A Comparison of Pattern Recognition Control and Direct Control of a Multiple Degree-of-Freedom Transradial Prosthesis

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ABSTRACT With existing conventional prosthesis control (direct control), individuals with a transradial amputation use two opposing muscle groups to control each prosthesis motor. As component complexity increases, subjects must switch the prosthesis into different modes to control each component in sequence. Pattern recognition control offers the ability to control multiple movements in a seamless manner without switching. In this paper, three individuals with a transradial amputation completed a home trial to compare direct control and pattern recognition control of a multiple degree-of-freedom prosthesis. Outcome measures before and after the home trial, together with subject questionnaires, were used to evaluate functional control. Although small, this trial has implications for the implementation of pattern recognition in commercial control systems and for future research studies.

INDEX TERMS Prosthetics, myoelectric, pattern recognition, transradial amputation.

I. INTRODUCTION

Individuals with a transradial amputation often retain much of the extrinsic musculature of the forearm that is normally used to control the hand and wrist. However, conventional myoelectric technology makes only limited use of the control information contained in these residual muscles. Flexors and extensors are used to generate two independent electromyographic (EMG) signals that control two directions of one motor. Each EMG signal is smoothed and rectified, and a threshold for activation is set such that the motor is on if the signal is above threshold, and off if the signal is below threshold. The motor can be controlled proportionally by considering the amplitude of the signal; higher amplitude signals cause the motor to move faster [1]. We refer to this approach as “direct control” or DC. With DC control, using a wrist motor and/or choosing different hand grasps requires the user to switch the prosthesis into different modes. Switching is most frequently achieved through a co-contraction that generates both flexor and extensor EMG signals simultaneously. It can also be achieved by a brief increase (i.e., a pulse) in a single EMG signal magnitude [1]. However, as the number of components and system complexity increase, the cognitive effort required to control the prosthesis using DC becomes more demanding [2], and control becomes slower.

Pattern recognition (PR) uses EMG information from muscles throughout the entire residual limb and also considers features other than signal magnitude [3]. Much work has been done on PR–based control offline, in virtual environments, and more recently in tethered prostheses [3], [4]. This paper describes a comparison between PR and DC control of a multiple degree of freedom (DOF) prosthetic system during a home trial by individuals with a transradial amputation.

II. METHODS AND PROCEDURES

A. SUBJECT FITTING AND TRAINING

Four people with a transradial amputation were recruited for participation; however, one subject was excluded from the resulting analysis as he found the prototype prosthesis too large to wear at home. All subjects were prior myoelectric
users; two subjects (subjects 2 and 3) were naïve to PR. Subject demographics are listed in Table 1.

Subjects were fit with a custom gel liner containing embedded electrodes. EMG signals were directed to a Texas Instruments ADS 1299 amplifier located at the distal end of the liner. A hardware gain of 2 was applied prior to sampling the data. Software gains for each channel were set by inspecting the signals using a graphical user interface such that the total gains (hardware and software) were set to typical ranges of 2000-8000. EMG data were sampled at 1000 Hz and digitally filtered between 20-500 Hz. The liners were fabricated with six pairs of electrode contacts. Two electrode pairs were located on the traditional flexor and extensor DC sites identified via conventional myoelectric testing by a certified prosthetist [1], [5]. Briefly, this procedure includes using a myoelectric testing tool with trial and error to locate control sites over agonist/antagonist residual muscle pairs that could be isolated and independently activated by the user. Gains were then manually set by the prosthetist to use the entire dynamic range of the recorded signal while the users made test contractions. Thresholds were set as best as possible so that any co-activation or muscle cross-talk did not cause erroneous movements. For pattern recognition control, four other electrode pairs were distributed evenly over the residual limb. The prosthesis was attached to the user by a combination of anatomical suspension (compression above the epicondyles) and a lanyard strap that was fed through an opening in the distal socket and then through a buckle on the outer socket (Figure 1). The subject manually connected the electronics from the liner to the controller via a wired plug. Subjects 1 and 2 used an Omnetics connector plug and, in an effort to streamline the fit and construction, Subject 3 used a Binder connector plug.

