Neurophysiological Evaluation of Haptic Feedback for Myoelectric Prostheses

Neha Thomas, Garrett Ung, Hasan Ayaz, *Senior Member, IEEE*, and Jeremy D. Brown, *Member, IEEE*

***Abstract*—Evaluations of haptic feedback in myoelectric prostheses are generally limited to task performance outcomes, which while necessary, fail to capture the mental effort of the user operating the prosthesis. Cognitive load is usually investigated with reaction time metrics and secondary task accuracy, which are indirect, and may not capture the time-varying nature of mental effort. Here, we propose wearable, wireless functional near infrared spectroscopy (fNIRS) neuroimaging to provide a continuous direct assessment of operator mental effort during use of a prosthesis. Utilizing fNIRS in a two-alternative forced-choice stiffness discrimination task, we asked participants to differentiate objects using their natural hand, a (traditional) myoelectric prosthesis without sensory feedback, and a myoelectric prosthesis with haptic (vibrotactile) feedback of grip force. Results showed that discrimination accuracy and mental effort are optimal with the natural hand, followed by the prosthesis featuring haptic feedback, and then the traditional prosthesis, particularly for objects whose stiffness were difficult to differentiate. This experiment highlights the utility of haptic feedback in improving task performance and lowering cognitive load for prosthesis use, and demonstrates the potential for fNIRS to provide a robust measure of cognitive effort for other human-in-the-loop systems.**

***Index Terms*—Cognitive load, neuroergonomics, functional near-infrared spectroscopy (fNIRS), haptic feedback, myoelectric prosthetics.**

I. Introduction

THE glabrous skin of the human hand contains an estimated 17 000 sensory afferents, which are categorized according to four main receptor types and their associated function [1]. This sheer density of receptors allows for high sensitivity to the various types of mechanical stimuli encountered in environmental exploration, and contributes to the hand's fine motor control capabilities. This functionality is lost, however, when the limbs of the upper-extremity are amputated, resulting in severe impediments to an individual's quality of life.

Manuscript received November 15, 2019; revised May 5, 2020, November 10, 2020, and March 5, 2021; accepted March 5, 2021. Date of publication; date of current version. The work of Neha Thomas was supported by NSF Graduate Research Fellowship. This article was recommended by Associate Editor D. B. Kaber. *(Corresponding author: Neha Thomas.)*

Neha Thomas is with the Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD 21218 USA (e-mail: neha.thomas@jhmi.edu).

Garrett Ung and Jeremy D. Brown are with the Department of Mechanical Engineering, Johns Hopkins University, Baltimore, MD 21218 USA (e-mail: gung1@jhu.edu; jdelainebrown@jhu.edu).

Hasan Ayaz is with the School of Biomedical Engineering, Science and Health Systems, Drexel University, Philadelphia, PA 19104 USA (e-mail: hasan.ayaz@drexel.edu).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/THMS.2021.3066856.

Digital Object Identifier 10.1109/THMS.2021.3066856

Amputees often use myoelectric prostheses to restore some of the functionality of the lost limb. The functionality of clinically available myoelectric prostheses, however, is limited due to the lack of touch-based (haptic) sensory feedback. In fact, the lack of touch-based sensory feedback has been implicated in the rejection and abandonment of myoelectric prostheses [2]. Amputees who do use myoelectric prostheses must rely heavily on visual feedback during all activities of daily living to estimate haptic information like grip force and terminal device aperture. Visually monitoring the operation of the prosthesis is not ideal or even feasible in low-light conditions or when objects are occluded from view. Additionally, the constant visual attention can impose a large cognitive burden [3], [4].

To reduce the cognitive burden on amputees, some commercial prostheses, such as the Ottobock SensorHand, have been endowed with smart grip controllers that automatically increase grip force when necessary to ensure a stable grasp [5], [6]. This reduced need for amputee intervention in the device's control loop allows amputees to focus their visual attention elsewhere. At the same time, these controllers limit embodiment of the prosthesis into the amputee's neuromuscular control scheme given that the amputee is normally unaware of these automatic adjustments. Likewise, these controllers are more prone to excessive object deformation, which is not ideal when grasping fragile or brittle objects [7]. Given these shortcomings, it is anecdotally known that some amputees will even choose to turn the automatic grip control feature off. If amputees had feedback of their grip force, they could potentially better regulate their grasping force to prevent object breaks, thereby improving their ability to manipulate objects.

Haptic feedback is a potentially effective means of providing touch-based sensory feedback in commercial prostheses, and has been shown to support prosthesis embodiment through a process known as extended physiological proprioception [8], [9]. In the context of prostheses, haptic feedback is typically provided by mapping information like grip aperture, grip force, object slip, and contact detection to various types of noninvasive mechanical stimulation on the surface of the skin [10]–[12]. The mechanical stimulation is usually in the form of cutaneous feedback modalities such as pressure, skin-stretch, and vibration [13]–[15]. In particular, vibrotactile feedback has been shown to be a relatively simple but effective means of providing feedback [15]–[20]. For example, Raveh *et al* [16] demonstrated with 12 myoelectric prosthesis users that vibrotactile feedback of grip force reduced the time spent performing activities of daily living. Stepp *et al* [17] also showed that participants improved their ability to relocate a virtual object with repeated training using vibrotactile feedback. In work done by Pylatiuk *et al* [21] five myoelectric prosthesis users were able to better regulate grasping force when they had vibrotactile feedback.

Haptic feedback has also been shown to reduce cognitive load compared to visual feedback alone [3], [4]. In these previous studies, cognitive load was evaluated based on an analysis of reaction time and accuracy in a secondary task. While secondary tasks are useful for assessing how well cognitive resources are shared, they still rely on indirect measures of mental effort, which artificially introduce lab-contrived distractions that are inconsistent with real-world use. Additionally, choosing the correct secondary task is non-trivial; the task can be neither too simple nor too complex. Furthermore, different secondary tasks are likely to yield different results, which hinders their reproducibility and generalizability. Also, secondary tasks only allow for measurements of cognitive load at discrete intervals throughout a task, which may not capture the continuous, time-varying nature of mental effort. Finally, for primary tasks that are relatively short (10–15 s), the feasibility of secondary tasks is limited.

Measures of cognitive load that do not use secondary tasks are also possible. For example, the NASA-TLX workload assessment subjectively estimates effort exerted performing a task through questions regarding mental, physical, and temporal effort, as well as the perceived performance and frustration levels of the survey participant [22]. As with secondary tasks, the TLX survey does not provide a continuous assessment of cognitive effort. In addition, individual interpretations of the rating scale can vary depending on past experience [23]. Other measures of cognitive load that do not involve secondary tasks include physiological measurements such as heart rate, eye tracking, electrodermal activity, and respiratory rate [24]–[27]. These physiological measurements, while continuous, can be highly sensitive to a participant's existing physical condition and motion artifacts, as well as environmental factors such as humidity and illumination [24]. For example, in the case of eye tracking, long eyelashes, glasses, and droopy eyelids are physical characteristics that may obstruct or even totally prevent the quality of eye tracking data [28]. Furthermore, using only one physiological measure may not result in high accuracy of mental workload classification [25]. In comparison to these measures, brain imaging may provide a sufficient measure on its own. It has been shown that electroencephalography (EEG) yielded the best classification accuracy compared to separate assessments of electrodermal activity, electrocardiogram, and pulse oximetry [25].

The benefit of brain imaging is that it offers a direct measure of cognitive load that is less susceptible to environmental conditions or the user's physical condition. In addition, measurements can be taken from multiple areas of the brain, allowing for richer and more complex datasets than the other physiological measures mentioned above. Various neuroimaging modalities exist, including EEG [29], and functional magnetic resonance imaging (fMRI) [30]. Each neuroimaging modality has unique benefits and limitations; EEG has a high temporal resolution but low spatial resolution and is sensitive to motion artifacts and muscle activity, fMRI has a high spatial resolution but low temporal resolution [31]. Furthermore, fMRI studies require that participants lay stationary inside a scanner within a large magnetic field, which prevents the use of electromechanical hardware and altogether limits the diversity of experimental paradigms.

In addition to EEG and fMRI, functional near infrared spectroscopy (fNIRS) has also demonstrated utility in cognitive load monitoring [32]. fNIRS operates on the principle of absorption and scattering of infrared light in the tissues of the prefrontal cortex, a region of the brain responsible for critical thinking, reasoning, and decision making. The reflected infrared light is used to calculate the relative concentration of oxygenated hemoglobin through the modified Beer–Lambert law. Increased oxygenated hemoglobin is associated with higher mental effort via neurovascular coupling [32]–[34]. Compared to other neuroimaging modalities, fNIRS boasts a higher spatial resolution than EEG and a higher temporal resolution than fMRI, combining the best characteristics of both. It is also less susceptible to motion artifacts than EEG and can be used in a variety of dynamic tasks, including those utilizing electromechanical hardware [35].

