IEEE TRANSACTIONS ON
HUMAN-MACHINE SYSTEMS
A PUBLICATION OF THE IEEE SYSTEMS, MAN, AND CYBERNETICS SOCIETY

Application of Cognitive Task Performance Modeling for Assessing Usability of Transradial Prostheses

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***Abstract*— The goal of this study was to investigate the use of cognitive modeling to assess the usability of an upper-limb prosthesis with a focus on mental workload responses. Prior studies have investigated usability of upper-limb prostheses with subjective surveys and physiological measures. However, these approaches have limitations, including subject recall of conditions and physiological response contamination by head and body movements and user speech during task performance as well as sensitivity to physical fatigue and room lighting conditions. Cognitive modeling was used to assess mental workload in use of a transradial upper-limb prosthesis. A case study was conducted with a participant with upper-limb amputation using two different types of electromyography (EMG)-based control schemes including conventional direct control (DC) and pattern recognition (PR) control in order to compare cognitive model outcomes with mental workload assessment using eye-tracking measures. Cognitive models time estimates were also compared with actual task completion time results from the case study to further assess the validity of cognitive modeling as an analytical tool for evaluating upper limb prosthesis usability. Findings of both the cognitive models and case study revealed the PR mode to be more intuitive, reduce cognitive load, and increase efficiency in prosthetic control as compared to the DC mode. Results of the present study revealed that cognitive modeling can be used as an analytical approach for assessing upper-limb prosthetic device usability in terms of workload outcomes. Future studies should validate the present findings with more precise time estimations and a larger user sample size.**

***Index Terms*— cognitive modeling, GOMSL, mental workload, prosthetics**

I. Introduction

Upper limb amputation causes severe functional disability. Ziegler-Graham *et al.* [1] reported that over 100,000 people in the U.S. have an upper limb amputation in which 57% of them are transradial (through the forearm). Such amputation makes activities of daily living very difficult or even impossible for the patient. To restore functional ability as fully as possible, amputee patients typically use upper-limb prostheses. However, prostheses are often reported to be challenging to use leading to poor utilization and device rejection [2-3].

A. Types of Prosthetic Control

Prosthetic technology has improved substantially in recent years. Different types of available upper-limb devices are mechanically complex, powered and capable of performing several functions [4-5]. Most commercially available upper-limb prostheses use two main types of control approaches based on electromyography (EMG; muscle activation signals), including: (1) direct control (DC); and (2) pattern recognition (PR) control schemes.

In a DC scheme, surface EMG signals from an agonist-antagonist residual muscle pair (e.g., finger flexor and extensor) in an amputee's limb are used to control the degrees of freedom (DOF) of the prosthetic device. The speed of the prosthetic hand motion is proportional to the magnitude of EMG signals. Control mode switching is necessary to operate multiple DOFs of a prosthesis, as a single agonist-antagonist muscle pair is only sufficient for control of two directions of movement in a single DOF. Therefore, the control scheme can be non-intuitive for users and difficult to implement when using a prosthesis with more than one powered DOF.

The PR [6] scheme requires more electrodes than the DC mode to control an equal number of DOFs with these electrodes identifying the intended motion of an amputated limb, based on residual muscle activation patterns. However, the EMG electrodes used in PR control do not have to be placed over independent muscle sites. The association between user intent and muscle activation pattern is constructed based on training data for the user of the prosthesis. This myoelectric control scheme directly maps the user intended motion and may be more intuitive for device application.

B. Mental Workload Assessment in Using Prostheses

Prior research has done some assessment of mental workload

This work was supported by grants from the Department of Health and Human Services (DHHS), National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR, Grant No. 90IF0064), and the National Science Foundation (NSF Grant No. 1527202).

