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Comparison of Cognitive Workload Assessment Techniques in EMG-based Prosthetic Device Studies

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***Abstract*— Previous studies have found that electromyography (EMG)-based prosthetic devices provide higher grasping force, increase functional performance, and have greater range of motion over conventional prostheses. However, cognitive workload (CW) is still one of the issues that can negatively affect device usability and satisfaction. In order to evaluate CW of prosthetic devices early in the design cycle, it is first necessary to select the most appropriate measures. Therefore, the objectives of this study were to: (1) review the CW measurement techniques used in prior EMG-based prosthetic device evaluations; and (2) provide guidelines to select the most appropriate measurement techniques. The findings suggested that cognitive performance models (CPM), subjective measures, task performance measures, and some physiological measures were sensitive in detecting CW differences among prosthetic device configurations and therefore could be useful tools in usability evaluation of these technologies. However, in order to reduce intrusiveness and cost, methods such as subjective workload measures, task performance, and CPM are more beneficial as compared to physiological measurements. Guidelines proposed in this study can be beneficial to select the most appropriate CW measurement techniques in order to improve sensitivity and accuracy and reduce intrusiveness and cost.**

Keywords—mental workload, EMG, prosthetic device, literature review

I. INTRODUCTION

Amputee patients use prosthetic devices to perform activities of daily living (ADLs). These devices can be categorized into four main types including passive, body-powered, externally powered (e.g., advanced prosthetic devices controlled by electromyography (EMG) or muscle activation signals), and hybrid prostheses [1]. Studies have shown that EMG-based prosthetic devices provide higher grasping force, increase functional performance, and have greater range of motion over conventional prostheses [2]. These devices have a natural look, are suitable for light everyday activities, and have been found to be beneficial for individuals experiencing phantom limb pain [2, 3].

Use of prosthetic devices requires substantial amount of cognitive resources. These resources are used to compensate for the lack of sufficient feedback and degrees of freedom from the amputated limb [4], which can also reduce task performance [5]. Furthermore, high cognitive workload (CW) while using the myoelectric prosthesis device can negatively affect patient rehabilitation. Amputee patients often report not using their prosthetic device for performing ADLs due to its high CW and poor usability [6]. Thus, understanding CW and underlying attentional resources in using prosthetic devices can be beneficial in order to improve evaluation and development of future technologies [7].

A. Myoelectric control scheme

Myoelectric prosthetic devices can be categorized based on their control scheme into seven categories including on/off, proportional, direct, finite state machine, pattern recognition, regression-based, and posture-based control schemes [8]. The on/off control is suitable for two degrees of freedom. For example, the prosthetic limb can be operated in both clockwise and counterclockwise directions [9, 10]. In the proportional control scheme, the speed of a servo-motor, moving in one direction, is proportionally controlled by the magnitude of EMG signal captured from one agonist-antagonist muscle pair [11-14]. Direct control (DC) is similar to the proportional control but it maps amplitude of each EMG channel to individual function and corresponding mechanical output [15-17]. Therefore, it is difficult to achieve independent control of the arm due to crosstalk in EMG signals in the DC method [8]. In the finite state machine control, hand gestures are predefined as states. Transition among states is also predefined or decoded from the inputs [8].

The pattern recognition (PR) technique is a data-driven control approach based on machine learning algorithms [18] and has been mainly used for transradial amputees with targeted muscle re-innervation surgeries [19]. There are many approaches such as Bayesian classifiers, fuzzy clustering algorithms, neural networks, and hierarchical control in the PR scheme [8]. The linear regression-based control scheme generates the effort to perform hand grip gesture from the surface EMG of an intact forearm muscle for feature

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extraction [20]. In posture control approach, the EMG signals are used as inputs for the principal component domain. Specific postures could then be achieved by linearly transforming those EMG signals. This method provides simultaneous myoelectric control of prosthetic arm [21, 22].

