TASK-BASED CALIBRATION OF PATTERN RECOGNITION FOR INDIVIDUALS WITH UPPER LIMB DIFFERENCE IN A VIRTUAL REALITY ENVIRONMENT

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ABSTRACT

Background

Pattern recognition (PR) control of myoelectric upper limb prostheses is clinically available and growing in popularity. PR systems require calibration to create map between electromyographic (EMG) signals and control outputs. Standard calibration (SC) builds a PR classifier from EMG data collected while a user attempts to perform the movement displayed on a computer screen or demonstrated by pre-programmed prosthesis movement. While convenient and effective to quickly calibrate a controller, SC may not elicit the same motor response as when performing a functional task. A new method of calibrating, called "task-based calibration" (TBC) is proposed, in which a user mimics the movement of a hand performing a functional task. This study assessed whether TBC may facilitate improved pattern recognition control compared to SC, in a virtual reality (VR) environment.

Methods

Six (n=6) individuals with unilateral transradial limb difference and varying level of PR experience participated in the study. A VR application was developed for the Oculus Quest 2. Data from 8 EMG channels were collected using custom electronics. With their residual limb, participants calibrated five motion classes (no motion, hand open/close, wrist pronation/supination). Both SC and TBC were performed by each person, in a randomized order. For TBC, participants mimicked a VR hand that picked up a cup off a shelf, turned it over, and placed it on a table. SC mimicked clinical practice techniques, with display in the VR headset.

Results

EMG patterns and contraction strength differed between SC and TBC. Overall, EMG activity during motions is lower in TBC compared to SC. Compared to SC, TBC captured a greater amount of EMG activity for data labeled as No Motion, when no prosthetic motion is intended. Building and testing a classifier with similar calibration types resulted in high accuracies. Building with data from one calibration type (e.g., SC) and testing with a different type (e.g., TBC) shows notably lower classification accuracy. Building with mixed (SC and TBC) data results in similar accuracies when tested with any available classifier type.

Conclusion

The data suggests that SC may not capture the same EMG elicited during performance of a task. These results may help understand why users face difficulty using PR control even after successfully calibrating and being able to repeat motions. Calibrating via TBC may facilitate better prosthetic control and improve the clinical experience of using a PR system.

INTRODUCTION

By the most recent estimations, approximately 8% of all acquired limb loss in the United States is categorized as major upper limb loss.[1] This population of individuals faces challenges such as pain, lack of a functional device, lack of aesthetically acceptable devices, and difficulty returning to work.[2] For the population of individuals with upper limb difference, functional prosthetic options can be divided into two categories, body-powered and externally powered.[3] Body-powered are often selected when a patient's functional needs can be met by available body-powered componentry, the patient can tolerate wearing a harness, and they have adequate strength and range of motion to control the cable(s) to operate componentry.[3] Externally powered are often selected as a primary or secondary prosthesis when a user cannot meet the conditions necessary for operation of a body-powered device, or when the externally powered can provide greater functional benefit.[3] One type of externally powered prosthesis is electromyographic (EMG), also called myoelectric, control. Conventional myoelectric control, called direct control (DC) relies on a dual-site EMG system, in which each of the two electrodes control a single motion. In order to control more than two motions, such as controlling both hand open (HO) and hand close (HC) as well as wrist pronate (WP) and wrist supinate (WS), a switching trigger, such as co-contraction or a muscle impulse, is necessary when using DC.

DC often uses packaged electrodes which have direct gain setting adjustability accessible to the clinician. In this manner, a clinician can easily adjust a single electrode's gain to increase or decrease its sensitivity to muscle activity and observe the direct effect of the adjustment on a patient's control. However, another myoelectric control option, called pattern recognition (PR), continuously reads in signal from multiple electrodes and uses these signals to infer user intent and engage the prosthesis to move in the desired motion. Through this method, multiple electrodes are used to control multiple motions, but not in a one-to-one ratio like DC. To accomplish this style of control, the PR system includes a controller unit that acts as the brains of the system to read in EMG signals and uses an algorithm to extract various features of the EMG that enable discrimination between each group of EMG signals collected for each desired motion. Because PR is controlled through an algorithm, in some cases of PR control there may be less direct ability to identify a source of poor control and make an appropriate adjustment than is capable with DC. DC has been commercially available for a longer period of time than PR, so some clinicians may feel more comfortable with what they are more familiar with and feel more comfortable with the challenges of DC than newer technology.