In the past several years, fNIRS has been increasingly utilized to assess cognitive load in a variety of scenarios. In a working memory task, Fishburn *et al* [36] confirmed that fNIRS is a viable alternative to fMRI, as it was sensitive to cognitive load and state. For skill assessment, Ayaz *et al* [32] demonstrated that fNIRS is sensitive to mental task load and practice level: expertise development in a task results in reduced mental effort, and that difficult tasks were more cognitively demanding than moderate ones. Due to its highly portable nature, fNIRS has also been used in gait assessment [37], [38] and in realistic, nonlaboratory-based settings such as the assessment of cognitive load in pilots in both flight simulators and and during real flight [39].

In a similar manner, fNIRS can be used to assess the effects of haptic feedback on cognitive load, which up to this point has not been investigated. In this manuscript, we present the findings of a study that utilized fNIRS to measure the cognitive load associated with performing a stiffness discrimination task using a myoelectric prosthesis featuring vibrotactile feedback of grip force. Vibrotactile feedback was chosen because it has often been proposed for myoelectric prosthesis and is simple to implement [16]–[19]. To provide context to these measures, we include as additional experimental conditions, a myoelectric prosthesis without haptic feedback, and the healthy intact hand. To the author's knowledge, this is the first investigation into neurophysiological markers of cognitive load for an upper-extremity myoelectric prosthesis user as well as the effect haptic feedback has on that load. We hypothesize that the use of the prosthesis without haptic feedback will result in the highest cognitive load due to the large reliance on visual cues compared to the other two experimental conditions. In addition, we hypothesize that the intact hand will carry the lowest cognitive burden and result in the best performance of the three conditions. With this work, we aim to highlight not only the cognitive benefits of haptic feedback for prosthesis use, but also a generalized method for assessing cognitive load in human-in-the-loop systems more broadly.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

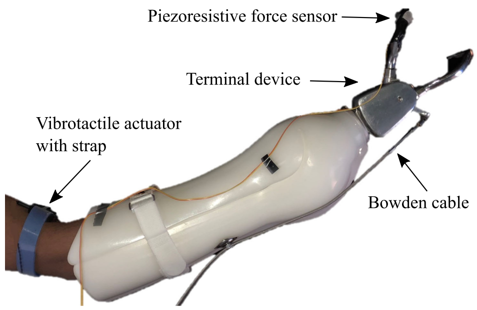

Fig. 1. Prosthesis terminal mated to custom socket for able-bodied individuals. Vibrotactile actuator is placed on the upper arm just above the elbow.

II. Methods

A. Participants

We investigated the ability of n=10 able-bodied individuals (8 male, 2 female, age = 21.4 ± 3.5 years) to perform an object discrimination task using a mock myoelectric prosthesis in three different feedback conditions. The duration of the experiment was approximately 60 min and participants were compensated at a rate of $10/h. All participants were consented according to a protocol approved by the Johns Hopkins School of Medicine Institutional Review Board (Study# IRB00147458).

B. Experimental Apparatus

The mock prosthesis (see Fig. 1) consists of a 1-DOF voluntary-closing prosthetic terminal device attached to a custom prosthetic socket, which was designed to be worn by nonamputee participants. A custom-built piezoresistive sensor based on work by Osborn *et al.* [40], was placed over one of the terminal device's fingers to measure grip force. The prosthetic terminal device was driven via a Bowden cable connected to a custom linear actuator drive, and operates in a manner similar to that featured in Thomas *et al.* [20], where actuation of the linear actuator pulls or releases the Bowden cable to close or open the terminal device, respectively.

Vibrotactile feedback was provided by a C-2 tactor controlled through a Tactor-Control Unit (Engineering Acoustics, Inc.). The C-2 tactor was encased within a 3-D printed housing and secured to the skin of the participant's upper arm just above the elbow and over the right bicep with a Velcro strap (see Fig. 1).

A Delsys Bagnoli 16-channel electromyographic (EMG) system with two surface electrodes was used to acquire EMG signals from the participant's right wrist flexor and extensor muscle groups.

Data acquisition and control were implemented at a 1 kHz sampling rate in MATLAB/Simulink R2017a through a Quanser QPIDe DAQ with Quanser's QUARC real-time Simulink blockset and a custom block containing the Engineering Acoustics API. The entire system was controlled by a Dell Precision T5810 desktop.

An fNIR Imager (Model 1100 W; fNIR Devices, LLC) with two-optode sensor pads was used to measure hemodynamic activity in the prefrontal cortex [41]. COBI Studio software was used to acquire the optical signals at a 4 Hz sampling rate [42].

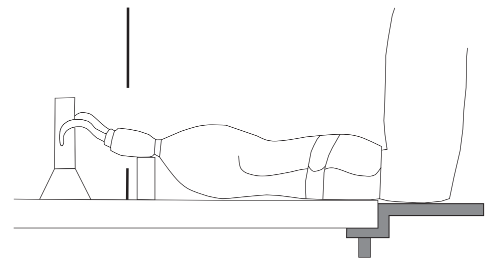

Fig. 2. Blocks are visible when individually presented to subjects. The terminal device rests on support block while the participant squeezes the object within the barrier's opening.

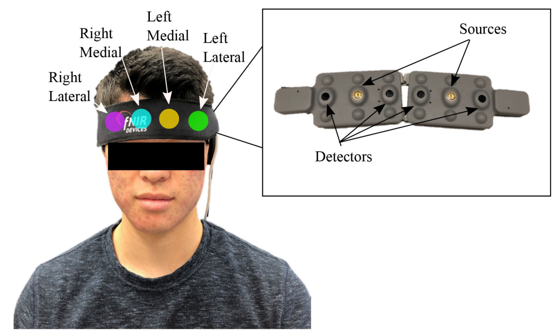

Fig. 3. fNIRS sensor pads are placed on the participant's forehead and covered with a headband. The sensor pad has two LED light sources and four detectors, yielding four channels of data from left/right medial/lateral prefrontal cortex.

The two sources of the fNIRS headband emit infrared light into the tissues of the prefrontal cortex, and the four detectors measure the reflected infrared light (see Fig. 3). This data is postprocessed using COBI Studio's built-in analysis tool, which applies the modified Beer–Lambert law to calculate the total hemoglobin concentration [32]. Event markers from Simulink were sent to COBI Studio via USB-Serial to synchronize data from the two data acquisition systems.

C. EMG Calibration and Processing

After the participants were consented in the study, they were seated at the experimental table to begin EMG calibration. The experimenter first asked the participant to flex or extend their wrist while palpating their forearm to locate the belly of the appropriate muscle. The experimenter placed one EMG electrode on the participant's right wrist flexor muscle group, one EMG electrode on the participant's right wrist extensor muscle group, and a ground electrode on the participant's right elbow. A compression sleeve was fitted over the participant's right arm to secure the wires and electrodes in place. The experimenter then helped the participant don the mock prosthesis on their right arm. The base of the terminal device rested on top of the support block (see Fig. 2) and the socket on an arm rest.

To calibrate the EMG signals, participants were asked to flex or extend their wrist several times for a period of seven seconds. Participants were told to keep contraction levels to minimum effort. The maximum EMG signals for both flexion and extension pulses were separately averaged and used to normalize the EMG signals for flexion and extension movements during the experiment. This approach has proved successful with our experimental apparatus in prior studies [20].

D. Prosthesis Control

The prosthesis terminal device opening and closing velocity was proportionally controlled by the wrist extension and flexion EMG signals, respectively. Participants used the prosthesis to squeeze objects which are described in detail in Section II-E1. During device closing, the prosthesis actuator command was set to zero once the prosthesis aperture reached a threshold (E_c) as measured by the encoder on the back of the motor. This software stop was incorporated to minimize the auditory cues originating from the linear actuator, and to prevent damage to actuator components. Similarly, during device opening, the prosthesis actuator was disabled once the prosthesis aperture reached another threshold (E_o) to prevent damage to the actuator components.

The control law for operating the prosthesis terminal device velocity u_p under proportional EMG control was

$$u_p = \begin{cases} S_{\text{net}} \cdot K_1, & S_{\text{net}} > 0 \,\&\; E \leq E_c \\ S_{\text{net}} \cdot K_2, & S_{\text{net}} < 0 \,\&\; E \geq E_o \\ 0, \text{ otherwise} \end{cases} \quad (1)$$

$$S_{\text{net}} = \|S_{\text{flex}}\| - \|S_{\text{ext}}\| \quad (2)$$

where S_{net} is the net EMG signal calculated using the normalized EMG wrist flexor signal $\|S_{\text{flex}}\|$ and the normalized EMG wrist extensor signal $\|S_{\text{ext}}\|$ as indicated in (2). K_1 is the proportional gain applied to S_{net} for device closing, E is the encoder reading on the back of the linear actuator motor, E_c is the encoder threshold during device closing, K_2 is the gain applied to the S_{net} for device opening, and E_o is the encoder threshold during device opening. If the device has closed beyond the threshold ($E > E_c$), or if the terminal device is fully opened ($E \leq E_o$), the motor command is set to zero.