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Digital Object Identifier 10.1109/THMS.2019.2903188

in use of upper limb prostheses using subjective ratings and physiological measures. For example, Gonzalez et al. [7] used the NASA Task Load Index (NASA-TLX) questionnaire and physiological measures, including electroencephalography (EEG), cardiac measures, respiration rate (RR) and electro-dermal activity (EDA) to compare participant cognitive load in device use with different feedback modalities. In another study, Deeny et al. [8] inferred prosthetic user cognitive workload from EEG signals. Using event-related potentials (ERPs), they found little difference in cognitive workload between DC and PR control of devices among able-bodied participants (using an upper-arm adapter). However, the cognitive workload measures used in these prior studies have major limitations. Subjective ratings, such as the NASA-TLX, suffer from recall bias as well as substantial individual differences in ratings [9]. Furthermore, the method does not provide a continuous measure of workload during task performance [10]. Beyond this, EEG signals are susceptible to contamination from head and body movements and donning an electrode cap with an attached wiring harness is obtrusive to subject performance.

To address the above issues in measuring mental workload, recent studies used continuous and unobtrusive approaches, which have been extensively applied in other domains [11], such as eye-tracking measures including blink rate, eye-closure intervals, and pupil size. In our previous investigation [12], we used an index of cognitive activity (ICA) based on pupil diameter changes over time to assess mental workload of using upper-limb prostheses in able-bodied participants. Results revealed that a PR control scheme was superior to a DC mode in terms of mental workload. However, due to head and body movements during task performance, some data points were removed which limited the generalizability of our findings.

C. Usability and Workload Evaluation using Cognitive Task Performance Modeling

Card, Moran, and Newell [13] proposed a modeling approach called Goals, Operators, Methods, and Selection rules (GOMS) to support representations of human performance, including learning time, execution time, task errors, etc. GOMS allows for prediction of the time an expert user takes to perform the composite actions of retrieving information from memory, choosing from decision alternatives, keeping track of what needs to be done, and executing motor movements. The GOMS method involves analyzing a task by breaking down operations in to three main categories, including: Perceptual (P), Motor (M) and Cognitive (C). Perceptual operators are further divided into two categories, including: visual and auditory. Motor operators include: moving hands, using a mouse, keyboard entry, etc. Memory and cognitive processes mainly include memory retrieval, executing steps in a mental procedure and choosing among methods [14].

GOMSL is an executable form of Natural GOMS Language (NGOMSL) and provides a structured language notation for developing cognitive task performance models that can be compiled and run on a computer [15]. GOMSL have been used extensively in prior studies as a computational modeling tool. For example, Kaber et al. [16] used GOMSL to compare the usability of two interface prototypes in the life science domain. The GOMSL model showed improvement in terms of performance with an enhanced interface as compared to an existing supervisory control interface for high-throughput screening operations. In addition, the cognitive outputs from the GOMSL model were correlated with actual performance data, which indicated that the approach was useful for assessing the usability of interfaces in the particular domain. In another study, Kaber and Kim [17] used a refined GOMSL model to assess the effect of auditory cueing in an adaptive automation system on human performance. The model considered human parallel processing in dual-task performance. Results revealed the model to accurately describe human performance and reaction times (RT) predicted by the model were close to actual human RTs. They concluded that the GOMSL model, which considered parallel processing, could represent actual human behavior in a dual-task piloting simulation. Finally, in a more recent study, Swangnetr et al. [18] also used GOMSL to model manual and automated task procedures in life science processes. By conducting a field study with three lab technicians and using a GOMSL model, they found positive correlations among GOMS operation counts, task time, and NASA-TLX ratings.

D. Problem Statement

Several studies have assessed usability and mental workload in patient use of upper-limb prostheses by using subjective surveys and physiological measures. However, these approaches have limitations due to the nature of measures (e.g., discrete instead of continuous) and data collection procedures (e.g., intrusive to performance and susceptible to contamination). In our previous study [12], we used eye-tracking measures to provide a continuous and unobtrusive psychophysiological indicator of cognitive workload in prosthetic use. In general, our findings support the use of such measurement technology but the approach was not without the limitation of loss of tracking when patients performed daily living activities in a large volume of space. In addition, the sample that we used for the previous study was a group of healthy college-age participants. We did not test the measurement approach on actual amputees.

