activity recorded with a wireless EEG system can be used to assess cognitive load.

INTRODUCTION

Efforts to improve upper-limb myoelectric prostheses often aim to provide a high degree of functionality to those living with limb-loss [1]. Despite technological advancement, these devices provide limited capabilities compared to intact limbs and impose a high cognitive load that results in fatigue and frustration [2], which can lead to device rejection [3]. Measurements to directly evaluate cognitive load are needed in order to further understand how efficient visuomotor behaviors develop during prosthesis use. For this, electroencephalography (EEG) is ideally suited as it allows the measurement of ongoing neural activity with high temporal resolution. Active processing in engaged and task-relevant areas of the brain is reflected by a suppression in the magnitude (power) of oscillations in the alpha range (8-12 Hz) [4], [5]. The development of skilled motor performance is characterized by the efficient allocation of processing resources to task-relevant areas of the brain [6]. Recently, this approach was used to demonstrate a decrease in alpha power detected across the scalp during prosthesis use compared to an anatomical hand, reflecting more conscious control [7]. Based on this work, we present a platform to assess brain dynamics during prosthesis use. The first section describes a customizable, lightweight myoelectric prosthesis simulator created for the platform. The second section describes the wireless EEG equipment and the analysis used in the platform. The project was approved by the Research Ethics Board of the University of New Brunswick (REB #2019-098) and all pilot testing was performed according to the REB guidelines. We conclude by showing pilot data of the alpha distribution on the cortex reflecting functional inhibition which can be indicative of high cognitive load.

METHODS AND PILOT RESULTS

Prosthesis simulator

A novel, custom built, lightweight (approx. 900 g) 3D-printed myoelectric prosthesis simulator was built (Figure 1). This device allows for people with intact limbs to control a prosthesis. The University of Alberta's Handi Hand [8] was mounted to a wrist brace with a medial offset, a position chosen to minimize the effect on modulating arm kinematics [9] and to reduce visual occlusion of the prosthesis [10]. Two electrodes (Myoware, Advancer Technologies) placed on the dorsal and ventral surfaces of the forearm record electromyographic (EMG) activity from wrist extensors and flexors to be used for hand control. Force sensitive resistors (Interlink Electronics®, CA USA) (FSRs) embedded in the fingertips of the index and thumb of the prosthetic hand detect pressure changes normal to the sensor that drive vibrating resonant motors providing haptic feedback to the user.

Control

Signals from the two EMG channels are amplified, high pass filtered at 20 Hz and notch filtered at 60 Hz. Signals are then rectified and integrated to drive a proportional open-close controller. Proportional control of the closing and opening velocity of the hand is done by mapping the maximal and minimal velocities to the maximal and minimal EMG activity recorded. To normalize the controller for each participant, they are asked to perform wrist flexion and extension maximal voluntary contractions (MVCs) for 5 seconds at the beginning of the session to determine the maximal amplitude for each of the electrodes. Similarly, the minimal activity for flexors and extensors is experimentally determined by recording the baseline EMG activity of each sensor during a period of 5 seconds while the arm is resting in the simulated prosthesis. The minimal activity is set to a value three standard deviations above the mean recorded activity to reduce unintentional activation of the channels.

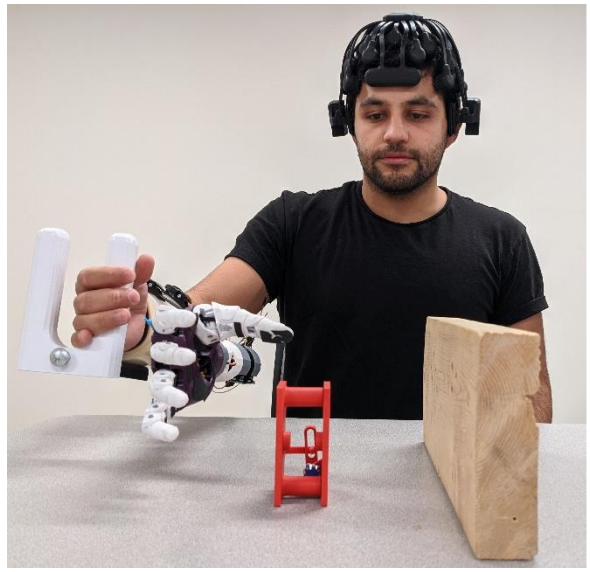

Figure 1. Experimental set-up displaying the custom prosthesis simulator and the dry-wireless EEG system. During experiments, the user's hand and arm are visually occluded.

Feedback

Changes in resistance captured by the FSRs at the fingertips control two haptic motor drivers (DRV265L, Adafruit Industries, New York, NY) that activate two corresponding linear resonant actuators (C10-100, Precision Microdrives, London, UK). These coin motors are in the inside lining of the forearm cuff and in direct contact with the skin of the forearm. The amplitude of the vibration of the haptic motors is mapped proportionally to the resistance change of the FSRs to represent the force detected at the fingertips. The magnitude of the minimally detectable vibration is determined individually for each participant and used as the lower edge of the mapping with the FSR signal.