B. *Cognitive workload measurement techniques*

CW can be measured using physiological measures, subjective rating scales, task performance measures [23], and cognitive performance models (CPM). Physiological measures (e.g., heart rate (HR) and heart rate variability (HRV)) provide information regarding psychological processes and their effect on body [24]. These measures are continuous and objective. However, physiological signals can be affected by head or body movements especially in experiments using prosthetic devices or electrode caps [25].

Subjective ratings quantify humans' understanding and judgments of their experienced mental demand. While these methods have high face validity, their interpretation and prediction performance is uncertain [24]. Performance measures are classified into two major categories including primary and secondary task measures. Primary task measures evaluate participants' performance on the main task. Secondary task measures explain the remaining cognitive capacity under the primary tasks. Secondary task measures are more diagnostic than primary task measurements. Performance measures have advantages in that they evaluate participants' response on the tasks directly. Also, they are useful where subject's capacity cannot afford to process mental demands such that performance degrades from the baseline or ideal level. However, these methods tend to have low scientific rigor which makes the interpretation of the results difficult [24].

CPMs such as Goals, Operators, Methods, and Selection rules (GOMs) can provide representations of human performance (e.g., learning time, execution time, or errors) [26]. These models can predict the amount of time that an expert needs to retrieve information from memory, select from decision options, and execute motor movements. CPMs can be coded, compiled, and run using computer program software such as Cogulator and CogTool [27, 28].

C. *Problem statement*

High CW of prosthetic devices led to usability issues and device rejection for amputee patients [29]. Considering the advantages of EMG-based prosthetic devices and techniques for measuring CW, it is necessary to understand what measurement techniques are suitable for assessing CW of these devices. Identification of appropriate CW measurement techniques can help researchers and device manufacturers to evaluate CW of prosthetic devices early in the design cycle in order to improve device usability. Thus, the objectives of this study were to: (1) review CW measurement techniques used in prior EMG-based prosthetic device evaluations; and (2) provide a guideline to select the most appropriate CW measurement technique in different conditions.

II. Method

A literature review was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [30]. Databases including PubMed, Cochrane, Compendex, Inspec, Proquest, IEEE, Engineering Research Database, and Web of Science (WOS) were searched in order to find relevant research published since 2005 (the year in which Defense Advanced Research Projects Agency (DARPA) started the Revolutionizing Prosthetics program) [31]. Additional search was also conducted using manual search in Google Scholar, as it is the most comprehensive search engine [32].

Eligibility criteria included: relevant, English-language papers, and any research studies (manually) identified with a focus on CW in EMG-based prosthetic devices. Keywords included *prosthe** (all words starting with 'prosthe') and *cognitive (or mental) workload* combined with *NASA-TLX*, *EMG*, *electroencephalogram (EEG)*, *heart rate*, *respiratory rate*, *skin conductance (SC)*, *skin temperature (ST)*, *blink rate*, and *pupillometry*. The literature search was completed in 2019. From the initial records found based on the title and abstract (n = 3,727), 145 studies were reviewed by the authors. Upon completion of the screening process, 26 studies were included in this study.

III. Results

Table 1 presents a summary of CW measurement techniques in prior studies assessing EMG-based prosthetic devices. These measurements and their sensitivity in assessing CW are explained in detail below.

A. *Physiological measurements*

Five major physiological measures of CW were used in prior studies including cardiac (e.g., heart rate variability), respiratory (e.g., respiratory rate), skin (e.g., skin conductance level), brain activity (e.g., late positive potential), and pupillometry (e.g., blink rate) measures (Table I). Brain activity and pupillometry measures were the most frequently used measures. Brain activity provides the ability to examine CW with high temporal resolution and a certain degree of freedom for movements during data collection. This facilitates the adaptability to clinical, operational, or real-world settings [33, 34]. Pupillometry responses are continuous and unobtrusive methods for measuring CW. Especially measures such as blink rate, eye-closure intervals, and pupil diameter changes over time were used to compare PR and DC devices in upper-limb prosthetic studies due to their robustness to body movement [25]. Blink rate was also a sensitive measure in comparing CW of prosthetic devices with different feedback modalities [35] as well as cardiac and respiratory measures [35, 36]. While both cardiac and respiratory measurement techniques were sensitive (i.e., showed significant differences in CW among different feedback modalities), results regarding the skin conductance measure were mixed (some studies found skin conductance to be sensitive while others did not find any significant effect) [35, 36].