E. Vibrotactile Feedback Operation

When participants flex their wrist, the EMG flexor signal increases, which in turn drives the prosthesis actuator to pull on the Bowden cable and close the terminal device. The signal from the piezoresistive force sensor on the prosthesis terminal device is used to drive the amplitude of the vibrotactile actuator. The frequency of the vibrations was always 250 Hz.

The control law for vibrotactile feedback amplitude was

$$u_V = K_F \cdot F^2 \quad (3)$$

where K_F is the gain, and F, the piezoresistive force sensor signal, is squared to provide better separation in the force signals for the test objects. This mapping was chosen over a linear mapping through pilot testing, as it yielded better discrimination of the stimuli.

1) Stimuli: Participants were asked to discriminate pairs of blocks with different stiffness. Three Ecoflex Smooth-On silicon blocks were used: soft (Shore Hardness 00–20), medium (Shore Hardness 00–30), and hard (Shore Hardness 00–50). Blocks were fit into custom 3D-printed holders and covered in a thin black cotton fabric to prevent the participant from distinguishing the blocks based on unintended visual blemishes. Sample blocks (Dragon Skin 10 with Shore hardness 10 A and Ecoflex 35 with Shore hardness 00–35), were provided only for the participant to practice, as described in Section II-F.

F. Protocol

Participants were randomly split into two groups (A and B). Group A performed the task in the following condition order: (1) natural hand, (2) myoelectric prosthesis without vibrotactile feedback, and (3) myoelectric prosthesis with vibrotactile feedback. Group B performed the task in the following condition order: (1) natural hand, (2) myoelectric prosthesis with vibrotactile feedback, and (3) myoelectric prosthesis without vibrotactile feedback. Before performing the tasks, participants completed a brief survey regarding their demographics, handedness, and experience with haptic devices, myoelectric devices, and fNIRS.

Prior to starting the experiment, participants were allowed to practice with sample blocks. As in the actual experiment, sample blocks were placed behind a physical barrier with a small opening that occluded the top part of the block to avoid distinguishable visual blemishes. The base of the prosthesis terminal device was placed on the support block (shown in Fig. 2) such that the fingers of the terminal device were within the opening of the physical barrier. Participants first practiced squeezing the sample blocks with the myoelectric prosthesis until comfortable with the controls. Afterward, the mock prosthesis was removed and a piezoresistive force sensor ring, similar to the sensor in Fig. 1, was placed on the index finger of their right hand. Participants were able to practice squeezing the sample blocks with their hand with the force sensor attached. The force sensor on the participant's hand was used to measure squeezing during the control condition.

Once the participant completed the practice session, the experimenter placed the fNIRS sensor pads on the left and right anterior lateral parts of the participant's forehead (see Fig. 3). A headband was placed over the sensor pad to block out ambient light.

The three test blocks (soft, medium, and hard) were presented in six pairwise permutations whose order was randomized. Each pairwise permutation was repeated three times for a total of 18 presentations per condition, or 54 trials for the entire session. The blocks in the pair were presented to the subject within the opening of the physical barrier one at a time. In all conditions, participants were able to observe the deformation of the objects as they squeezed them. Participants were only allowed to squeeze each block once, and no repeats of the block pair were allowed unless EMG or sensor issues arose between the first and the second block. The duration and force of the squeeze was not controlled and could vary for each block and participant. After squeezing the second block, participants verbalized their answer of which block they thought was stiffer. Correct answer feedback was not provided for any trial. After each block pair presentation, participants were given a 15 s break to allow time for the fNIRS hemodynamic response. See Fig. 4 for representative time-series signals from the relevant sensors within a single trial. After every

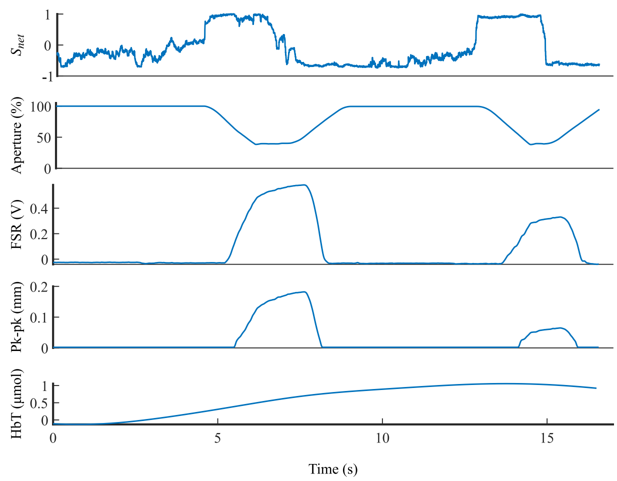

Fig. 4. Example trial during the vibrotactile ON condition featuring a medium and soft block. From top to bottom: The normalized net EMG signal, the aperture in percentage where 100% refers to the aperture of the completely opened prosthesis and 0% refers to the aperture of the completely closed prosthesis, the force sensitive fabric sensor voltage output, the peak to peak displacement of the vibrotactile actuator, and the average change in total hemoglobin concentration (HbT).

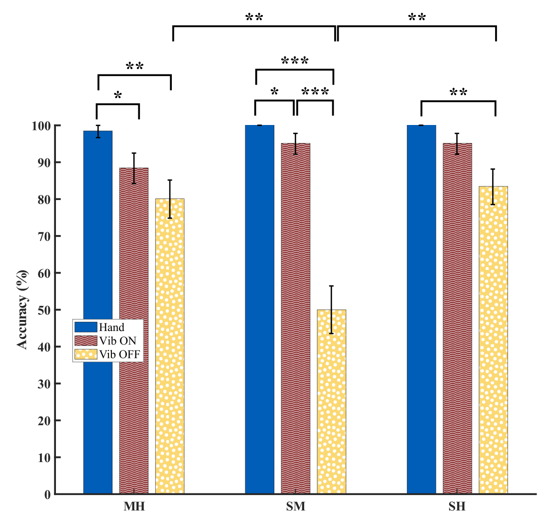

Fig. 5. Average accuracy for each condition and block combination. Error bars represent standard deviation. *indicates $p < 0.05$, **indicates $p < 0.01$, and ***indicates $p < 0.001$).

third block pair presentation, participants were given a 30 s break. During the break, participants completed a two-question survey regarding their ability to discriminate stiffness in the previous block pair and their current physical comfort level.

After completing all three conditions, subjects completed a postcondition survey, based largely on the NASA-TLX questionnaire [22]. The survey was a mix of short-answer and slider-scale (0–100) qualitative questions about participants' perceived performance and evaluation of the task. Only the postcondition survey questions will be discussed in detail.

G. Metrics and Statistical Analysis

Mixed models were used to analyze all results. Fixed effects for models were chosen based on the lowest Bayesian information criterion.

1) Task Performance: A logistic mixed-effects model was used to analyze task accuracy across all three conditions, where participants were the random effects, and participant group, trial, and the interaction between block combination and condition were fixed effects. Note: Some of the block combinations and conditions (for instance, the intact hand in the soft-medium and soft-hard block combination) had no errors (100% accuracy). As it was possible to perfectly predict the accuracy performance based on the combination of these variables (complete separation), it was not possible to run the logistic models on these data. Therefore, we instead ran the models on a perturbed dataset, in which one of the trials in each perfect session was replaced with one erroneous trial. Thus, the performance results of the logistic models presented here are actually slightly weaker than the original data.

2) fNIRS Performance: A linear mixed-effects model was used to analyze average change in total hemoglobin concentration, where participants were the random effects and the interaction between block combination and feedback condition were fixed effects.

3) Neural Efficiency: In this experiment the neural efficiency metric captures the relationship between performance and the cognitive load required to achieve that performance during each condition. The neural efficiency metric is calculated using the z-scores of the accuracy of stiffness discrimination $z(P)$ and cognitive effort $z(\mathrm{CE})$ data for each condition as shown in (4) and as described in [43]

$$\mathrm{NE} = \frac{z(P) - z(\mathrm{CE})}{\sqrt{2}}. \tag{4}$$

A linear mixed-effect model was used to analyze the differences in neural efficiency between each condition, where participants were the random effects and the condition and participant group were the fixed effects.

4) Survey: The first question asked participants to rank how physically demanding the condition was and the second question asked participants to rank how mentally demanding the condition was. The third question asked how hurried or rushed the task was, while the fourth question asked participants to rate their perceived accuracy in each condition. Question five asked participants to rate how discouraged or frustrated they were during the task. The final question asked participants to rate how much they used visual, touch-based, and auditory cues during each condition. Auditory cues from the prosthetic hand's motor and gear transmission could be heard during operation of the prosthesis. A linear mixed effects model was used to analyze rating results. Group and condition were fixed effects while the participants were included as a random effect.