Subjects were trained to use the device in both PR and DC control modes using clinical best practices. Functional training for PR control was completed as described in [6]. During the first few visits, while the socket was being constructed, the subjects practiced PR or DC control of the prosthesis in a virtual environment [7] and with a physical prosthesis that was placed on the table-top beside them. After the socket was constructed, they then completed a minimum of 4 hours of therapy under a licensed Occupational Therapist with the device in each mode before beginning the home trials. For the DC phase, the prosthetist was present to optimize gains and thresholds as necessary. For the PR phase, the subject was trained on finding unique and repeatable patterns and how to utilize prosthetic-guided-training, described more thoroughly under “Control Configuration”. Functionally, training started with simple grasp and release and then moved to the operation of all movements when performing functional tasks such as opening containers, folding laundry and other bimanual tasks.

B. PROSTHETIC DEVICE

The prosthetic device used for testing included a powered wrist rotator, a powered wrist flexor and a hand (Michelangelo Hand, Ottobock USA) that allows two hand grasps: key grasp and chuck grasp. The wrist rotator and flexion unit were prototype devices and were custom fabricated by Ottobock. An embedded controller that could be reconfigured using software to allow for either DC or PR control was fabricated for each patient and placed inside the prosthesis assembly. The controller also recorded summary statistics including the amount of time that the device was powered on, and how often the prosthesis was being commanded to move.

C. CONTROL CONFIGURATION

PR or DC control was selected electronically through software, so the prosthetic device, socket, and subject interface were unchanged for both phases of the study. Subjects were randomized with respect to the control method used first (PR or DC), with the exception of Subject 1. Since this trial

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**TABLE 1. Subject demographics.**

| Subject | Age | Gender | Time since amputation | Limb length (LE to DE) | Home Device used prior to participation | Home Device Usage | Testing order |
|---------|-----|--------|-----------------------|------------------------|----------------------------------------|------------------|--------------|
| 1       | 62  | M      | >20 years             | 15.0 cm                | Otobock Hand                          | Occasional       | PR-DC        |
| 2       | 63  | M      | 4 years               | 25.0 cm                | Otobock Hand and Wrist rotator         | Daily            | DC-PR        |
| 3       | 84  | F      | >30 years             | 22.8 cm                | Otobock Hand                          | Daily            | PR-DC        |
would be the first use of PR control in a home environment, it was felt necessary to test the device in this configuration first.

During the conventional DC phase of the study, subjects were fit and trained with necessary control adjustments made as would be done in any clinical fitting. Each subject was presented with a variety of control methods for switching between hand grasps and between hand and wrist functions. The final DC configuration was similar for each subject: A quick “Hand Open” pulse (wrist extension) was used as one switch and a brief “Hand Close” pulse (wrist flexion) was used as the second switch. One of these switches was used to cycle between the two hand grasps; the other was used to cycle between hand and wrist functions. Each subject selected their preferred method for each mode switch. The sequence of modes (e.g., Hand->Rotation->Flexion or Hand->Flexion->Rotation) was also set according to which sequence the subject found most intuitive.

Thresholds and gains were optimized for the open and close signals as well as the two switch pulses. During the study it was occasionally necessary to adjust the gains and thresholds for optimal performance, especially when a repair was required (see Discussion).

Pattern recognition myoelectric algorithms typically use supervised machine learning algorithms to learn patterns from recorded EMG signals [3]. If the patterns change, or control deteriorates, then new calibration data must be collected to update the pattern recognition model. A method called prosthesis-guided-training (PGT) has recently been proposed to allow for convenient recalibration of pattern recognition systems [6], [8]. Whenever the user desires, they may push a calibration button to signal to the prosthesis to move through a sequence of pre-programmed movements. The user is instructed to attempt to mimic the movements of the prosthesis using their residual limb muscles and data are collected using a microprocessor attached to the prosthesis and the commanded movement is used to label each sample of EMG data. Each time the user pressed the calibration button the prosthesis moved through the following sequence: a 3 second movement from the current position to a ‘home’ position. The home position is where the wrist pronation/supination angle is 0 degrees, the wrist flexion/extension angle is 0 degrees, and the terminal device is fully open. The subjects are instructed to not make any muscle contractions during the homing sequence and the data gets labelled as no-movement (NM dataset). Next, the following movements are made automatically twice by the prosthesis, wrist pronation, wrist supination, wrist flexion, wrist extension, hand open, chuck grasp, hand open, key grasp. Each movement was programmed to last three seconds, and there was a two second rest between each movement. During these two second rests, data collection was suspended by the embedded system. The instructions provided to the subjects were to mimic the movement of the prosthesis using the muscle contraction that they would like to use when performing activities of daily living.