B. Subjective measurement

NASA Task Load Index (NASA-TLX) questionnaire was the only subjective measurement technique used in prior studies. NASA-TLX identifies the overall workload as well as

TABLE I. A SUMMARY OF COGNITIVE WORKLOAD MEASUREMENTS IN EMG-BASED PROSTHETIC STUDIES

Ref.	Device configuration	CW Measurements								Significance
		Physiological					Subjective (NASA-TLX)	Task performance	CPM	
		Cardiac	Respiration	Skin conductance	Brain Activity	Pupillometry				
[2]	On/off, proportional						✔			p<.05
[47]	On/off						✔			N/A
[34]	On/off						✔			N/A
[22]	Posture						✔			N/A
[12]	Proportional						✔			p=.024
[18]	PR						✔			N/A
[53]	DC, PR				✔					P200: p<.01 P300: p<.01 LPP: p<.01
[15]	DC, PR				✔					LPP: p<.05
[20]	Regression						✔			N/A
[46]	Posture						✔			N/A
[35]	Posture	✔	✔	✔	✔		✔			NT: p<.01 EEG: p<.05 HR: p<.05 RR: p<.01
[36]	Posture			✔		✔	✔			BR: p<.05 NT: p<.05 SCL: p<.01
[40]	DC, PR							✔		N/A
[38]	Proportional, FSM						✔			p<.05
[48]	On/off						✔			N/A
[10]	On/off				✔	✔				TLS: p<.001 GS: p<.001 EEG: p<.001
[44]	On/off							✔		p=.024
[41]	DC, PR							✔		N/A
[13]	Proportional				✔		✔			EEG: p<.001 NT: p<.001
[39]	Proportional				✔					EEG: p<.001
[14]	Proportional						✔			N/A
[16]	DC						✔			p<.05
[17]	DC						✔			p<.05
[42]	DC, PR					✔		✔		TP: p=.0472 NPI: p=.0016
[25]	DC, PR					✔		✔	✔	PS: p<.0001 TP: p <.0001
[45]	DC, PR					✔		✔		TP: p <.0001 PS: p<.0001

Note. N/A= No statistical analysis (descriptive statistics only), BR=Blinking rate, CPM= Cognitive performance model, EEG= Electroencephalogram, FSM= Finite state machine, GS=Gaze shifting, HR=Heart rate, HRV=Heart rate variability, LPP=Late Positive Potential, NPI=Number of Pupil Increases Per Second, NT=NASA-TLX, PS=Pupil size, RR= Respiratory rate, SCL=Skin conductance level, TLS=Target locking strategy, TP=Task performance.

the magnitude of each factor (i.e., mental demand, physical demand, temporal demand, performance, effort, and frustration level) in motor tasks [37]. Another reason for frequent use of NASA-TLX is its unobtrusiveness. Unlike some physiological measurements that are sensitive to body motions or environment, subjective workload measures are collected after the trial (or experiment) and therefore do not interfere with the task execution. NASA-TLX was found to be a sensitive measure to assess CW of different EMG-based prosthetic devices in half of the studies [2, 12, 16, 17, 35, 36, 38, 39] (other studies only provided descriptive statistics). These investigations were focused on comparing different device configurations (e.g., on/off, proportional, posture, and direct control), control methods (e.g., linear, non-linear proportional control), sensory feedback (visual, auditory, vibrotactile), and training duration.