To address these issues, the objective of the present study was to use a cognitive task performance modeling method to assess mental workload in upper-limb prosthetic use as an indicator of device and control mode usability. We also conducted a case study with a participant with upper-limb amputation in order to compare the findings of the cognitive performance modeling approach with mental workload assessment using eye-tracking measures.

II. METHOD

A. Case Study

1) Demographic Information

A 42-year-old male with upper-limb amputation participated in this study. (This patient was not part of our prior study [12]). He had experienced unilateral transradial amputation for his right side at the age of 40 due to a job accident. At the time of the study, he was using his preferred artificial limb with a grasping feature, on a regular basis. He also had previous experience with body-powered and electrical prosthetic devices. No complications related to the amputation were reported. The University of North Carolina at Chapel Hill Institutional Review Board approved our research protocol.

2) Experiment Setup

An EMG-based 2-DOF transradial prosthesis, which supported both DC and PR control modes was used in this study (see Fig.1). The prosthesis consisted of an active terminal device (ETD, Motion Control Inc. USA) for EMG capture and commercial wrist rotator (MC Wrist Rotator, Motion Control, Inc., USA). The device was mounted on the participant using a customized socket with embedded surface EMG electrodes in order to provide input signals for the control schemes.

A total of six EMG electrodes were used. Two electrodes were placed on the DC sites identified by the certified prosthetist, using a standard clinical procedure for fitting a myoelectric prosthesis. The prosthetist used MyoBoy™ and associated software (Ottobock, Germany) to select two EMG recording sites to elicit clear and independent EMG activation while the participant attempted wrist/finger flexion and extension in the missing arm. These two electrodes were used for the DC control scheme. Four additional EMG electrodes were placed around the residual limb. Together with the two DC control electrodes, these six EMG electrodes were used for the PR mode. The four electrodes were placed by palpation and confirmation of EMG recordings that produced high signal-to-noise ratio and varied activation pattern while the participant was instructed to perform hand open/close and pronation/supination in the missing limb.

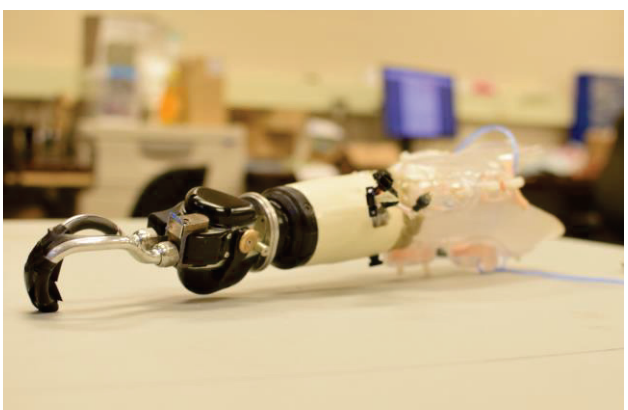

Fig 1. Prosthetic Device

A linear discriminant analysis classifier was used to identify four active classes of intended patient movement, including hand open, hand closed, wrist pronation, and wrist supination, as well as one inactive class (i.e., no movement). Accordingly, a prosthesis motor selector was activated for the intended movement. Similarly, the speed of motor movement was proportional to the magnitude of the muscle activity level. With the PR scheme, the participant could control the DOFs of the prosthesis using intuitive residual muscle contractions. For a detailed description of the EMG signal processing and data classification techniques involved in the control schemes, please see White et al. [12].

A Clothespin Relocation Task (CRT) is a commonly applied daily activity task for assessing upper limb prostheses [19]. In this study, the participant performed the CRT using both control schemes. The CRT workstation (Fig. 2) was mounted on a table, adjusted to a comfortable height for the participant. An eye-tracking system (Facelab 5.1, Seeing machine, Australia) was used to capture pupillometry data, as a basis for cognitive workload assessment. Related to this, the study was conducted in a laboratory with no windows. The illumination level was consistent (130-180 Lux) in order to prevent the effect of pupil light reflux to eye-tracking responses. The Facelab system consisted of two cameras and an infrared light emitting pod (see Fig. 2). When reflected on the eyes, the light emitted from the pod is captured by the cameras along with the outline of the pupil. Changes in pupil size are detected by the system with a sampling frequency of 60 Hz and were used as a basis for identifying fluctuations in cognitive workload. Van Orden et al. [20] previously found pupil diameter to systematically change with visual display target density. In addition, several other studies in the driving domain have found pupil size to be a valid indicator of cognitive workload in secondary (in-vehicle) task performance during driving [21-22].