An alternative to achieving myoelectric control of multiple degrees of freedom, is PR control. PR utilizes multiple electrodes to directly control multiple degrees of freedom, eliminating the need for switching.[4] Up to eight pairs of electrodes are placed over the residual limb with most commercial systems and, through a calibration sequence, the pattern of EMG activity across all electrodes are used to continuously classify EMG signals into one of the programed motions, or as no intended motion.[5] Calibration is the process of tuning a PR system to each user's individualized intended motions. The user is prompted to perform a specific motion and EMG is recorded while doing so. Once EMG has been recorded for all intended motions, a PR classifier is built. Once a classifier is built and the system is calibrated, the PR system will continuously read all EMG channels and determine which motion, if any, the EMG pattern is most similar to and classifies the intended motion so that the prosthesis can function accordingly. Historically, calibration has progressed from offline to real-time computer-based, to device-based.[5] With the increase of smartphone use, many PR systems are now revisiting and integrating computer or app-based calibration. Further, advances to the data processing methods and algorithm used to classify PR based on a calibration have improved the reliability of PR control.[6]

Through these evolutions, PR has been developed to be a commercially available and clinically used control method for upper limb prostheses. While these systems have the benefit of increased potential, there also can be more challenges. Given that PR control is established through a calibration routine, which associates patterns of EMG activity with each specific prosthetic motion the user intends to utilize. Understanding the relationship between the EMG elicited during calibration and the EMG elicited during use may be one way in which a PR system can become more robust, improve control, and increase adoption of the technology.

Standard calibration (SC) routines, such as those available in clinically available commercial systems, build a PR classifier from EMG data collected while a user attempts to perform the movement displayed on a computer screen or demonstrated by pre-programmed prosthesis movement.[5] These current calibration sequences used in commercial systems do not adequately account for many variables that can occur when a prosthesis is being used and impact EMG signal, such as socket fit, skin impedance, and motion artifact. Some research has been conducted to study the effects of various internal and external influences on PR control, for example dome size and orientation,[7] classifier adaptation,[8] and multi-positional calibration.[9] However, the impact of SC routine prompting on elicited EMG has not been explored.

When an individual has intent to complete a task, muscle activity is elicited to modulate both joint position and joint stiffness.[10] For example, the biceps brachii is the main elbow flexor in the human body. Activities that require elbow flexion include picking up a full milk jug or lifting a water bottle to one's mouth. Because the strength needed to accomplish both these tasks are different, the muscle activity elicited to accomplish both these tasks differ from each other. And not only is the biceps brachii active, but also multiple other agonistic and antagonistic muscles. Like the primary muscle, the muscle activity of the agonist and antagonist muscles are also modulated in direct relation to the intended task. The modulation of muscle activity determines the stiffness of the joint so that it can support the object being held. However, current calibration sequences do not account for the differences in EMG activity that joint stiffness modulation creates. Similarly, muscle activation during functional use of an arm varies so that the generated force by the muscles is appropriate and proportional to the force necessary to successfully complete each specific task.[11] The research conducted in past studies indicate that EMG activity is expected to be highly dependent on the intended task. As such, collection of EMG data through SC may not most effectively capture the muscle patterns generated when a user attempts to perform a functional task with their prosthesis.