III. Results

A. Task Performance

Differences across the conditions are shown in Fig. 5. In the main result, there was a significant main effect of intercept (β = 1.65, SE = 0.75, $p < 0.05$) and trial ($\beta = 0.06$, SE = 0.02,

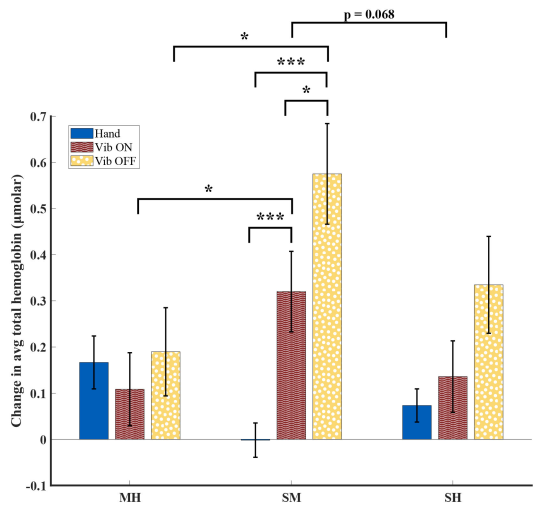

Fig. 6. Average change in total hemoglobin concentration for each condition in the right medial prefrontal cortex. Error bars represent standard error of the mean. * indicates $p < 0.05$, and *** indicates $p< 0.001$.

$p < 0.01$). Group B performed significantly worse than Group A (β = -0.91, SE = 0.39, $p < 0.05$).

Medium-hard block combination: The intact hand was significantly better than vibrotactile ON ($\beta = 3.45$, SE = 1.16, $p < 0.05$) and vibrotactile OFF ($\beta = 4.48$, SE = 1.21, $p < 0.01$).

Soft-medium block combination: The intact hand was significantly better than vibrotactile ON ($\beta = 2.42$, SE = 1.23, $p < 0.05$) and vibrotactile OFF ($\beta = 5.86$, SE = 1.19, $p < 0.001$). Vibrotactile ON was also significantly better than vibrotactile OFF ($\beta = 3.44$, SE = 0.71, $p < 0.001$).

Soft-hard block combination: The intact hand was significantly better than vibrotactile OFF ($\beta = 4.26$, SE = 1.20, $p < 0.01$).

Vibrotactile OFF condition: The soft-hard combination accuracy was significantly better than the soft-medium accuracy ($\beta = 1.65$, SE = 0.43, $p < 0.01$). The medium-hard combination accuracy was also significantly better than the soft-medium combination accuracy ($\beta = 1.44$, SE = 0.41, $p < 0.01$).

B. fNIRS Measures

Here, we present the average change in total hemoglobin concentration in the right medial prefrontal cortex as an indicator of cognitive load. Before experimentation began, it was found that the detector on the fNIRS sensor pad measuring oxygenation from the right lateral prefrontal cortex was not functioning. Therefore, this channel will not be discussed. All other channels—left lateral, left medial, and right medial prefrontal cortex were operational. However, we only highlight the most significant results in the interest of brevity, which occurred in the right medial prefrontal cortex for trials where participants answered correctly (see Fig. 6). Please see Fig. 8–12 and Tables II–VI in the Appendix for the results from the other brain areas, and results including incorrectly answered trials.

An increased hemoglobin concentration is related to an increased cognitive load. In the main result, there was a significant effect of intercept ($\beta = 0.33$, SE = 0.09, $p < 0.001$).

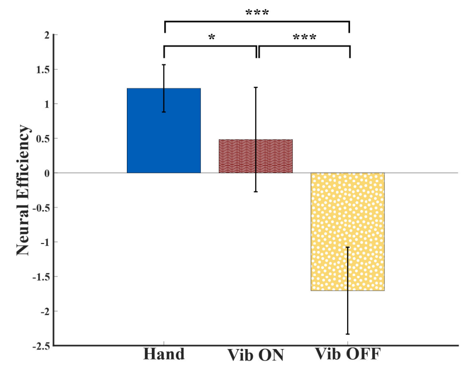

Fig. 7. Neural efficiency bar plot for each condition. * indicates $p < 0.05$, and *** indicates $p < 0.001$.

Soft-medium block combination: Vibrotactile OFF resulted in significantly higher cognitive load than vibrotactile ON ($\beta = 0.24$, SE = 0.12, $p < 0.05$) and the intact hand ($\beta = 0.58$, SE = 0.12, $p < 0.001$). Vibrotactile ON also resulted in significantly higher cognitive load than the intact hand ($\beta = 0.33$, SE = 0.10, $p < 0.001$).

Vibrotactile OFF condition: Cognitive load during the soft-medium block combination was significantly higher than it was in the medium-hard block combination ($\beta = 0.39$, SE = 0.13, $p < 0.05$).

Vibrotactile ON condition: The soft-medium block combination had a higher load than the medium-hard block combination ($\beta = 0.22$, SE = 0.10, $p < 0.05$). In addition, the soft-medium block combination approached significantly higher levels of cognitive load than the soft-hard combination ($\beta = 0.19$, SE = 0.10, $p = 0.0685$).

C. Neural Efficiency

High neural efficiency is associated with low cognitive load and high performance. There was a significant effect of intercept ($\beta = 1.22$, SE = 0.22, $p < 0.01$). There was no difference between the two participant groups. The intact hand had a higher neural efficiency compared to vibrotactile ON ($\beta = 0.74$, SE = 0.27, $p < 0.05$) and vibrotactile OFF ($\beta = 2.93$, SE = 0.27, $p < 0.001$). Vibrotactile ON also had a higher neural efficiency than vibrotactile OFF ($\beta = 2.19$, SE = 0.27, $p < 0.001$). These differences are shown in Fig. 7.

D. Surveys

All comparisons for postexperiment surveys are outlined in Table I. In all comparisons, there was no significant effect of group. Both prosthesis conditions were rated significantly more physically demanding than the intact hand condition ($p < 0.001$). There was no significant effect of intercept ($\beta = 8.77$, SE = 7.38, $p = 0.25$). Both prosthesis conditions were rated as significantly more mentally demanding than the intact hand condition ($p < 0.001$). There was no significant effect of intercept ($\beta = 7.5$, SE =8.8, $p = 0.41$). Participants rated both prosthesis conditions as significantly worse in terms of perceived performance accuracy ($p < 0.001$). Vibrotactile ON was rated as significantly better in perceived performance accuracy than vibrotactile OFF ($p <$

TABLE I
β AND SE VALUES AND FOR EACH COMPARISON BETWEEN CONDITIONS, WHERE H IS HAND, N IS VIBROTACTILE OFF, AND V IS VIBROTACTILE ON

	Physical		Mental		Rushed		Accuracy		Frustration		Visual		Haptic		Auditory	
	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
H - N	-34.3***	7.11	-48.5***	9.29	-2.2	1.28	54.3***	6.01	-47.8***	7.42	-35.6**	10.71	82.7***	6.56	-23**	7.51
H - V	-22.8***	7.11	-41***	9.29	-2.1	1.28	23.6***	6.01	-25.5**	7.42	9.8	10.71	17.4*	6.56	-21.2*	7.51
V - N	-11.5	7.11	-7.5	9.29	-0.1	1.28	30.7***	6.01	-22.3***	7.42	-30.2**	10.32	65.3***	6.56	-1.8	7.51

0.001). There was a significant main effect of intercept ($\beta =$ 87.7, SE $=$ 5.23, $p < 0.001$). Participants rated both prosthesis conditions as significantly more frustrating than the intact hand condition (vibrotactile OFF: $p < 0.001$; vibrotactile ON: $p < 0.01$). Vibrotactile ON was rated as significantly less frustrating than OFF ($p < 0.001$). There was no significant effect of intercept ($\beta =$ -1.03, SE $=$ 8.06, $p = 0.89$).

The reported use of visual cues in the vibrotactile OFF condition was significantly more than in the intact hand condition ($p < 0.01$). The reported use of visual cues in the vibrotactile ON condition was significantly less than in the vibrotactile OFF condition ($p < 0.01$). There was a significant main effect of intercept ($\beta = 50.7$, SE $= 13.1$, $p < 0.01$). Participants rated use of haptic cues as significantly less in the prosthesis conditions compared to the intact hand condition (vibrotactile OFF: $p < 0.001$; vibrotactile ON: $p < 0.05$). Participants rated use of haptic cues as significantly more in vibrotactile ON compared to vibrotactile OFF ($p < 0.001$). There was a significant effect of intercept ($\beta = 88.6$, SE $= 6.2$, $p < 0.001$). Participants rated use of auditory cues in the prosthesis conditions as significantly more than the intact hand (vibrotactile OFF: $p < 0.01$; vibrotactile ON: $p < 0.05$). There was no significant difference in reported auditory cue use between vibrotactile ON and OFF ($\beta =$ -1.8, SE $= 7.51$, $p = 0.81$). There was no significant effect of intercept ($\beta =$ -3.6, SE $= 9.87$, $p = 0.72$).