3) Experiment Procedure

The case study was conducted across two days to avoid carryover effects and muscle fatigue from one (device use) session to another.

In order to minimize potential differences among test days, both sessions were conducted at the same location and with the same experiment setup. The temperature and lighting of the lab facility was consistently maintained and the same experimenters were present for training and testing. The patient used the PR mode in his first visit and the DC mode in the second visit. Sufficient training was provided with each control scheme prior to testing. The patient was instructed to imagine his phantom limb performing a series of movements (i.e., hand

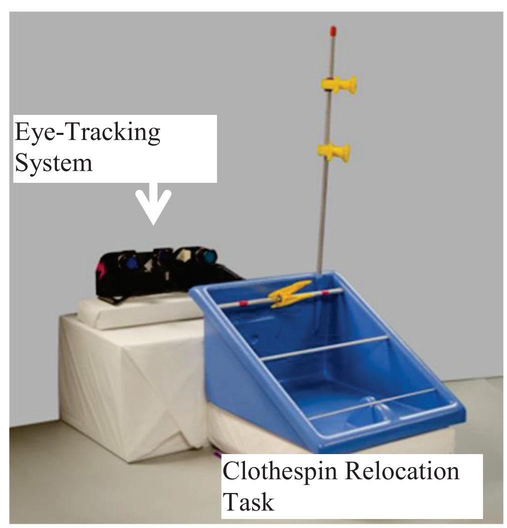

Fig 2. Clothespin Relocation Task and Eye Tracking System

open, hand closed, pronation, supination) for both control schemes. The patient was also instructed to imagine device mode switching for DC scheme, which involved “making a closed fist”. A virtual reality (VR)-based simulation was developed to present the imagined hand movements for the patient through a computer monitor. Meanwhile, he was required to use his abled hand to demonstrate each movement that was being imagined with the phantom limb. The patient practiced combinations of the above movements until he felt comfortable with the control scheme. In addition, he was provided with several break periods to prevent muscle fatigue. For the PR scheme, the EMG signals during the VR training were recorded to train the motion pattern classifier. Subsequently, the patient repeated the above training with the prosthesis activated until he could perform different motions with the prosthetic hand as desired.

After the completion of VR and active prosthesis training, the participant was trained on the CRT. He was required to use the prosthesis to move three clothespins from a top horizontal bar at the base of the workstation to a vertical bar extending upward on the clothespin apparatus (see Fig. 2). The patient continued the CRT training until he could successfully move three pins without error and verbally stated that he felt comfortable with the task.

Following the training session, the eye tracking system was calibrated for the patient. In addition, he was given instructions regarding the formal test trials. The patient was required to move as many clothespins as possible from the horizontal rod to the vertical rod and back within a 2-minute trial. The number of successfully relocated clothespins was recorded. A 2-minute break was provided after each trial. The experiment included 10 trials. After the completion of all trials, the prosthesis and the socket were removed from the patient.

4) Data Analysis

Three dependent variables were measured in this case study including: (1) CRT performance calculated in terms of the average number of successfully relocated pins within a test trial; (2) average pupil size for a test trial and (3) average pin completion time per trial. Our pilot testing revealed that there were more valid eye-tracking data points for the right eye than the left, which was likely due to the location of the cameras, as part of the apparatus setup, relative to the participant’s eyes when using the CRT workstation. As a result, the pupil size response was determined for the right eye across all trials. Besides the quantitative measures, we also asked the participant to make subjective comparison of the two control schemes in terms of device satisfaction.