One technology upper limb prosthesis users may benefit from is virtual reality (VR). VR is being adopted in the physical rehabilitation sector for a multitude of reasons and uses. VR can facilitate the implementation of a controlled and regulated environment capable of performing robust tracking while still allowing users to engage in representative real-world environments.[12] Further, VR can be employed when a physical object is not necessary, appropriate, or available for use in the specific scenario. In a rehabilitation setting, this may include outcomes testing,[12,13] pre-prosthetic training,[6] non-pharmaceutical pain management,[14] and evaluating novel approaches to prosthesis programming.[8,9] VR provides an opportunity to perform a functional task in a controlled environment and under known conditions for use to calibrate PR systems in realistic use-case scenarios.

Therefore, in this paper a new method of calibrating upper limb myoelectric pattern recognition systems is proposed using VR, called “task-based calibration” (TBC). In comparison to SC, TBC builds a PR classifier from EMG data collected and labelled while a user mimics a hand that is performing a real-world task in a virtual environment. The purpose of this research was to implement EMG control of an arm using the Oculus Quest 2 VR system through which new calibration methods can be created and trialed, without the need for new prosthetic hardware or components. The secondary purpose of this research was to use this system to assess whether TBC facilitates improved pattern recognition control compared to SC.

METHODS

Study Design and Recruitment

A pilot study was conducted to compare results between SC and TBC. The study was approved by Northwestern University Institutional Review Board. Individuals with unilateral transradial limb difference were recruited from an approved research registry. Participants were included if they had a unilateral transradial limb difference, healed residual limb, and detectable myosignals on bilateral forearms. Participants were excluded if they were had cognitive or visual deficit impacting ability to understand, view, or interact with the virtual environment, had open wounds on their upper extremities, or were not primarily English speaking.

Experimental Protocol

The study was completed over the course of two days. Day 1 involved completing the protocol on the non-amputated side, and day 2 involved completing the protocol on the amputated side. Prior to beginning, the study was explained to each individual and written informed consent was obtained. Day 1 served as the control for each participant. The same data were recorded on Day 1 and Day 2, but only Day 2 data was analyzed.

Figure 1 shows the experimental setup while one subject is immersed in the VR world for Day 2 of the study. A designated chair was positioned within a predefined virtual boundary to ensure physical safety of each individual while they were immersed in the VR environment. Eight pairs of EMG dome electrodes plus one ground was placed circumferentially around the forearm and verified at the outset of each session. For the non-amputated side, a gel liner with embedded dome electrodes was used. For the amputated side, adhesive-backed snap electrodes were used. A custom electrode harness was connected to the EMG domes and to a custom pattern recognition controller. After confirming acceptable EMG signal, the remaining experimental apparatuses were donned, including the controller contained a Bluetooth module for directional communication between the controller unit and the VR app.

Figure 1. The experimental setup as shown while a subject is immersed in the VR world and completing one calibration of TBC, visible on the left computer screen, on Day 2 of the study.

VR Environment

A custom virtual reality application was developed for the Oculus Quest 2 virtual reality headset using Unity3D and Visual Studio. The application consisted of four scenes: connect, SC, TBC, and outcomes. Throughout the duration of the experiment, the VR environment was screencast to an external screen enabling the research staff members to see what the participants were seeing.

The connect scene allowed the research staff of each experiment to connect the controller to the VR app. The SC scene mimicked clinical practice techniques displayed in the VR headset. This included a virtual prosthesis, cueing text, and countdown visuals. A screenshot of the primary view of SC scene is shown in figure 2A. When calibrating via SC, verbal cueing was used based on the displayed visuals, as often performed when clinically training new users. SC was always calibrated in the following order: No Motion, Pronate, Supinate, Open, Close. Each motion was recorded once per calibration sequence. A 1.5 second rest period preceded each 2.5 second recording period. Participants were allowed to practice the calibration sequence until they felt familiar with the order of motions and then calibrated as many times as needed to achieve a level of control that they felt was usable. Care was taken by the research staff to ensure patients did not practice to such an extent that they would experience muscle fatigue while performing the recorded calibrations. To test SC control, the virtual prosthesis would move after calibration.