IV. DISCUSSION

In this study, we presented a comparison between two contrasting sensory feedback paradigms for upper-extremity prosthesis control, along with a comparison of both approaches to the gold standard, the intact healthy hand. Evaluations included standard task performance measures, and most notably, a neurophysiological measure of mental effort. To the authors' knowledge, this study marks the first investigation into neurophysiologically assessed effects of haptic feedback in a prosthesis. Here, we demonstrate the utility of fNIRS for cognitive load assessments in prostheses, and highlight the cognitive and task performance benefits of adding haptic feedback to a myoelectric prosthesis. As expected, we found that the intact hand performed better than both the standard myoelectric prosthesis and the myoelectric prosthesis with vibrotactile feedback in regard to task accuracy and mental effort. In addition, we showed that vibrotactile feedback has the potential to reduce mental effort compared to the standard prosthesis in the absence of such feedback. While it is anecdotally known that haptic feedback can reduce cognitive load, direct measures of brain activity has never been used to validate this with a prosthesis.

Overall, we found that discriminability varied greatly for different block pairs and feedback conditions. For vibrotactile OFF in particular, discrimination was the easiest with the soft-hard and medium-hard pairs, followed by the soft-medium block pair. The soft-hard and medium-hard discrimination accuracy were both above chance, indicating that participants were likely utilizing visual cues and possibly other incidental cues such as sense of effort, EMG efference copy, and reaction forces from the Bowden cable actuation scheme that were transmitted through the socket. The soft and the medium blocks were closer in stiffness than the other block pairs, which means the visual deformation cues for these blocks were very similar. The extra visual attention required to distinguish between these two blocks is what likely caused the increased cognitive load over other easier combinations. This was also demonstrated by fNIRS measures, indicating that they are sensitive to the mental demand associated with tasks of varying difficulty; a finding that is in line with fNIRS research in other fields [32], [39].

Meanwhile, for the intact hand and vibrotactile ON, discriminability did not significantly differ between the three block pairs, thus indicating the robustness of these conditions in terms of performance accuracy. Likewise, for the intact hand, cognitive load did not significantly differ between the three block pairs. Cognitive load did, however, differ by block pair in the vibrotactile ON condition; cognitive load of the soft-medium pair was significantly higher than the medium-hard pair, and the cognitive difference between the soft-medium and soft-hard pairs was approaching significance. In postanalysis, to determine the percentage of vibrotactile stimuli pairs that were below the just noticeable difference for vibrotactile stimulation just proximal to the elbow in the soft-medium pair, a value of 0.4 was used (larger than 0.3 at 250 Hz for the volar forearm [44]). The percentage of vibrotactile stimuli pairs below this value was 0% for the soft-medium pair. Therefore, it is likely that the particular difficulty in discriminating the soft-medium pair did not arise from a lack of contrast in the vibrotactile cues, but rather the interplay between visual cues and haptic cues. One participant expressed they were unsure how to use both cues together, and another participant mentioned that the vibration cues did not always match the visual cues. In some cases, the information from the separate modalities seemed either contradictory or difficult to integrate together. Additionally, it has previously been shown that that visual cues are weighted more than haptic cues [45]; therefore, it is possible that in the cases where participants felt a mismatch between the cues, they chose to rely on vision.

Within the medium-hard and soft-hard block pairs, vibrotactile ON did not appear to be better than OFF for both performance and cognitive load. This result alludes to the fact that haptic feedback may be most useful in cases, where the task is challenging without any haptic feedback. Previous work showed there was no difference in grip force for a grasp and lift task between both torque and vibration feedback and no feedback, likely due to the fact that the task was easy to accomplish without any haptic feedback [46]. Similarly, Markovic *et al* [47] found that vibrotactile feedback was only useful in complex, dynamic tasks.

The intact hand consistently performed better than vibrotactile OFFin all block pairs, and better than vibrotactile ON in the medium-hard and soft-medium block pairs. The soft-hard pair was likely easy enough to perform with both vibrotactile ON and the intact hand, which is why no significant difference in accuracy was found between them. Regarding cognitive load, the intact hand resulted in a significantly lower cognitive demand for the soft-medium block pair only. It is likely the case that the other block pairs were too simple to garner cognitive load differences. In a similar manner, in previous studies such as *n*-back working memory as well as air traffic control and flight simulator tasks resulted in similar cognitive load between tasks, where the difficulty level was similar [41].

Neural efficiency outcomes furthermore indicate that the intact hand showed a high performance with low cognitive load, while vibrotactile OFF overall had a low performance with high cognitive load. Vibrotactile ON was in between, indicating that haptic feedback bridges the traditional operation and the ideal operation, the intact hand.

Survey questions largely support the performance and mental workload measurements. Participants felt their perceived accuracy to be the highest with the intact hand, followed by the vibrotactile ON, and finally vibrotactile OFF. Levels of frustration followed exactly the opposite trend. Participants also felt their mental workload was lower with the intact hand compared to both vibrotactile ON and OFF, but felt no difference overall between vibrotactile ON and OFF. This aligns closely with results from the soft-hard and medium-hard block pairs, for which no difference were found between vibrotactile ON and OFF for both performance and mental effort. Participants did, however, express use of visual cues more in the vibrotactile OFF condition than the vibrotactile ON condition. For the soft-hard and medium-hard block pairs, the visual cues likely improved participants' accuracy over chance. However, the visual cues for the soft-medium block pair were likely more subtle and difficult to interpret, as indicated by the mental workload observed for this particular pair in the vibrotactile OFF condition.

While survey results showed that participants felt overall inaccurate in the vibrotactile OFF condition (37.4%), their performance in the medium-hard and soft-hard block pairs exceeded pure guessing (50%). Even anecdotally, a few participants commented during the experiment that they were unable to tell the differences between blocks in the OFF condition. This indicates that, even if it is possible for participants to decently discriminate stiffness without haptic feedback, they do not feel confident in their assessment. Haptic feedback can help mitigate this uncertainty and could improve users' confidence during object interactions. This is in line with the work of Markovic *et al.* who concluded based on participants' subjective evaluations, that even if haptic feedback does not significantly improve performance, it could still benefit the users' subjective experience [47].

It is also worth considering that participants' reported use of auditory cues was not significantly different between vibrotactile OFF and ON. Given that visual feedback was the same in both conditions, the differences in cognitive load and performance are most likely due to the availability of haptic cues. In fact, there was a significant difference in participants' reported use of haptic cues, with the intact hand being the condition, where haptic cues were used the most, followed by vibrotactile ON, and then vibrotactile OFF. That participants reported higher usage of haptic cues in the intact hand compared to vibrotactile ON indicates that users may not have trusted the vibration stimulus, due to lack of familiarity and sensory richness compared to their natural haptic cues. Structured longitudinal training with vibrotactile feedback may help participants to more confidently interpret the cues, as was demonstrated in a virtual object task over a two-week period [17].

In addition, cognitive load was not ideal with respect to the intact hand within the soft-medium pair. Given that the ultimate goal is for haptic feedback to return mental effort to levels consonant with healthy hand, fNIRS measures can provide useful insights as to the best approaches for achieving that goal. For example, longitudinal fNIRS measures can be utilized to assess the benefits of training with a particular feedback modality as it has previously been shown that long-term training reduces cognitive load due to learning and skill-building [48], [49]. fNIRS measures of cognitive load may also be used to compare different types of haptic feedback, as other, potentially more intuitive forms of feedback may incur a lower cognitive load without requiring any extensive training. Finally, it is possible to use fNIRS measures as a cognitive load bench-marking tool for comparing different iterations of the same haptic feedback device in order to optimize its design and operation.

While this experimental investigation provided insight into the utility of haptic feedback from both a task performance and mental effort perspective, there are a few limitations that should be addressed in future studies. First, while our task was informative, it was still quite simple. Given that this is the first investigation with fNIRS into the effect of haptic feedback, we specifically chose a simple task to avoid task-related confounds. Second, our results were only confirmed in an able-bodied participant population. While a mock prosthesis simulates the experience of a unilateral amputee for testing purposes, validation of these findings in an amputee population is required before any translation to clinical practice. Particularly insightful would be a comparison of the mental effort between a unilateral amputee's intact limb and their prosthesis. Finally, since our fNIRS sensor covering the right lateral prefrontal cortex was not functioning, we are missing some potentially significant information. Our fNIRS measures showed that the most significant differences occurred in the right medial prefrontal cortex. Future investigations should pay very close attention to this region.