After the data were collected, a pattern recognition system was automatically trained. First, a threshold was computed using the NM data collected using equation 1:

\[
TH_{nm} = \frac{1}{NR} \sum_{i=1}^{N} \sum_{r=1}^{R} |x_{ir}^{nm}|
\]

(1)

Where \(TH_{nm}\) is the threshold for movement, \(N\) is the number of points in the NM dataset, \(R\) is the number of recorded channels, and \(x_{ir}^{nm}\) is the \(i^{th}\) sample from the \(r^{th}\) channel of the NM class. For this work, \(N\) was 3000, and \(R\) was 8. \(TH_{nm}\) corresponds to the mean absolute value of the NM class averaged across all channels.

Next, for each of the recorded contractions time-domain and auto-regressive (TDAR) features were extracted from the EMG signals using a sliding window strategy as described by Englehart and Hudgins [9]. We used windows of length 200 ms with 25 ms increments (i.e., 175 ms of the frame had overlapping data). We also used equation (2) applied to each frame to determine if the user was actively contracting during the prompted movement.

\[
TH_m = \frac{1}{NC} \sum_{i=1}^{N} \sum_{r=1}^{C} |x_{ir}^{mc}|<m
\]

(2)

Patterns were assigned to the NM class if:

\[
TH_m < 1.1 \times TH_{nm}
\]

(3)

These processing steps were performed to make the system more user-friendly. The threshold automatically prevented patterns from being labelled as an active movement when a person was not trying to contract their muscles even though they were being prompted to make a contraction.

Features were classified using a linear discriminant analysis (LDA) classifier. The LDA classifier is often used in myoelectric control research and a full derivation may be found in many texts. Using the notation from [10], the discriminant functions \(\delta_c\) may be found using equation (4):

\[
\delta_c(x) := x^T \Sigma_{-1} \mu C - \frac{1}{2} \mu C^T \Sigma_{-1} \mu C + \log \pi C
\]

(4)

where \(x^T\) is the transpose of the test pattern to be classified, \(\mu C\) is the mean of class \(c\), \(\Sigma_{-1}\) is the inverse of the pooled covariance matrix, and \(\pi C\) is the is the prior probability for each class. The pooled covariance matrix can be calculated by:

\[
\Sigma = \frac{1}{C} \sum_{c=1}^{C} \Sigma_c
\]

(5)

The output of the control system is classified as belonging to the class with the highest probability:

\[
y = \arg \max_c(\delta_c(x))
\]

(6)

Pattern recognition classifiers only provide a decision of which movement was intended by the user. The purpose of the enhanced proportional control algorithm was to estimate the speed with which the user wished to perform the movement. This algorithm uses a weighted average of EMG amplitudes to compute the speed as described by Scheme et al. [11].
A subject dependent velocity based smoothing ramp between 100-500 ms as described by Simon et al. [12] was also used. The velocity based smoothing ramp acts as a mean-filter and attenuates the speed at which any spurious misclassification is activated.

**D. HOME TRIALS, PATTERNS RECOGNITION PERFORMANCE, AND OUTCOMES TESTING**

Subjects used the device at home for a minimum of 4 weeks in each configuration. Due to periodic mechanical failures, it was not possible to achieve 4 consecutive weeks of use. Subjects were requested not to use their home/conventional prosthesis during the study unless the experimental prototype was returned for repair. We quantified PR performance by computing classification error, which is frequently used to quantify PR system performance and reflects the proportion of time movements are misclassified by the control system. Classification error was computed by performing leave-one-out-cross-validation using two sets of Prosthesis Guided Training data collected after subjects had received functional training but prior to the home-trial, and using two sets of Prosthesis Guided Training data collected after the home trial was completed.