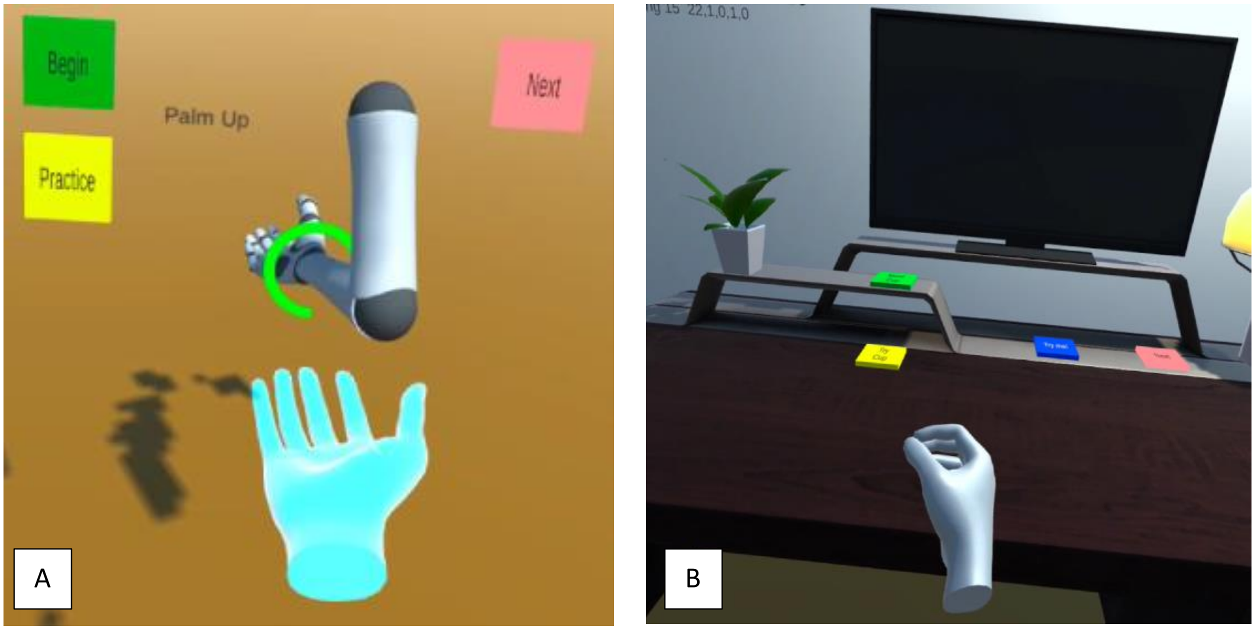

Figure 2. Screenshots of primary views of standard calibration (1A) and task-based calibration (1B) scenes.

For TBC, participants mimicked a VR hand that picked up a cup off a shelf, turned it over, and placed it on a table. A screenshot of the primary view of TBC scene is shown in figure 2B. When calibrating via TBC, participants were only instructed to follow along with the gray hand displayed on screen. Upon initiating the movement sequence, the gray hand would move away from its position near the start button while collecting the “No Motion” class and then open as it moved to the side of the desk and toward the cup. The hand would pronate in the open position as it reaches up for the cup, close on the cup handle, and then supinate to turn the cup right-side up and place it on the desk in front of the participant. Participants were allowed to practice the calibration sequence until they felt familiar with the order of motions and then calibrated as many times as needed to achieve a level of control that they felt was usable. Care was taken by the research staff to ensure patients did not practice to such an extent that they would experience muscle fatigue while performing the recorded calibrations. To test TBC control, a button was present in the scene that allowed the displayed virtual hand to move in open, close, and rotation based on motion class decisions.