Our statistical model indicated a learning effect. Although this effect was relatively very small compared to the other effects, the authors are still interested in a future investigation into the longer term effects of training on cognitive load and performance. It was also found that fNIRS measures did not indicate significant differences between all block pair comparisons. Whether this is due to the overall sensitivity of fNIRS measures, or the actual nature of these subtasks is not entirely clear. Nevertheless, our fNIRS measures were able to differentiate between several difficulty levels, thereby laying the groundwork for future investigations into the use of haptic feedback with more complex tasks.

fNIRS as an emerging neuroimaging technique went through significant methodological development over the previous two decades [50]. Today, the number of review articles on a wide spectrum of fields such as cognitive and social sciences, psychology, neuroscience, medicine, and neuroengineering testifies to the maturity achieved by this noninvasive optical neuroimaging modality. fNIRS has been demonstrated to capture vascular response related brain activity similar to fMRI but in increasingly miniaturized, portable, wearable form-factor, that can be battery-operated, wireless and allow participants to be untethered and ambulatory [43], [51]. fNIRS has been demonstrated to capture higher PFC activation during increased cognitive load in diverse array of task domains, including working memory paradigms [52], [53], decision making [54], attention [55], driving [56] and flight simulators [57], actual flights conditions [39], air traffic control and UAV operations [32], and even outdoor navigation [58] and wheelchair control [59].

As the fNIRS neuroimaging technique further develops, utilization in neuroergonomic assessment of prosthetics and other human–machine interfaces are expected to expand. As a final thought, it is worth considering that the approach employed in this work can be adapted into broader contexts within human-in-the-loop systems to identify the tasks, which carry high cognitive load. Furthermore, researchers can seek to minimize this quantifiable measure of cognitive load in order to reduce mental burdens on the user, thereby optimizing the system as a whole. It is also possible to use fNIRS to adapt the system to the user's mental state. For example, Yuksel *et al.* implemented a brain-adaptive piano training system, where the difficulty level was increased in response to the user's decreased cognitive load in real-time. This resulted in higher accuracy and speed over the nonadaptive control condition [60]. A similar approach may be used in prostheses, where the operation of the prosthesis is modified in real-time based on the user's level of mental fatigue; for example, enabling automatic grasp-modifications algorithms in response to increased cognitive load, or turning off haptic feedback when cognitive load is low.

V. Conclusion

In this study, we compared mental effort and performance in a stiffness discrimination task for the intact hand, standard myoelectric prosthesis, and myoelectric prosthesis with vibrotactile feedback. Results indicated that performance and mental effort improved with vibrotactile feedback over the clinical standard, for especially difficult subtasks. In this simple experiment, we clearly show the reliability of fNIRS to accurately determine the most difficult subtask in a routine and determine how cognitive load compares across conditions within that task. In addition, this study lays the groundwork for future investigations into neurophysiological assessment of haptic devices. Furthermore, this methodology can be applied to any application, where an understanding of cognitive load is critical to improving the human experience in human–robot collaboration scenarios.

Disclosure: fNIR Devices, LLC manufactures the optical brain imaging instrument and licensed IP and know-how from Drexel University. Dr. Ayaz was involved in the technology development and thus offered a minor share in the startup firm fNIR Devices, LLC.

Appendix

H, *V*, and *N* indicate the intact hand, vibrotactile ON, and vibrotactile OFF conditions. MH, SM, and SH indicate the medium-hard, soft-medium, and soft-hard block combinations.

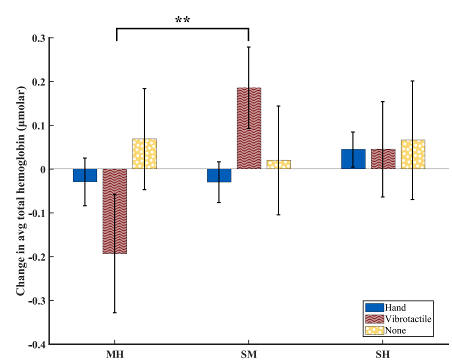

Fig. 8. Average change in total hemoglobin concentration for each condition in the left lateral prefrontal cortex. Error bars represent standard error of the mean. ** indicates $p < 0.01$.

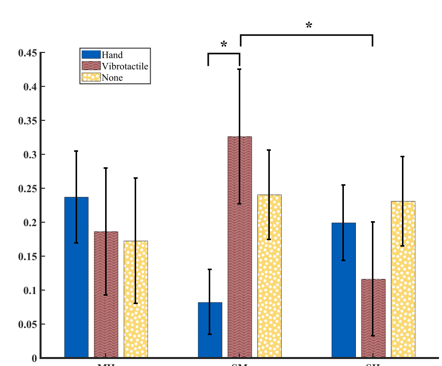

Fig. 9. Average change in total hemoglobin concentration for each condition in the left medial prefrontal cortex. Error bars represent standard error of the mean. * indicates $p < 0.05$.

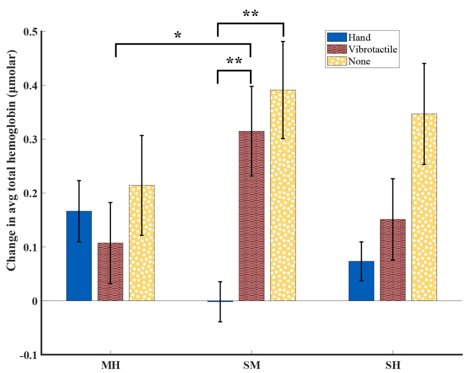

Fig. 10. Average change in total hemoglobin concentration for each condition in the right medial prefrontal cortex. Error bars represent standard error of the mean. * indicates $p < 0.05$, and ** indicates $p < 0.01$.

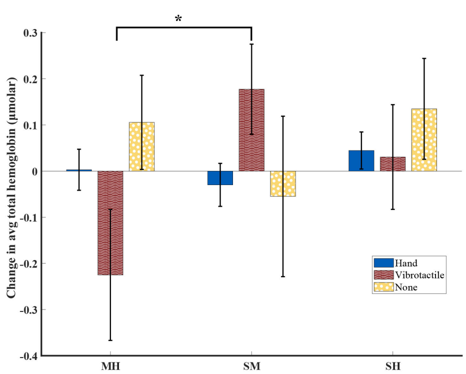

Fig. 11. Average change in total hemoglobin concentration for each condition in the left lateral prefrontal cortex, using only correct trials. Error bars represent standard error of the mean. * indicates $p < 0.05$.

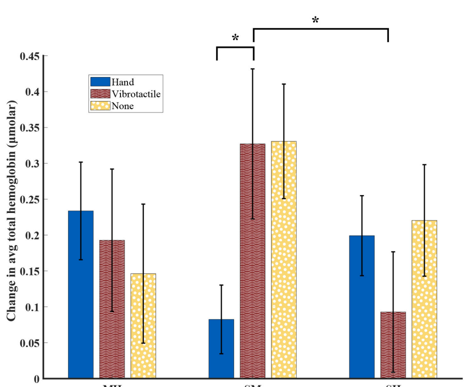

Fig. 12. Average change in total hemoglobin concentration for each condition in the left medial prefrontal cortex, using only correct trials. Error bars represent standard error of the mean. * indicates $p < 0.05$.

TABLE II
LEFT LATERAL HBT

	Intercept β			Intercept SE		
	0.19			0.14		
	Hand		Vib		None	
	β	SE	β	SE	β	SE
SM - MH	-6.9^{-4}	0.13	0.38**	0.13	-0.05	0.13
SM - SH	-0.07	0.13	0.14	0.13	-0.05	0.13
MH - SH	-0.07	0.13	-0.24	0.13	2.5^{-3}	0.13
	MH		SM		SH	
	β	SE	β	SE	β	SE
N - H	0.1	0.13	0.05	0.13	0.02	0.13
N - V	0.26	0.13	-0.17	0.21	0.02	0.13
V - H	-0.16	0.13	0.22	0.13	6.6^{-4}	0.13

TABLE III
LEFT MEDIAL HBT

	Intercept β			Intercept SE		
	0.33***			0.09		
	Hand		Vib		None	
	β	SE	β	SE	β	SE
SM - MH	-0.15	0.10	0.14	0.10	0.07	0.10
SM - SH	-0.12	0.10	0.21*	0.10	9.5^{-3}	0.10
MH - SH	0.04	0.10	0.07	0.10	-.06	0.10
	MH		SM		SH	
	β	SE	β	SE	β	SE
N - H	-0.06	0.10	0.16	0.10	0.11	0.10
N - V	-0.01	0.10	-0.09	0.10	0.02	0.13
V - H	-0.05	0.10	0.24*	0.10	-0.08	0.10