The independent variable for the study was the prosthetic control scheme (i.e., DC vs. PR). Following calculation of descriptive statistics (mean and standard deviation) for each condition, paired t-tests were performed on the successful pin count and pupil size dependent variables in order to compare the two control schemes. The results are reported in the following section. Based on our prior investigation on able-bodied users [12], we expected (E1) better task performance (i.e., more successfully relocated pins) and lower cognitive workload (E2; i.e., smaller average pupil size; 20) when using the PR mode as compared to DC control mode.

B. Cognitive Task Performance Modeling

Cognitive performance models were constructed using GOMSL code in order to analytically compare demands in using upper limb prostheses under the different control modes (i.e., DC vs. PR). The scenario for this comparison was a complete cycle of the CRT, which includes moving three clothespins from the top horizontal bar at the base of the workstation to the vertical bar extending upward on the clothespin apparatus and back. For each task method coded in GOMSL, the number of perceptual (P), motor (M) and cognitive operators (C) was obtained. We expected (E3) outcomes of the GOMSL models to be predictive of the cognitive workload outcomes for the case study (i.e., lower cognitive workload in using the PR mode than when using the DC mode).

C. Task Completion Time Comparison

The task completion (pin relocation) times from the case study were used for comparison with GOMSL model outcomes. The models were used to estimate prosthetic control times for the DC and PR control modes. The objective of this comparison was to further validate the use of the cognitive performance modeling as an analytical method for assessing prosthetic usability in terms of workload measures.

For those task operations classified as cognitive and/or perceptual (i.e., store <information>, delete <information>, and look for <object whose name is>), established GOMS time estimates were used [23]. However, manual tasks involved in prosthetic control could not be coded by any conventional GOMS operators; therefore, <user-defined> operators were used for all such tasks. GOMS models apply a nominal 50 ms cognitive processing time for each step/operation in a model, based on an underlying theory of human cognition [23]. An additional operation processing time is added to the cognitive processing time to account for specific perceptual, cognitive or motor requirements of an operation. To address the manual task modeling limitation of GOMS, conventional methods-time measurement (MTM) sequence models were used to code manual task movements in prosthetic control [24]. MTM provides time values for fundamental movements of reach, move, turn, grasp, position, disengage, and release. It is important to note that MTM was developed to predict motor performance for able-bodied limbs. In addition, both GOMS and MTM reflect times for error free, expert performance.

We expected (E4) the GOMSL+MTM model time estimates of CRT completion under the DC and PR control modes to be predictive of the actual task performance times obtained from video recordings of the patient using the two control modes. We also expected (E5) the GOMSL model to predict longer task completion times for the DC mode than CRT completion under the PR mode. Paired t-tests were used to compare task completion times projected by the GOMSL models with case study results for the different prosthetic control modes. Correlation analyses were also applied to identify any relations among the trends of responses.

III. RESULTS

A. Case Study

Table 1 presents the descriptive statistics on the successful pin relocation and pupil size responses. In general, the average pin count was higher for the PR control mode than the DC and the pupil size was smaller for PR control.

TABLE 1
DESCRIPTIVE STATISTICS FOR PERFORMANCE AND EYE-TRACKING RESPONSES: MEAN (SD)

Dependent Variable	DC	PR
CRT Successful Pins	6.8 (1.67)	13 (2.37)
Pupil Size (mm)	3.43 (0.1)	3.16 (0.27)

The t-test revealed a significant effect of the control scheme on CRT performance across trials ($t(9)=6.66$, $p<0.0001$). On average, the patient was able to successfully relocate almost twice as many pins using the PR control mode as compared to the DC scheme. The t-test also revealed a significantly smaller average pupil size ($t(9)=-6.76$, $p<0.0001$) for the PR control mode, indicating lower cognitive load during task performance.

Table 2 presents the findings of the subjective device evaluation. The participant was asked to answer each question using a 5-point Likert scale (1: very unsatisfied, 5: very satisfied). Results revealed that the patient had a neutral opinion about the DC mode but was satisfied with the performance of the PR control mode.