The outcomes scene contained a true-to-scale version of the box and blocks standardized outcome measure. A screenshot of the primary view of outcomes scene is shown in figure 3. In this scene, participants used their pattern recognition control to move as many blocks as possible, one at a time, from one side of the box to the other side of the box in 60 seconds. The system detected a hand opening to pick up a block if three consecutive “Open” PR decisions were made by the classifier and the hand was not already fully open. Similarly, the system detected a hand closing to pick up a block if three consecutive “Close” PR decisions were made by the classifier and the hand was not already fully closed. The number of blocks moved was manually counted during each trial. In this scene, the active classifier was randomized for each trial to be either SC control or TBC control. Prior to the scored trials, participants were allowed one practice round with each style of calibration. Three trials with each style of control were scored, for a total of six scored trials.

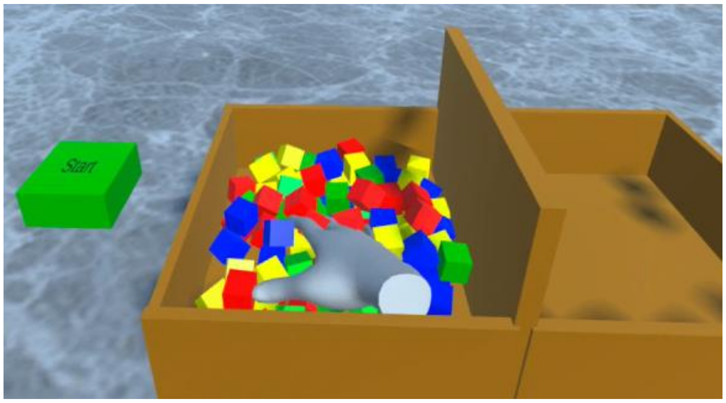

Figure 3. Screenshot of primary view of virtual box and blocks outcome scene.

Data Analysis

Throughout the experiment, certain data were saved to the controller device for later analysis. During each calibration, the name of each motion being calibrated and associated raw EMG was recorded and saved by the controller. During each use trial, the controller continuously recorded and saved motion class decision, proportional control speed, and raw EMG.

Qualitative EMG analysis was performed to the raw EMG recorded during SC in comparison to TBC. Attributes evaluated included order of recording, duration of recording, and amplitude of EMG signals. Qualitative EMG analysis was performed on the raw EMG, motion class decisions, and proportional control speed during performance of the virtual outcome measures.

The scores for each trial of virtual box and blocks were also recorded for analysis. For each participant, the SC mean score and TBC mean score was taken. From these, a single-tailed paired t-test was conducted in Microsoft Excel (Microsoft Corp., Redmond, WA) to determine significance in scoring differences between SC and TBC. A group mean and standard deviation was also calculated for all SC versus all TBC scores. These were also compared for significance using a paired single-tailed t-test.

To help explain any potential differences between SC and TBC, offline classification accuracy was also performed on the data sets. To do so, each participant's calibration data was divided into two per calibration style. One half of each data set was used to train a classifier offline using MATLAB R2016a (MathWorks, Natick, MA). The other half was then run through the classifier. Accuracy was defined to be the percentage of motion decisions from the second half of the dataset that were classified correctly based on their original label. Further, a mixed data set was created wherein each half of data consisted of equal parts SC and TBC data. Offline classification accuracy was performed for all possible combinations of building and testing.

Results

Study Recruitment

Eight individuals were recruited for the study, and six completed the full protocol. Table 1 shows the demographics for all participants who completed the study. Participants included male and female individuals with upper limb difference with varying amounts time since amputation, prosthetic use, and PR experience (no experience n=1; some past research or home use n=4; and sporadic current home use n=1) participated in the study.

Table 1. Subject demographics of the participants (n=6) who completed the study

Subject ID	Age	Sex	Etiology	Years Since Amputation	Recent Px Use	PR Experience	TMR*
TR32	32	F	Congenital	n/a	None	N	N
TR37	35	M	Trauma	8	None	Y	Y
TR49	59	M	Trauma	44	Myo	Y	N
TR55	28	M	Trauma	3	Myo	N	N
TR63	33	M	Trauma	5	BP	Y	Y
TR68	21	M	Trauma	3	Myo	N	N

*Targeted muscle reinnervation (TMR) is a surgical procedure which transfers severed nerves from an amputated limb into residual muscle, allowing more EMG signals to be read from the surface of the skin.[15]

One participant did not show up for their first visit and subsequently did not return any phone calls or emails to reschedule. Another participant was excluded after beginning the first day of the experiment for not being able to understand the requirements to calibrate TBC. All participants who arrived for a session were compensated for their time and travel.