TABLE IV
RIGHT MEDIAL HBT

	Intercept β			Intercept SE		
	0.31**			0.09		
	Hand		Vib		None	
	β	SE	β	SE	β	SE
SM - MH	-0.17	0.10	0.21*	0.10	0.18	0.10
SM - SH	-0.08	0.10	0.16	0.10	0.04	0.10
MH - SH	0.09	0.10	-0.04	0.10	-0.13	0.10
	MH		SM		SH	
	β	SE	β	SE	β	SE
N - H	0.05	0.1	0.39**	0.10	0.27	0.10
N - V	0.11	0.10	0.08	0.10	0.20	0.10
V - H	-0.06	0.10	0.32**	0.10	0.08	0.10

TABLE V
LEFT LATERAL HBT - CORRECT TRIALS

	Intercept β			Intercept SE		
	0.19			0.12		
	Hand		Vib		None	
	β	SE	β	SE	β	SE
SM - MH	-0.02	0.13	0.40**	0.13	-0.10	0.16
SM - SH	-0.07	0.13	0.15	0.13	-0.16	0.16
MH - SH	-0.05	0.13	-0.25	0.13	-0.06	0.14
	MH		SM		SH	
	β	SE	β	SE	β	SE
N - H	0.08	0.14	5.8^{-3}	0.16	0.09	0.13
N - V	0.29	0.14	-0.21	0.16	0.10	0.14
V - H	-0.21	0.13	0.22	0.10	-5.1^{-3}	0.13

ACKNOWLEDGMENT

The authors would like to thank Jacob Carducci for building and maintaining the actuator, and Colette McGarvey for creating the test objects, also would like to Dankmeyer, Inc. for providing the custom-built mock prosthesis and also would like to thank Luke Osborn and Mark Iskarous for assistance with the piezoresistive sensor fabrication.

TABLE VI
LEFT MEDIAL HBT—CORRECT TRIALS

	Intercept β			Intercept SE		
	0.32***			0.09		
	Hand		Vib		None	
	β	SE	β	SE	β	SE
SM - MH	-0.15	0.11	0.13	0.11	0.15	0.14
SM - SH	-0.12	0.11	0.23*	0.11	0.08	0.14
MH - SH	0.04	0.11	0.10	0.11	-0.06	0.11
	MH		SM		SH	
	β	SE	β	SE	β	SE
N - H	-0.07	0.11	0.23	0.13	0.02	0.11
N - V	-0.03	0.12	-0.01	0.13	0.13	0.11
V - H	-0.05	0.11	0.24*	0.11	-0.11	0.11

REFERENCES

[1] A. B. Vallbo and R. S. Johansson, "Properties of cutaneous mechanoreceptors in the human hand-related to touch sensation," *Human Neurobiol.*, vol. 3, pp. 3–14, 1984.

[2] E. Biddiss and T. Chau, "Upper-limb prosthetics: Critical factors in device abandonment," *Amer. J. Phys. Med. Rehabil.*, vol. 86, no. 12, pp. 977–987, Dec. 2007.

[3] H. Yamada, Y. Yamanoi, K. Wakita, and R. Kato, "Investigation of a cognitive strain on hand grasping induced by sensory feedback for myoelectric hand," in *Proc. IEEE Int. Conf. Robot. Automat.*, May 2016, pp. 3549–3554.

[4] M. Zhou, D. B. Jones, S. D. Schwaitzberg, and C. G. L. Cao, "Role of haptic feedback and cognitive load in surgical skill acquisition," in *Proc. Hum. Factors Ergonom. Soc.*, 2007, pp. 631–635.

[5] G. Puchhammer, "The tactile slip sensor: Integration of a min- iaturized sensory device on an myoelectric hand," *Orthopadie-Technik Quart.*, vol. 1, pp. 7–12, 2000.

[6] Ottobock, "SensorHand Speed," Tech. Rep. [Online]. Available: https://shop.ottobock.us/Prosthetics/Upper-Limb-Prosthetics/Myo-Hands-and-Components/Myo-Terminal-Devices/SensorHand-Speed/p/8E39~58#product-documents-section

[7] E. D. Engeberg and S. G. Meek, "Adaptive sliding mode control for prosthetic hands to simultaneously prevent slip and minimize deformation of grasped objects," *IEEE/ASME Trans. Mechatronics*, vol. 18, no. 1, pp. 376–385, Feb. 2013.

[8] J. Doubler and D. Childress, "An analysis of extended physiological proprioception as a prosthesis-control technique," *J. Rehabil. Res. Develop.*, vol. 21, no. 1, pp. 5–18, 1984.

[9] J. A. Doubler and D. S. Childress, "Design and evaluation of a prosthesis control system based on the concept of extended physiological proprioception." *J. Rehabil. Res. Develop.*, vol. 21, no. 1, pp. 19–31, May 1984.

[10] H. J. Witteveen, H. S. Rietman, and P. H. Veltink, "Vibrotactile grasping force and hand aperture feedback for myoelectric forearm prosthesis users," *Prosthetics Orthotics Int.*, vol. 39, no. 3, pp. 204–212, Jun. 2015.

[11] M. R. Motamedi, J.-B. Chossat, J.-P. Roberge, and V. Duchaine, "Haptic feedback for improved robotic arm control during simple grasp, slippage, and contact detection tasks," in *Proc. IEEE Int. Conf. Robot. Automat.*, May 2016, pp. 4894–4900.

[12] D. D. Damian, M. Fischer, A. Hernandez Arieta, and R. Pfeifer, "The role of quantitative information about slip and grip force in prosthetic grasp stability," *Adv. Robot.*, vol. 32, no. 1, pp. 12–24, 2018.

[13] P. Patterson and J. Katz, "Design and evaluation of a sensory feedback system that provides grasping pressure in a myoelectric hand," *J. Rehabil. Res. Dev.*, vol. 29, no. 1, pp. 1–8, 1992.

[14] J. Wheeler, K. Bark, J. Savall, and M. Cutkosky, "Investigation of rotational skin stretch for proprioceptive feedback with application to myoelectric systems," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 1, pp. 58–66, Feb. 2010.

[15] K. Bark, J. W. Wheeler, S. Premakumar, and M. R. Cutkosky, "Comparison of skin stretch and vibrotactile stimulation for feedback of proprioceptive information," in *Proc. Symp. Haptic Interfaces Virtual Environ. Teleoperator Syst.*, Mar. 2008, pp. 71–78.

[16] E. Raveh, J. Friedman, and S. Portnoy, "Evaluation of the effects of adding vibrotactile feedback to myoelectric prosthesis users on performance and visual attention in a dual-task paradigm article," *Clin. Rehabil.*, vol. 32, no. 10, pp. 1308–1316, 2018.

[17] C. E. Stepp, Q. An, and Y. Matsuoka, "Repeated training with augmentative vibrotactile feedback increases object manipulation performance," *PLoS ONE*, vol. 7, no. 2, Feb. 2012, Art. no. e32743.

[18] A. Blank, A. M. Okamura, and K. J. Kuchenbecker, "Identifying the role of proprioception in upper-limb prosthesis control," *ACM Trans. Appl. Perception*, vol. 7, no. 3, pp. 1–23, Jun. 2010.

[19] M. D'Alonzo, C. Cipriani, and M. C. Carrozza, "Vibrotactile sensory substitution in multi-fingered hand prostheses: Evaluation studies," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, vol. 2011, Jan. 2011, Paper 5975477.

[20] N. Thomas, G. Ung, C. McGarvey, and J. D. Brown, "Comparison of vibrotactile and joint-torque feedback in a myoelectric upper-limb prosthesis," *J. NeuroEng. Rehabil.*, vol. 16, no. 1, pp. 1–18, Dec. 2019.

[21] C. Pylatiuk, A. Kargov, and S. Schulz, "Design and evaluation of a low cost force feedback," *J. Prosthetics Orthotics*, vol. 18, no. 2, pp. 57–61, 2006.

[22] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (task load index): Results of empirical and theoretical research," *Adv. Psychol.*, vol. 52, no. C, pp. 139–183, Jan. 1988.

[23] S. G. Hart, "NASA-TASK LOAD INDEX (NASA-TLX); 20 YEARS LATER," in *Proc. Hum. Factors Ergonom. Soc.*, 2006, pp. 904–908.

[24] M. Lohani, B. R. Payne, and D. L. Strayer, "A review of psychophysiological measures to assess cognitive states in real-world driving," *Front. Hum. Neurosci.*, vol. 13, Mar. 2019, Art. no. 57.

[25] A. Jimenez-Molina, C. Retamal, and H. Lira, "Using psychophysiological sensors to assess mental workload during web browsing," *Sensors*, vol. 18, no. 2, Feb. 2018, Art. no. 458.

[26] C. Ikehara and M. Crosby, "Assessing cognitive load with physiological sensors," in *Proc. 38th Annu. Hawaii Int. Conf. Syst. Sci.*, 2005, pp. 295a–295a.

[27] R. Zheng, *Cognitive Load Measurement and Application: A Theoretical Framework for Meaningful Research and Practice*. England, UK: Routledge, 2017.