C. Task performance

Task performance measures were especially used for comparing the DC and PR control modes [40] (Table I) when the patients were performing ADL tasks (i.e., clothespin relocation task (CRT) [41, 42], Southampton Handness Assessment Procedure (SHAP) [40], Box and Blocks (B&B) task, Jebsen-Taylor test (JT) [40], and Cubbies tasks [40]). These measures included the time to complete the task (TCT) (for the CRT, JT, and Cubbies task), the number of items transported (for the B&B task), and the index of function (IoF) (for the SHAP task; a metric of the operator's hand function compared with that of a peer norm) [43]. Task performance measures such as TCT and number of transported items were found to be sensitive (i.e., led to significant findings) in four out of six studies [25, 42, 44, 45] comparing different prosthetic configurations (e.g., DC, PR, on/off) and feedback modalities.

D. Cognitive performance model

Only one study used CPM to assess CW of prosthetic devices [25]. CPM allows estimation of task performance, working memory chunks (measure of CW), and number of perceptual, cognitive, and motor operators in using prosthetic devices without the need to conduct human-subject experiments. Zahabi et al. [25] found that additional working memory demands to learn and memorize a certain movement in the DC mode (e.g., mode change or gestures) led to higher CW relative to the PR scheme. This type of analysis is not possible with physiological measurements and is not easy to discriminate in subjective ratings.

IV. Discussion

Four metrics including sensitivity, intrusiveness, cost, and accuracy were established based on the screened studies to identify the most appropriate CW measurement techniques considering a system perspective (e.g., inputs, outputs, and noise). Regarding the inputs, human effort, time and monetary values can be considered as "cost". Regarding outputs, a degree to which the selected technique can generate meaningful outcomes with statistical significance is defined as "sensitivity". In addition, "accuracy" should be used as a common metric for testing the capabilities of a measurement technique. Lastly, for the noise part of the system, "intrusiveness" can be analyzed as a metric for measuring internal validity of the technique.

A. Sensitivity

Distribution of various CW measurement techniques across different studies is presented in Table II. A majority of prior investigations (except some that used NASA-TLX or performance measures) used statistical analysis to compare CW of different EMG-based prosthetic devices. The reasons for relying on descriptive statistics results in some studies were the small sample size [46] or study focus [47, 48]. Among the studies that used statistical analysis, except for one study that used skin conductance level (SCL), all measurements led to significant findings. Therefore, it can be concluded that all CW measurements were sensitive in terms of identifying differences in CW of prosthetic devices, except for the skin conductance level.

To improve sensitivity of SCL, researchers need to pay close attention to the experimental environment, participants' health status and their selection of variables. Environmental factors such as room temperature and humidity can impact the

TABLE II. Distribution of Cognitive workload measurements across studies

Category / CW Measurement	No. of studies	No. of studies with statistical analysis	No. of studies with descriptive statistics only	No. of studies with significant findings ($p<.05$)	No. of studies that found no statistical difference ($p>.05$)
Cardiac	1	1	0	1	0
Respiratory	1	1	0	1	0
Skin conductance	2	2	0	1	1
Brain activity	6	6	0	6	0
Pupillometry	5	5	0	5	0
NASA-TLX	16	8	8	8	0
Task performance	6	4	2	4	0
Cognitive performance model	1	1	0	1	0

SCL, which can lead to inconsistent results [49]. Medications and hydration can also change the SCL and result in inconsistent findings [49]. Beyond this, studies have found that the accumulative SCL or different time and frequency-domain features of SCL were useful features in assessing CW [50, 51].

B. Intrusiveness

Intrusiveness is an important factor in selecting CW measurement techniques for the study especially in case of experiments with prosthetic devices due to the experiment setup (e.g., use of EMG sensors attached to the muscles, adhesive straps to prevent movements between the device and limb) and human head and body movements during the task. As shown in Table I, a majority of studies used non-physiological measurements which did not require attachments on the human body and were not intrusive. Instead, subjective measures were frequently used since they are usually administered after the experiment. In addition, use of CPM and task performance measures can be useful to measure CW as they do not require any attachments on human body and can be captured automatically or by reviewing the video recordings of the experiment session. Among the physiological measurements, cardiac, respiratory, and pupillometry measures can be less intrusive than using brain activity and EEG signals [25, 52].