Qualitative EMG Analysis

Differences in calibration EMG amplitude existed between raw EMG recorded during SC versus TBC. An example representative of the EMG collected during each type of calibration from the population is shown below in figure 4 (SC top, TBC bottom). Each figure is plotted with raw EMG in the order of data collection for each type of calibration, and the motion class is identified above each set of data. In qualitatively analyzing the difference in EMG amplitude between SC and TBC, more activity was noted during the No Motion recording of TBC versus SC. However, for the remaining motion classes, TBC EMG amplitude tended to be smaller than the EMG elicited during SC.

Due to the nature of SC versus TBC, the recorded motions also differed in order and duration of recording. The order of motions for SC was set based on the order of calibration in a current commercial PR system (Coapt Gen2). However, the order of motions for TBC was based on task programmed and the order of motions necessary to complete the task. This resulted in difference in calibration order between SC and TBC. Further, because the calibration of each motion in TBC was based on a dynamic, simulated activity of daily living, the length of time each motion was recorded varied based on the demands of the specific task. In contrast, the SC duration of calibrations are standardized because they do not reflect any real-world activity.

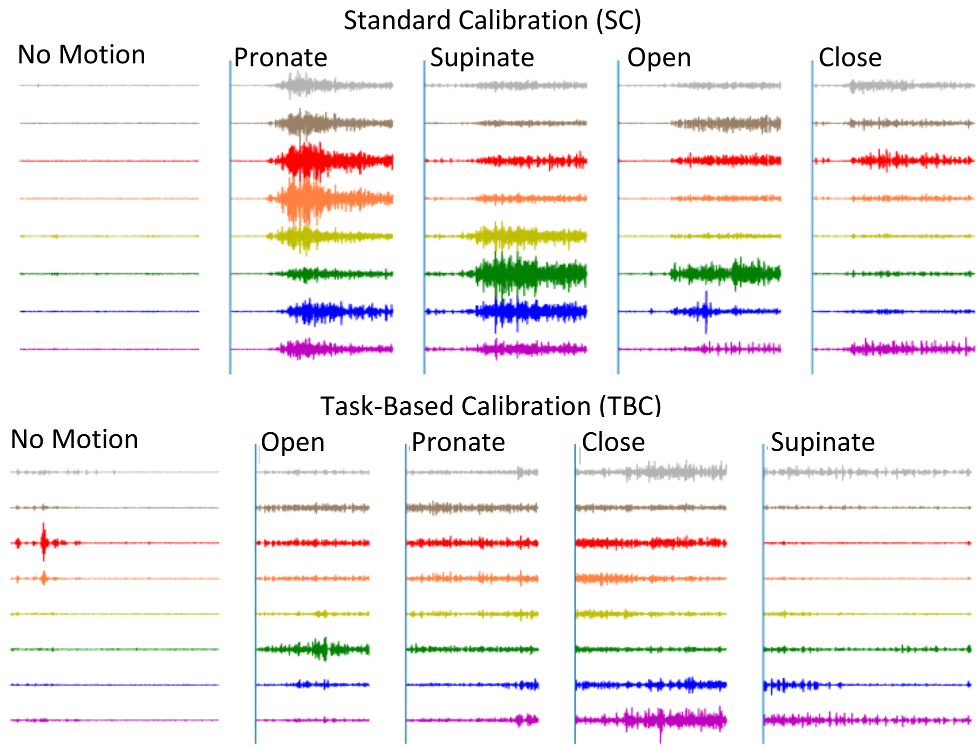

Figure 4. EMG recorded during one trial of SC (top) and TBC (bottom), from a single participant.