TABLE 2
SUBJECTIVE EVALUATION RESULTS

Question	DC Mode	PR Mode
How satisfied are you with the function of this prosthetic?	3	4
How satisfied are you with the movement of this prosthetic?	3	4
How satisfied are you (or would you expect to be) with this prosthetic for daily living activities?	3	4

B. Cognitive Performance Modeling

Table 3 shows the goals and methods, obtained from hierarchical task analysis of the CRT. The number of operations identified were based on review of video recordings of the patient performing the CRT. The table reveals that performance of the CRT using the PR control mode substantially decreased the number of cognitive operators as compared to use of the DC mode. In addition, the total number of motor operators under the PR mode was found to be less than the DC mode. However, there was no difference in the number of perceptual operators between DC and PR control modes.

C. Task Completion Time

Table 4 presents the GOMSL model estimates and CRT case-study times for the DC and PR control modes during one task cycle (i.e., moving three pins from the horizontal rod to the vertical rod and back). Results of both GOMSL model estimates and CRT case-study times revealed that for all methods for goal, using the PR control reduced task completion time as compared to the use of the DC mode (GOMSL: $t(11)=9.365$, $p<0.0001$; Case-study data: $t(11)=8.112$, $p<0.0001$). However, the GOMSL model time estimates were shorter than the average task time of the case study (DC: $t(11)=11.243$, $p<0.0001$, PR: $t(11)=7.387$, $p<0.0001$). In addition, the difference between the task time estimates using GOMSL and the case-study data for the DC mode was significantly greater than for GOMSL estimates vs. the PR control mode data ($t(11)=6.989$, $p<0.0001$). Having said this, correlation analyses on the GOMSL estimates and the case study data within control mode revealed strong and significant linear associations of the model outcomes with actual task performance (DC: $r=0.778$, $p<0.0029$, PR: $r=0.572$, $p=0.05$).

TABLE 3
CRT GOALS, METHODS, ALONG WITH ASSOCIATED NUMBERS OF PERCEPTUAL, MOTOR, AND COGNITIVE OPERATIONS

Goal	Method	DC Mode			PR Mode		
		# Perceptual Operators	# Motor Operators	# Cognitive Operators	# Perceptual Operators	# Motor Operators	# Cognitive Operators
Move 1st pin from horizontal rod to vertical rod	1.1 Grab pin on horizontal rod	1	2	2	1	2	1
	1.2 Place pin on vertical rod	1	7	5	1	5	1
Move 2nd pin from horizontal rod to vertical rod	2.1 Grab pin on horizontal rod	1	7	6	1	5	2
	2.2 Place pin on vertical rod	1	7	5	1	5	1
Move 3rd pin from horizontal rod to vertical rod	3.1 Grab pin on horizontal rod	1	7	6	1	5	2
	3.2 Place pin on vertical rod	1	6	5	1	4	1
Move 3rd pin from vertical rod to horizontal rod	4.1 Grab pin on vertical rod	0	2	2	0	2	2
	4.2 Place pin on horizontal rod	1	7	5	1	5	1
Move 2nd pin from vertical rod to horizontal rod	5.1 Grab pin on vertical rod	1	7	6	1	5	2
	5.2 Place pin on horizontal rod	1	7	5	1	5	1
Move 1st pin from vertical rod to horizontal rod	6.1 Grab pin on vertical rod	1	7	6	1	5	2
	6.2 Place pin on horizontal rod	1	6	5	1	4	1
Total		11	72	58	11	52	17