Outcomes were measured before and after each home trial. The outcome measures included the Southampton Hand Assessment Protocol (SHAP), the Jebsen-Taylor Test of Hand Function, the Box and Blocks Test, a Clothespin Relocation Task, and a ‘Cubbies Task’ [15]–[18]. These measures were selected, in part, based on the recommendations of the American Academy of Orthotists and Prosthetists State of the Science meeting on Upper Limb Prosthetic Outcome Measures [19]. Performance measures were also chosen to evaluate arm function and included tasks where wrist movement would improve function. For example, with the Clothespin Relocation Task, individuals would pick up the clothespin from a horizontal bar, rotate the wrist, and place the clothespin on a higher vertical bar. Since no timed task could be identified that required wrist flexion, a ‘Cubbies Task’ was created (Figure 2). For this task, a cubic system with 9 openings in a 3 X 3 configuration was placed on a table, which was adjusted such that the top of the cubic set was at the subject’s eye level. A block was placed in each cubicle, and three blocks were placed along the top, for a total of 12 blocks. Subjects were instructed to pick up the blocks one at a time, starting at the top on the opposite side to the prosthesis and going down each column. After picking up the block, subjects placed it on the table in front of the cubbies. If a block was dropped, the therapist placed the block back in the correct opening. The total time to complete the task was recorded. Our expectation was that this task would provide an assessment of subjects’ ability to adjust wrist flexion in order to pick up the blocks at each level and place them on the table.

In addition to these functional and timed tasks, subjects were given a survey at the end of each phase to ask questions about the ease of use, fatigue experience during each control method, ability to perform tasks, etc. After completing both phases, subjects were then asked which control they preferred and what aspects they liked most about each control method.

Finally, home-usage statistics were recorded electronically for each subject. Each time the power was cycled to the controller, it logged how long it remained powered on, and the percentage of time the controller was sending commands to move the prosthesis. The amount of time that the controller was powered on (in minutes) was divided by the number of days that person used it at home to compute an average daily usage statistic.

**III. RESULTS**

**A. HOME USAGE**

There was large variability in how much each subject wore the prosthesis during the home trial phases (Table 2). All subjects wore the PR control system more than the DC control system. The difference in wear time between DC and PR control trials was most pronounced for Subject 1. All subjects commanded the prosthesis to move more frequently when using pattern recognition compared to direct control.

**B. OUTCOMES TESTING**

Table 3 (pre-home trial) and Table 4 (post-home trial) present the results of the outcome testing for the three subjects as well as the average and standard deviation. The SHAP result is
TABLE 3. Outcome Results Prior to Home Trial for the SHAP and box and blocks tasks, a larger value indicates improved performance. For the Jebsen-Taylor, clothespin relocation, and cubbies tasks, a smaller value indicates better performance.

| SHAP Index of Function | Box and Blocks Task: number of blocks moved in 1 minute | Jebsen-Taylor Test: time to complete all tasks (s) | Clothespin Relocation Task: time to move 3 pins (s) | Cubbies Task: time to move 12 blocks (s) |
|------------------------|--------------------------------------------------------|--------------------------------------------------|-------------------------------------------------|----------------------------------------|
|                        | PR | DC | PR | DC | PR | DC | PR | DC | PR | DC |
| Subject 1              | 45 | 3  | 7  | 24 | 298| 518| 54.9| 84.1| 81.6| 70.9|
| Subject 2              | 45 | 39 | 5  | 14 | 436| 281| 65.1| 26.9| 181.0| 58.0|
| Subject 3              | 23 | 22 | 5  | 6  | 305| 287| 99.4| 66.2| 360.5| 224.1|

TABLE 4. Outcomes Results After Home Trial for the SHAP and box and blocks, a larger value indicates improved performance. For the Jebsen-Taylor, clothespin relocation, and cubbies tasks, a smaller value indicates improved performance.