C. Cost

The cost for measuring CW of prosthetic devices in laboratory-based experiments can be defined based on time, money, effort and human resources (i.e., experimenter(s) and participants). Among all the CW measurement techniques used in prior studies, the CPM is the most cost-effective approach since it does not require a large number of participants (can be even used in case studies) and experiment setup as compared to other measurement techniques [25]. However, CPM is a time-consuming technique and requires researchers to be familiar with CPM languages (e.g., GOMS family) and software. Beyond the CPM, subjective and task performance measures can also be used as low-cost CW measurement techniques as compared to physiological approaches. These techniques may require simple experiment setups (e.g., paper and pencil for questionnaires, timer, video recorder) and an experimenter(s) familiar with human subject data collection procedures to handle the entire protocol for conducting the test and questionnaire. However, use of physiological measurement techniques require specific equipment (e.g., EMG sensors, HR monitors, etc.) and software for data collection, processing, and analysis. Furthermore, due to the high sampling rate and frequency of data collection, the post-processing of data can be time-consuming and may require additional training.

D. Accuracy

Comparison of CW measurement techniques in terms of response accuracy was not possible across the studies due to differences in the sample size, device configurations, and experimental tasks. However, some studies used multiple measurement techniques (e.g., combination of physiological and subjective measures) and found similar results [36]. Furthermore, findings of CPM were in line with physiological (e.g., pupillometry data) and task performance measures [45] which indicates that these measures can be used interchangeably. However, some brain activity signals such as P200 and P300 were found to have low accuracy in detecting CW differences among the PR and DC modes [53].

E. Guideline

Based on the findings of the literature review, we created a guideline table for selecting the most appropriate CW measurement techniques in assessing prosthetic devices considering factors such as intrusiveness, cost, accuracy, and sensitivity (Table III). Based on this guideline, researchers can select among the CW measurement techniques.

V. Conclusion

The objectives of this study were to: (1) review the CW measurement techniques used in prior EMG-based prosthetic device studies; and (2) provide a guideline to select the most appropriate CW measurement techniques based on the experiment setup and capabilities. Our review revealed that CW has been measured using four main techniques including: (1) physiological measures (cardiac, respiration, skin conductance, brain activity, and pupillometry); (2) subjective measures (i.e., NASA-TLX); (3) task performance; and (4) cognitive performance models. In addition, a majority of these methods (except the SCL) were sensitive in detecting CW differences among prosthetic device configurations and therefore could be useful tools in usability evaluation of these technologies. However, in order to reduce intrusiveness and cost, methods such as subjective workload measures, task performance, and CPM are more beneficial as compared to physiological measurements. The proposed guideline can be beneficial for the researchers to select the most appropriate

TABLE III. Guidelines for selecting appropriate CW measurement techniques

Objective / CW Measurement	Improve sensitivity	Reduce intrusiveness	Reduce cost				Increase accuracy
			Post-processing and analysis time	Small sample size	Expertise	Equipment	
Cognitive performance modeling	✓	✓		✓		✓	✓
Subjective measures	✓	✓	✓		✓	✓	✓
Task performance	✓	✓	✓		✓	✓	✓
Physiological measures	✓ (Except SCL)			✓			✓ (Except some brain activity signals)

CW measurement techniques based on their objectives (increasing sensitivity and accuracy, reducing intrusiveness and cost).

One limitation of this study was that the sensitivity analysis was based on the studies included in the literature review and whether they found significant differences or not. Future studies should use quantitative approaches such as meta-analysis to objectively compare different CW measurement techniques. Furthermore, this study was only focused on EMG-based prosthetic devices due to their frequent use and advantages over other configurations. However, to provide a more holistic assessment, future studies should consider all prosthetic device configurations including body-powered and hybrid configurations.

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