Virtual Outcome Measure

Figure 5 shows the results from participant performance on the virtual box and blocks outcome measure. There was no significant difference in virtual box and blocks performance when using a system calibrated with SC (mean 11.67 ± SD 4.95) compared to TBC (mean 11.06 ± SD 7.12).

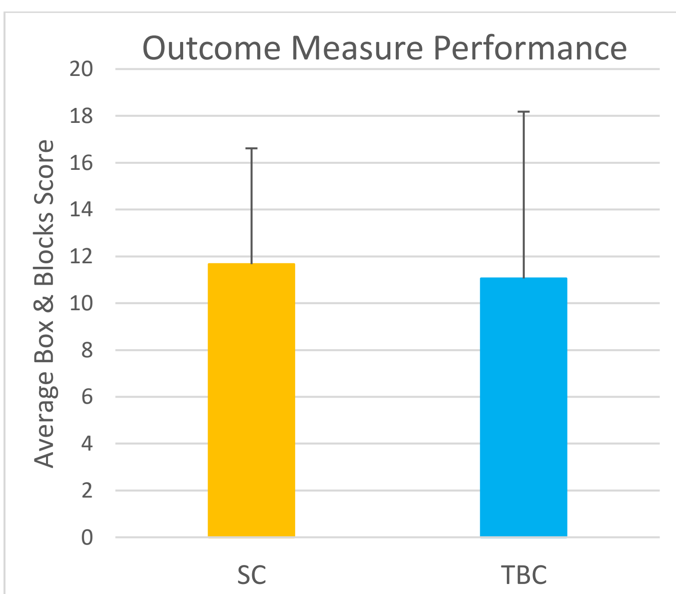

Figure 5. Mean score and standard deviation from virtual box and blocks performance by participants when using a virtual prosthesis controlled by SC (left) and TBC (right) classifiers.

Offline Classification Accuracy

In attempt to gain a better understanding of why the box and blocks results were similar despite observable differences in EMG activity, computational data analysis was performed via offline classification accuracy. Accuracy was defined as the percentage of data points accurately predicted as the correct motion class when calibrated data was split to use half for building a classifier and half to test the classifier. Accuracy was calculated with sets of only SC and only TBC data, as well as mixed sets that consisted of data from both SC and TBC. Table 1 shows the accuracy for all combinations of building and testing sets.

Table 2. Offline classification accuracies for each combination of building and testing sets of data

		Building		
		Standard	Task	Standard + Task
Testing	Standard	82.4 ± 12.5	46.7 ± 18.9	73.8 ± 14.0
	Task	38.6 ± 10.2	77.0 ± 11.3	74.5 ± 12.6
	Standard + Task	57.9 ± 6.8	61.9 ± 8.8	74.9 ± 9.3

SC-SC (build-test) classification accuracy is the current gold standard to evaluate most PR systems and also had the highest offline accuracy (82.4 ± 12.5%). Building with one type of unmixed data and then testing with the other, as expected, results in the lowest accuracy (SC-TBC 38.6 ± 10.2% and TBC-SC 46.7 ± 18.9). TBC-TBC accuracy is 77.0 ± 11.3%, performed better than building and testing with different types of data, but still slightly lower than SC-SC. Testing with a mixed classifier results in accuracies of similar caliber irrespective of whether the classifier was built from SC or TBC (SC-mix 57.9 ± 6.8%; TBC-mix 61.9 ± 8.8%). The offline accuracy analysis of a classifier built with mixed data shows that for any of the three types testing data, (Column 3) accuracy results are consistent (mean 74.4 ± 0.45%).

Discussion

The purpose of this research was to investigate the use of TBC for upper limb prosthetic pattern recognition control. The research showed that users were able to comfortably engage in a simulated real-world presented in VR. Anecdotal feedback indicated that the VR system was easier to interact with and control when using each person's limb-different side rather than their non-amputated side. This may be due to the fact that with an anatomical arm, a person's proprioceptive limb position may not have always matched with the visual limb position displayed in VR under PR control. As many studies in the area of prosthetic control are first piloted on those without limb difference, this research shows that it is important to be aware of the different ways these two populations can interact with a VR or prosthetic system and the influence such difference could have on study results.