EEG recordings

Cortical activity is recorded using EEG sampling at 1000 Hz. The electrodes are positioned on the head based on the standard 10/20 Channel system, with all referenced to the left and right earlobe. Data are transmitted wirelessly via Bluetooth from the cap directly to a PC and recorded using the software provided by the system manufacturer (Cognionics Data Acquisition, Version 3.6).

Blink and eye artifacts are removed using Principal Component Analysis and visual assessment [11]. EEG signals are then band-pass filtered from 0.1 to 100 Hz. Time-frequency decomposition of the signal is performed through short-time FFT on Hanning-tapered and zero-padded (up to 2000ms) overlapping segments (50% overlap) of 500 ms. These windows are recorded from 1000 ms before and after initial contact with the object to assess grasping force modulation (total time window of 2000 ms). Alpha power of EEG spectra has been previously used as a proxy to quantify functional inhibition of cortical areas [5], [7], [12], [13]. With this model, a greater level of alpha activity reflects a higher level of functional inhibition [5]. After the FFT transformation, power (μV^2) in the alpha range (8-12 Hz) is averaged across overlapping FFT segments for each channel and trial. Channels on the scalp are divided in 7 functional regions of interest (RoI); left temporal (T7), left central (C3), frontal (Fz), right central (C4), right temporal (T8), parietal (Pz) and occipital (O1, O2). Power is then averaged across these channels to yield values for each region. Finally, the values are divided by the average baseline value obtained during the resting state to obtain an index of change in activity from the resting state [14].

Using this method, we have been able to qualitatively identify high levels of alpha power reflective of functional inhibition of the occipital lobe during an eyes-closed recording. The occipital lobe is responsible for the processing of incoming visual information [15]. A sample recording from one participant is presented in Figure 2. This increase in alpha activity in posterior regions of the brain indicating low cortical activation has been well described since the late 1920's [15]. The wireless EEG setup presented here can identify alpha activity changes across the scalp.

DISCUSSION

A common goal in developing new myoelectric technology is to increase the clinical effectiveness of prostheses [3]. Despite advances in technology, most devices impose a high cognitive burden that can result in fatigue and frustration [2], and eventual prosthesis rejection [3], [16], [17]. Here, we present a platform to assess cognitive load during prosthesis use. The development of our prosthesis simulator facilitates experimentation with individuals not affected by limb-loss, allowing us to increase the statistical power of our studies. Furthermore, this system was manufactured using light-weight 3D printed parts, allowing for less constrained movements compared to previous simulators requiring suspension systems to offset the weight [10].

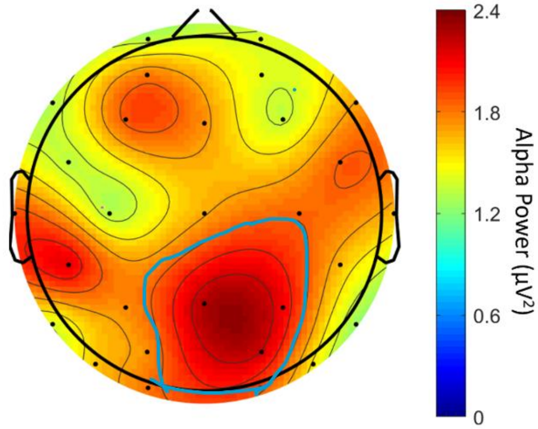

Figure 2. Sample alpha activity obtained during an eyes closed recording. Increased inhibitory alpha activity is present over the occipital lobe (outlined in blue), the area responsible for processing visual information [14].

Previous work has sought to assess cognitive load during prosthesis use using EEG [18], [19], however, only one previous study has attempted to directly evaluate the functional cortical dynamics using alpha level inhibition [7]. This work was able to demonstrate an overall reduction on alpha activity across the scalp during prosthesis use, indicating higher levels of cognitive load compared to the use of the anatomical hand. Based on this work, we present a platform aimed to help researchers and prosthesis developers investigate the effects of their prosthetic implementations on cognitive load. The advantage of our platform lies in the wireless EEG system utilized, as it does not restrict the movement of the user and avoids having large cable artifacts [20]. Furthermore, unlike the previous study using EEG to assess alpha activity [7], our protocol also includes a baseline normalization step, in which the relative differences in alpha activity between resting state and prosthesis use allows for the analysis of alpha changes exclusively due to prosthesis use, and allows for normalization across multiple assessment days [21].

From a practical perspective, it is important to understand how prosthesis users develop efficient control of a prosthesis. Adaptive learning processes rely on the engagement of appropriate mental resources during practice and performance [14], [22], [23], and high levels of cognitive load have been shown to hinder them [22], [24]. We hope to utilize this platform in the future to provide a method of assessing cognitive load during real time and move away from subjective or performance-based assessments of cognitive load as these are prone to subjective interpretations, distractions, and ceiling effects to tasks with high success rates [13]. Furthermore, EEG based assessments can provide insights about the cortical mechanisms responsible for the high levels of cognitive load, and drive evidence-based interventions on how to address them. Currently, we are conducting work using this EEG based approach to investigate the effects of adding augmented feedback on the cognitive load required to operate a myoelectric prosthesis, as augmented feedback could potentially reduce the visual attention and cognitive burden required to operate a prosthesis [18].

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