| SHAP Index of Function | Box and Blocks Task: number of blocks moved in 1 minute | Jebsen-Taylor Test: time to complete all tasks (s) | Clothespin Relocation Task: time to move 3 pins (s) | Cubbies Task: time to move 12 blocks (s) |
|------------------------|--------------------------------------------------------|--------------------------------------------------|-------------------------------------------------|----------------------------------------|
|                        | PR | DC | PR | DC | PR | DC | PR | DC | PR | DC |
| Subject 1              | 66 | 38 | 18 | 15 | 255| 284| 21.0| 105.0| 56.7| 60.8|
| Subject 2              | 55 | 33 | 7  | 6  | 389| 387| 37.6| 47.9 | 79.2| 107.0|
| Subject 3              | 34 | 38 | 8  | 5  | 353| 322| 14.1| 56.5 | 92.1| 149.8|

the Index of Function Score; here a higher value indicates improved performance. The Jebsen-Taylor result is the total sum time taken to complete the 7 different tasks (a time-out was set at 120 sec for each task), thus a lower value indicates the ability to perform the tasks faster—i.e., improved performance. The Box and Blocks result represents the number of blocks moved across the barrier in 1 minute, so a higher number reflects better performance. Clothespin Relocation Task results represent the time taken, in seconds, to move 3 pins from the horizontal to the vertical bar. The Cubbies Task results indicate the time, in seconds, required to move all 12 blocks from the cubbies to the table. For the latter two tasks, a lower number indicates better performance.

C. CLASSIFICATION ERROR RATE

Classification error rates were not obtained for Subject 1. A software bug caused the data to be improperly saved but this was corrected prior to subjects 2 and 3 completing the trial. The classification error rates for Subjects 2 and 3 prior to the home trial were 9.3% and 16.4%, respectively. Error rates after completing the home trial were 12.9% and 10.2%, respectively. These data were collected during Prosthesis Guided Training sessions reflecting realistic EMG patterns and error rates obtained when wearing a prosthesis.

D. SUBJECTIVE FEEDBACK

In general, during the PR control phase, subjects reported that it took time to learn how to consistently distinguish various movements. Subjects also noted that sometimes the prosthesis moved unintentionally using PR control, which made their prosthesis less reliable; however this improved when they learned to make more distinguishable movements. Subjects 1 and 2 stated that they felt PR was difficult at first but got easier and that their performance improved with practice. Subject 3 felt it was difficult to consistently control the two hand grasps in PR throughout the home trial. She also felt that controlling the additional DOFs was challenging regardless of the control method used. During the DC phase, all subjects commented that they often had unintentional switching between the DOFs, and that performing mode-switching was inconvenient. Overall, subjects 1 and 2 preferred PR control. Subject 3 preferred DC.

IV. DISCUSSION

A. RESULTS

Subjects were able to successfully complete a home trial using PR control, which had previously only been used in a laboratory environment. Additionally, the number of DOFs that were controlled in this study was higher than available in a commercially available prosthesis, as powered wrist flexion units are not currently commercially available.

The outcome measures taken prior to the home-trial did not show an overwhelming bias toward either control method, although many of the measures tended to be better when using DC control. This is not surprising since all three subjects used DC control at home so they had much more practice and were very familiar with the DC control system.
After completing the home trial, subjects tended to have better performance with PR control. The three tests that stand out with the greatest improvement were the Clothespin Relocation Task, the Cubbies Task, and the SHAP. Interestingly all of these tests required wrist use; wrist rotation for the Clothespin Relocation Task and wrist flexion/extension for the Cubbies Task and SHAP [20].

Subject 1 was only an occasional prosthesis user prior to being enrolled in the study, and did not choose to use the prosthesis much in the conventional control portion of the trial even though attempts were made to make the DC system intuitive. As a result, this subject’s post-home trial scores should be considered carefully. Comparisons between the pre home-trial PR and DC may be readily made; however, comparisons between the post home-trial PR and DC may include a component attributed to the amount of time the user actually used the system.

It is not surprising that the results were similar with PR and DC for the Blocks and Box task. This simple task required no wrist movement and could even be performed with a straight elbow. Opening and closing of the terminal device is a simple task that the subjects had great experience with in the DC controlled devices they used at home. However, we see that PR control became much more important and useful when wrist movement was needed or grasp switching was required as in the SHAP and for harder tasks that require use of two functions. Thus PR control appears to have been easier and faster than switching modes in DC control. This is logical and consistent with the seamless sequential control that PR provides.