EMG activity recorded during TBC differs from that recorded during SC. Despite these differences, virtual box and block scores were similar between the two classifiers. The benefit of creating a classifier using both calibration styles is corroborated by the offline analysis. Results of the study show that a classifier built on mixed calibration yields similar results and high accuracy for any use strategy. Notably, the amplitude of EMG activity was smaller when recorded TBC versus SC. This results aligns with past research, which has shown that when provided an external focus on attention (focus on moving for a specific goal), EMG activity is smaller than when prompted to move a body segment with an internal focus on attention (focus on the movement itself).[16] When attempting to use a PR prosthesis to complete a task, a user's focus of attention is external, on completing the intended task. These results shows that TBC may be a successful method to engage external foci of attention when calibrating a system instead of a traditional internal focus of attention that may exaggerate EMG differences between calibration and functional use.

The results of this study may have been impacted by participants not knowing which classifier was active during performance of the virtual box and blocks and therefore adopting a strategy that would work for both calibration types. Since the participants did not know which classifier was active during which trial of the outcome measure, participants may have utilized a mix of their two EMG mechanisms to optimize their performance across the full set of trials. Therefore, this study could be repeated and have the outcome measures performed with participants knowing which classifier is active during each trial, thus preventing any bias toward the use of a mixed calibration control. Lastly, classification accuracy of a mixed data set was only conducted in offline analysis. Trialing the effects of varying calibration styles on physical prosthesis control would be the most effective method to determine the value of task-based calibration.

However, this research was limited by its scope, sample size, and technical development. The work conducted in this experiment consisted of pilot research on the novel topic of task-based calibration for improved functional pattern recognition control of upper limb prostheses. Based on the findings of this study, future efforts on this novel approach to pattern recognition control may be beneficial in informing the feasibility and practicality of task-based calibration. Enhancing TBC to collect more data for each class and with different motion sequencing would create a more robust data set from which a classifier can be built. This would allow for equal amounts of data to be recorded for each motion, as well as unpair any motions that occur in sequence as a result of the specific task. One prudent way to achieve this goal would be to increase TBC to include a second, or even third simulated real-world task.

The task selected for this experiment, picking up an upside-down cup, forced users to always pronate their wrist when their hand was open, and similarly, supinate their wrist when their hand was closed. Future tasks should be selected that still require users to perform the same motions, but in different orders to avoid similar motion pairing. For example, picking up a piece of paper that is on a table, turning it over, and placing it back down would still require participants to open and close their hand, but these motions would be performed while the wrist is neutral and while the wrist is pronated or supinated. Therefore, the data collected from this task would be more robust and diverse than the data collected from a single cup task.

Similarly, TBC yields itself to an effective method of calibrating PR systems for simultaneous control of motions.

While VR can be used for calibration development, the ultimate success of PR performance must be based on physical prosthesis control. Using the current algorithms of PR systems, VR is needed to allow users to calibrate a system while performing a task. However, the enhancement of PR systems using more advanced algorithms, such as artificial neural networks is an increasing area of research to decode EMG activity and identify motion outputs.[17] Improvements to the efficiency of calibrating PR systems for upper limb prosthesis users can be achieved through a combination of many ongoing areas of research, including the development of better-representative calibration sequences, such as TBC.

CLINICAL RELEVANCE/CONCLUSIONS

This research suggests that the way current commercial PR systems are classified, using SC, may not capture an accurate representation of the EMG elicited during functional prosthetic use. These results may help explain why users face difficulty using PR control even after successfully calibrating and being able to repeat motions. Calibrating via TBC may facilitate better prosthetic control and improve the clinical experience of using a PR system. Further, the principles of TBC or mixed calibration could be employed even in current clinical practice by asking users to pretend to perform a task while calibrating.

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