TABLE 4

COMPARISON OF GOMSL TIME ESTIMATES WITH CASE STUDY TIMES

	Time Estimates for DC Mode (ms)		Time Estimates for PR Mode (ms)	
	GOMSL	Case Study Mean(SD)	GOMSL	Case Study Mean(SD)
Moving the pins from the horizontal rod to the vertical rod				
Pin 1	712	2629 (768)	628	1844 (346)
Grab the pin on the horizontal rod	2663	7033 (1185)	1675	3713 (647)
Place the pin on the vertical rod				
Pin 2	3652	8561 (2960)	2663	3551 (434)
Grab the pin on the horizontal rod	2663	6804 (1532)	1675	4040 (876)
Place the pin on the vertical rod				
Pin 3	3652	7433 (2669)	2663	3540 (1750)
Grab the pin on the horizontal rod	2457	6996 (1836)	1469	4783 (1411)
Place the pin on the vertical rod				
Moving the pins from the vertical rod to the horizontal rod				
Pin 3	662	3137 (1493)	378	1861 (714)
Grab the pin on the vertical rod	2663	6877 (1661)	1675	3118 (964)
Place the pin on the horizontal rod				
Pin 2	3652	5626 (1663)	2663	3678 (606)
Grab the pin on the vertical rod	2663	7197 (1493)	1675	3284 (1124)
Place the pin on the horizontal rod				
Pin 1	3652	6986 (1885)	2663	3448 (1097)
Grab the pin on the vertical rod	2457	8120 (1886)	1469	3371 (622)
Place the pin on the horizontal rod				

IV. DISCUSSION

With respect to the case study, both of our expectations were supported. First, results revealed that CRT performance to be substantially superior (E1) when using the PR control mode, which relies on intuitive muscle contractions. The finding supported our initial investigation on able-bodied users [12]. Furthermore, the result is in line with prior studies comparing PR and DC control modes in various daily activity tasks such as CRT [8, 25-26]. In addition, using the PR mode substantially decreased cognitive workload (E2) as compared to the DC mode (i.e., smaller average pupil size). This result also supports our use of unobtrusive eye-tracking measures as indicators of cognitive workload in using upper-limb prostheses.

In regard to the cognitive performance modeling approach, findings supported our expectations. GOMSL model outcomes were similar to the findings of the case study in terms of cognitive workload (E3; i.e., cognitive workload using PR mode < cognitive workload using DC mode). Using the DC mode, a patient needs to store the current mode of operation (whether the device is in open/close mode or rotation mode), recall from working memory (WM) whenever there should be a change in the mode, delete information from WM whenever the task has been completed, and finally return to new method processing with goal accomplished. However, under the PR mode, there was no need to change modes during task performance. Therefore, there was no need to store or recall information to and from WM, which substantially reduced the number of cognitive operations in the PR mode. In addition, using the PR mode substantially decreased the number of motor operations. In our previous study, making use of the CRT and the same prosthetic control modes [12], we found the DC mode to have lower usability across all investigated measures for able-bodied individual prosthesis use, which was likely due to the lack of intuitiveness of the DC mode. The DC mode required wrist flexion/extension to control one DOF (either hand open/closed or wrist pronation/supination) at a time with participants having to make a clenched fist to change between the DOFs. The extra motor operators for the DC mode in the GOMSL analysis in the present study can be attributed to the requirement for participants to make a fist to change between the DOFs. The findings of the present study provide support for the use of the cognitive performance modeling method to assess mental workload in use of upper-limb prostheses.

Regarding the results of the task completion time comparison, our first expectation (E4) was supported. For all methods for goals, there was a similar trend in terms of task completion time between GOMSL model estimates and actual task performance times obtained from video recordings for both the DC and PR control modes. Correlation analyses and t-test supported this expectation. Furthermore, our additional expectation (E5) for longer CRT completion time predictions for DC of the prosthetic as compared to PR control was also supported.

In order to further assess the reliability of cognitive models, we compared the GOMS model time estimates with the findings of our previous study with able-bodied participants. Table 5 presents the time per pin for the cognitive models and the mean time per-pin for the best performance trial across all of the able-bodied participants in our previous study [12]. The best time was used in this comparison as GOMSL assumes expert performance, and while none of the participants could be considered experts, the best time across all of the trials would be the closest to “perfect” performance in the dataset. The time per pin for the cognitive model was determined by taking the average time per pin across the six pins being relocated. This approach was applied because the number of pins relocated in a 2-minute time varied between participants. Participants were also not told exactly where to place each pin. The time per pin for the able-bodied participants was determined by dividing the

2-minute trial length by the highest number of successful pin placements for a trial with each device. The difference between the time estimates for the able-bodied data and the cognitive model is less than 1s for each control mode with the able-bodied data for both devices being higher than the cognitive model. This finding could be attributed to the fact that the able-bodied participants were not experts with the devices and did make errors.