Many previous studies have reported finding classification error rates of 10% or less using able-bodied control subjects and transradial amputees [3], [21]. EMG data collected using Prosthesis Guided Training, which includes transient and steady-state EMG signals, have been shown to have slightly lower classification error rates [22], as was also shown in this study. Although the data is limited, only marginal changes in classification error rates were observed, whereas the change in outcome measures showed consistent improvements. This study shows that classification error rates of approximately 10% are suitable for home use of PR-controlled prostheses. It also demonstrates that improvements in control may not necessarily be related to improvements in classification error rates but rather with experience using a physical prosthesis. Fourteen out of 15 outcome measures showed improvements when using PR vs 6 out of 15 for DC after the home trial. A lengthier home-trial may reveal even further improvements and this phenomenon should be addressed in future studies.

B. SUBJECTIVE FEEDBACK

Two of the three subjects preferred PR control. Subject 3 preferred DC but performed better in many measures with PR control. She acknowledged a personal bias in that she felt that the prosthesis was more than she could imagine using. She was a long-time myoelectric hand user, but did not appreciate the benefits of the additional DOFs, using either type of control.

Subjects were able to use both types of control to complete a variety of activities such as preparing food, eating, dressing, and performing household chores. All subjects stated that these were hard systems to control (using both DC and PR) because of all of the possible movements. They had previous experience using only a 1 or 2 DOF prosthesis.

C. LIMITATIONS

1) SUBJECT NUMBERS

Due to the small sample size, it is not appropriate to perform a statistical analysis of the data. However, this study demonstrated that pattern recognition control can successfully be implemented at home by individuals of different ages, genders, and residual limb lengths.

2) PROSTHESIS USAGE

The patients and clinicians recognized that this device was oversized. This was the primary reason that one subject was withdrawn from the study. He typically wore dress-shirts at work which did not fit well under the prototype device. The remaining subjects felt comfortable enough with the size to complete the trial and did not report that this limited their use of the prosthesis.

The home-trial was frequently interrupted due to mechanical failures of the experimental prosthesis. Each subject had at least one failure during each study phase. Failures were mostly related to the early development stage of the 2-DOF wrist hardware and to the electronics connection between the liner and the prosthesis. Often components were
repaired/replaced within a few days, although some repairs took as long as a few weeks. During these mechanical failures and on other occasions within this study, the settings of the DC system had to be adjusted to maintain high performance. With PR control systems these manual adjustments are unnecessary as the machine learning creates an updated control mapping each time the Prosthesis Guided Training routine is initiated.

The amount of time the prosthesis was worn, and the percentage of time it was commanded to move was recorded by the controller. However, because the prosthesis was not instrumented with position feedback, it was not possible to determine if the user was intentionally commanding it to move. For example, the hand could be fully closed and the controller could have been sending additional hand closing commands without the user noticing.

3) CLASSIFICATION ERROR RATE ANALYSIS

Within this study, classification error rates for only two of the three subjects could be computed due to a software bug, which was ultimately corrected. Additionally, raw EMG signals were not recorded for subjects each time they recalibrated their prosthesis. As a result, we are careful not to place undue emphasis on the changes in classification error rates pre and post home-trial testing.

4) APPLICATION OF OUTCOME MEASURES

There are few validated outcome measures appropriate for upper limb amputee research [19]. The measures chosen for application in this study were a selection of those listed as “recommended” or “consider” by the American Academy of Orthotists and Prosthetists State of the Science meeting [19], with the addition of two timed measures (Clothespin Relocation and Cubbies Tasks) designed to evaluate use of a specific DOF (wrist rotation and wrist flexion, respectively).

In some timed tests, subjects could alter how they completed the task to circumvent the use of the certain DOFs. For example, if it was more difficult to access wrist rotation when using DC, the subject could compensate by using shoulder and elbow movement to position the terminal device. In this study, subjects were encouraged to use all DOFs during outcome measures but were not forced to do so. A future study will combine motion analysis with the timed tasks to additionally assess the quality of performance.

V. CONCLUSION

Despite the limitations of this study, we show that it is possible to control a complex four-motor prosthesis system using PR in a home environment. Subjects were able to control wrist rotation, wrist flexion, and two hand grasps using their residual limb musculature. PR control appears to have enabled better control when wrist function was necessary to complete the task, likely due to the seamless mode changes enabled by PR control, compared to the mode switching required for DC control. We also found that experience using PR was a very important factor. After the home trial 14 out of 15 outcome measures showed improvement. Future studies involving more subjects will allow statistical analysis. More robust componentry would minimize breakdowns and interruptions in the protocol and reduce subjects’ frustration.