[28] Tobii Pro, "Tobii pro glasses 3," 2020. [Online]. Available: https://www.tobiipro.com/siteassets/tobii-pro/user-manuals/tobii-pro-glasses-3-user-manual.pdf/?v=1.3

[29] D. Dasari, G. Shou, and L. Ding, "ICA-Derived EEG correlates to mental fatigue, effort, and workload in a realistically simulated air traffic control task," *Front. Neurosci.*, vol. 11, 2017, Art. no. 297. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/28611575http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC5447707

[30] L. F. Van Dillen, D. J. Heslenfeld, and S. L. Koole, "Tuning down the emotional brain: An fMRI study of the effects of cognitive load on the processing of affective images," *Neuroimage*, vol. 45, pp. 1212–1219, 2009.

[31] F. Biessmann, S. Plis, F. C. Meinecke, T. Eichele, and K.-R. Muller, "Analysis of multimodal neuroimaging data," *IEEE Rev. Biomed. Eng.*, vol. 4, pp. 26–58, Oct. 2011. [Online]. Available: http://ieeexplore.ieee.org/document/6035960/

[32] H. Ayaz, P. A. Shewokis, S. Bunce, K. Izzetoglu, B. Willems, and B. Onaral, "Optical brain monitoring for operator training and mental workload assessment," *NeuroImage*, vol. 59, no. 1, pp. 36–47, Jan. 2012.

[33] W. Kuschinsky, "Coupling of function, metabolism, and blood flow in the brain," *Neurosurgical Rev.*, vol. 14, no. 3, pp. 163–168, Sep. 1991.

[34] J. Harrison *et al.*, "Cognitive workload and learning assessment during the implementation of a next-generation air traffic control technology using functional near-infrared spectroscopy," *IEEE Trans. Human-Mach. Syst.*, vol. 44, no. 4, pp. 429–440, Aug. 2014.

[35] R. McKendrick, R. Mehta, H. Ayaz, M. Scheldrup, and R. Parasuraman, "Prefrontal hemodynamics of physical activity and environmental complexity during cognitive work," *Hum. Factors*, vol. 59, no. 1, pp. 147–162, 2017.

[36] F. A. Fishburn, M. E. Norr, A. V. Medvedev, and C. J. Vaidya, "Sensitivity of fNIRS to cognitive state and load," *Front. Hum. Neurosci.*, vol. 8, no. 1, pp. 1–11, Feb. 2014.

[37] S. Perrey, "Possibilities for examining the neural control of gait in humans with fNIRS," *Front. Physiol.*, vol. 5, pp. 1–4, May. 2014.

[38] A. Mirelman *et al.*, "Increased frontal brain activation during walking while dual tasking: An fNIRS study in healthy young adults," *J. NeuroEng. Rehabil.*, vol. 11, no. 1, pp. 1–7, May 2014.

[39] T. Gateau, H. Ayaz, and F. Dehais, "*In silico vs*, Over the clouds: On-the-fly mental state estimation of aircraft pilots, using a functional near infrared spectroscopy based Passive-BCI," *Front. Hum. Neurosci.*, vol. 12, May 2018, Art. no. 187. [Online]. Available: http://journal.frontiersin.org/article/10.3389/fnhum.2018.00187/full

[40] L. Osborn, W. W. Lee, R. Kaliki, and N. Thakor, "Tactile feedback in upper limb prosthetic devices using flexible textile force sensors," in *Proc. IEEE RAS/EMBS Int. Conf. Biomed. Robot. Biomechatronics*, Aug. 2014, pp. 114–119.

[41] H. Ayaz, B. Onaral, K. Izzetoglu, P. A. Shewokis, R. McKendrick, and R. Parasuraman, "Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: Empirical examples and a technological development." *Front. Hum. Neurosci.*, vol. 7, Dec. 2013, Art. no. 871. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/24385959http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3866520

[42] H. Ayaz, P. A. Shewokis, A. Curtin, M. Izzetoglu, K. Izzetoglu, and B. Onaral, "Using MazeSuite and functional near infrared spectroscopy to study learning in spatial navigation," *J. Visualized Experiments*, no. 56, 2011, Art no. e3443.

[43] A. Curtin and H. Ayaz, "Neural efficiency metrics in neuroergonomics: Theory and applications," in *Neuroergonomics.* H. Ayaz and F. Dehais, Eds. Cambridge, MA, USA: Academic Press, 2019, ch. 22, pp. 133–140. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780128119266000221

[44] L. A. Jones and N. B. Sarter, "Tactile displays: Guidance for their design and application," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 50, no. 1, pp. 90–111, 2008.

[45] M. O. Ernst and M. S. Banks, "Humans integrate visual and haptic information in a statistically optimal fashion," *Nature*, vol. 415, no. 6870, pp. 429–433, Jan. 2002.

[46] J. D. Brown *et al.*, "An exploration of grip force regulation with a low-impedance myoelectric prosthesis featuring referred haptic feedback," *J. NeuroEng. Rehabil.*, vol. 12, no. 1, Dec. 2015, Art. no. 104. [Online]. Available: http://www.jneuroengrehab.com/content/12/1/104

[47] M. Markovic *et al.*, "The clinical relevance of advanced artificial feedback in the control of a multi-functional myoelectric prosthesis," *J. NeuroEng. Rehabil.*, vol. 15, no. 1, 2018, Art. no. 28.

[48] A. Curtin and H. Ayaz, "The age of neuroergonomics: Towards ubiquitous and continuous measurement of brain function with fNIRS," *Jpn. Psychol. Res.*, vol. 60, no. 4, pp. 374–386, Oct. 2018.

[49] R. McKendrick, H. Ayaz, R. Olmstead, and R. Parasuraman, "Enhancing dual-task performance with verbal and spatial working memory training: Continuous monitoring of cerebral hemodynamics with NIRS," *NeuroImage*, vol. 85, pp. 1014–1026, Jan. 2014.

[50] M. Ferrari and V. Quaresima, "A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application," *Neuroimage*, vol. 63, no. 2, pp. 921–935, Nov. 2012.

[51] M. A. Yücel, J. J. Selb, T. J. Huppert, M. A. Franceschini, and D. A. Boas, "Functional near infrared spectroscopy: Enabling routine functional brain imaging," *Curr. Opin. Biomed. Eng.*, vol. 4, pp. 78–86, Dec. 2017.

[52] Y. Liu, H. Ayaz, and P. A. Shewokis, "Multisubject "learning" for mental workload classification using concurrent EEG, fNIRS, and physiological measures," *Front. Hum. Neurosci.*, vol. 11, Jul. 2017, Art. no. 389. [Online]. Available: http://journal.frontiersin.org/article/10.3389/fnhum.2017.00389/full

[53] C. Herff, D. Heger, O. Fortmann, J. Hennrich, F. Putze, and T. Schultz, "Mental workload during n-back task-quantified in the prefrontal cortex using fNIRS," *Front. Hum. Neurosci.*, vol. 7, Jan. 2014, Art. no. 935. [Online]. Available: http://journal.frontiersin.org/article/10.3389/fnhum.2013.00935/abstract

[54] S. I. Di Domenico, A. H. Rodrigo, H. Ayaz, M. A. Fournier, and A. C. Ruocco, "Decision-making conflict and the neural efficiency hypothesis of intelligence: A functional near-infrared spectroscopy investigation," *NeuroImage*, vol. 109, pp. 307–317, Apr. 2015.

[55] A. Curtin *et al.*, "Visuospatial task-related prefrontal activity is correlated with negative symptoms in schizophrenia," *Sci. Rep.*, vol. 9, no. 1, pp. 1–12, Dec. 2019.

[56] H. J. Foy and P. Chapman, "Mental workload is reflected in driver behaviour, physiology, eye movements and prefrontal cortex activation," *Appl. Ergonom.*, vol. 73, pp. 90–99, Nov. 2018.

[57] T. Gateau, G. Durantin, F. Lancelot, S. Scannella, and F. Dehais, "Real-time state estimation in a flight simulator using fNIRS," *PLoS One*, vol. 10, no. 3, Mar. 2015, Art no. e0121279.

[58] R. McKendrick *et al.*, "Into the wild: Neuroergonomic differentiation of hand-held and augmented reality wearable displays during outdoor navigation with functional near infrared spectroscopy," *Front. Hum. Neurosci.*, vol. 10, May 2016, Art. no. 216. [Online]. Available: http://journal.frontiersin.org/Article/10.3389/fnhum.2016.00216/abstract

[59] S. Joshi *et al.*, "Neuroergonomic assessment of wheelchair control using mobile fNIRS," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 6, pp. 1488–1496, Jun. 2020.

[60] B. F. Yuksel *et al.*, "Learn piano with BACh: An adaptive learning interface that adjusts task difficulty based on brain state," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, 2016, pp. 5372–5384.