TABLE 5
COMPARISON OF GOMSL TIME ESTIMATES AND ABLE-BODIED BEST PERFORMANCE

Control mode	Cognitive Model time estimates (ms)	Best time (ms)
DC	5466	6316
PR	3758	4138

In general, our results revealed that GOMSL models can be used to evaluate the cognitive workload associated with upper-limb prosthetic use and to infer device usability. However, it is important to reiterate that the GOMSL model time estimates were shorter than the average task times in the case study. We believe the difference between the time estimates was due to the limitations of using the MTM analysis for estimating <user-defined> operation times. For example, in certain grasping tasks, the hook of the prosthesis had to be rotated 90 degrees for use. However, during actual device control, the participant may have imagined greater rotation based on the degree of device responsiveness and speed, as demonstrated during the training session (a conditioning issue). The MTM model, on the other hand, assumed perfect device responsiveness and gripper rotation of only 90 degrees. In addition, the GOMSL model time estimates are based on large user population and may not be representative of specific patient performance.

Beyond these differences, the deviation of GOMSL task time estimates and observed times for the DC mode was significantly higher than for the PR mode. Under DC, the patient needed to change the device mode from open/close to rotation several times during task performance. The GOMSL task time estimates were based on MTM sequence models, assuming normal operation with no delays. In actual task performance, there was some delay for the patient in changing modes as well as increased mental workload. Consequently, it took longer for the patient to perform the same task with the DC mode as compared to the PR control mode, inflating model and experiment time differences.

V. Conclusion

The objective of this study was to investigate the use of a cognitive performance modeling method to assess cognitive workload and usability of using upper-limb prosthetic devices. Findings revealed that GOMSL models can be used to predict cognitive demands in using upper-limb prostheses.

The use of a cognitive performance modeling approach allows for prediction of prosthetic use demands in the absence of experimentation, although observation of actual device use can be useful for other purposes at the same time as workload analysis (e.g., comfort, learning potential, etc.). In addition, cognitive performance modeling provides for an explanatory analysis of cognitive load for patients with upper-limb amputation in using prostheses to perform daily living tasks. From our analysis, it is clear that additional WM demands of the DC mode actually lead to workload increases relative to the PR prosthesis control. This type of explanation is not possible with physiological measures and is much more general when using subjective ratings.

One limitation of the present study was the sample size. We conducted a case study, in part, due to the limited number of transradial amputee patients in the Raleigh, NC area and the selection criteria for the study. Future studies with larger sample sizes are necessary to further validate the use of cognitive performance modeling in measuring mental workload of prosthesis devices along with use of inferential statistics. Another limitation in this study is that GOMSL modeling assumes expert performance and the participant in this study was not an expert. Additional studies should test subjects on numerous dates to allow for more familiarity with the control modes and limit the number of errors. In addition, future work should validate the findings of this study by comparing the performance of patients in more cognitively demanding daily living activities.

The other limitation of this study was the use of MTM analysis for estimating the time in <user-defined> operations as part of GOMSL models. Although MTM is a very well-established and validated technique for work task time estimates and work design, the modeling approach makes a number of assumptions relative to specific motion behaviors. For example, in moving objects, MTM assumes the weight for move tasks is in the hand, whereas the prosthesis used in the present study, represented the majority of the upper-extremity load and was attached to the arm. It is likely that the physical device configuration led to longer move times than represented in MTM tables. Beyond this, there is no parameter in MTM for hinging of the hand at the wrist and a time estimate for this action was used to address hand hinging steps in the CRT procedure. Finally, the prosthetic device that we used had a response delay and the motion speed of the prosthesis could be adjusted using computer control. It is possible the device motion speed was not representative of the expert worker speeds included in the MTM tables. In future studies, we plan to improve our estimates of <user-defined> GOMSL operations based on the analysis of video recordings of prosthetic use in activities of daily living.

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