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REFERENCES

[1] T. W. Williams, “Control of powered upper extremity prostheses,” in Functional Restoration of Adults and Children With Upper Extremity Amputation, R. H. Meier and D. J. Atkins, Eds. New York, NY, USA: Demos Medical Publishing, 2004, pp. 207–224.
[2] S. Deeny, C. Chicoine, L. Hargrove, T. Parrish, and A. Jayaraman, “A simple ERP method for quantitative analysis of cognitive workload in myoelectric prosthesis control and human-machine interaction,” PLoS ONE, vol. 9, no. 11, p. e112091, 2014.
[3] E. Scheme and K. Englehart, “Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use,” J Rehabil. Res. Develop., vol. 48, no. 6, pp. 643–660, 2011.
[4] T. A. Kuiken et al., “Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms,” J. Amer. Med. Assoc., vol. 301, pp. 619–628, Feb. 2009.
[5] J. W. Michael, “Externally powered prostheses for the adult transradial and wrist disarticulation amputee,” in Functional Restoration of Adults and Children With Upper Extremity Amputation, R. H. Meier D. J. Atkins, Eds. New York, NY, USA: Demos Medical Publishing, 2004, pp. 187–197.
[6] A. M. Simon, B. A. Lock, and K. A. Stubblefield, “Patient training for functional use of pattern recognition-controlled prostheses,” J. Prosthet Orthot, vol. 24, no. 2, pp. 56–64, Apr. 2012.
[7] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “Prosthesis-guided training increases functional wear time and improves tolerance to malfunctioning inputs of pattern recognition-controlled prostheses,” presented at the Myoelect. Symp. (MEC), Fredericton, NB, Canada, 2011.
[8] K. Englehart and B. Hudginis, “A robust, real-time control scheme for multifunction myoelectric control,” IEEE Trans. Biomed. Eng., vol. 50, no. 7, pp. 848–854, Jul. 2003.
[9] M. Vidovic, H.-J. Hwang, S. Amsuss, J. Hahne, D. Farina, and K.-R. Muller, “Improving the robustness of myoelectric pattern recognition for upper limb prostheses by covariate shift adaptation,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 24, no. 9, pp. 961–970, Sep. 2015.
[10] E. Scheme, B. Lock, L. Hargrove, W. Hill, U. Kuruganti, and K. Englehart, “Motion normalized proportional control for improved pattern recognition-based myoelectric control,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 22, no. 1, pp. 149–157, Jan. 2014.
[11] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “A decision-based velocity ramp for minimizing the effect of misclassifications during real-time pattern recognition control,” IEEE Trans. Biomed. Eng., vol. 58, no. 8, pp. 2360–2368, Aug. 2011.
[12] Y. Huang, K. B. Englehart, B. Hudginis, and A. D. C. Chan, “A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses,” IEEE Trans. Biomed. Eng., vol. 52, no. 11, pp. 1801–1811, Nov. 2005.
[13] L. H. Smith, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “Determining the optimal window length for pattern recognition-based myoelectric control: Balancing the competing effects of classification error and controller delay,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 19, no. 2, pp. 186–192, Apr. 2011.
[14] C. M. Light, P. H. Chappell, and P. J. Kyberd, “Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: Normative data, reliability, and validity,” Arch. Phys. Med. Rehabil., vol. 83, no. 6, pp. 776–783, Jun. 2002.
[15] V. Mathiowetz, G. Volland, N. Kashman, and K. Weber, “Adult norms for the box and block test of manual dexterity,” Amer. J. Occupat. Therapy, vol. 39, pp. 386–391, Jun. 1985.
[16] R. H. Jebsen, N. Taylor, R. B. Trieschmann, M. J. Trotter, and L. A. Howard, “An objective and standardized test of hand function,” Arch. Phys. Med. Rehabil., vol. 50, no. 6, pp. 311–319, Jun. 1969.

[17] L. A. Miller, K. A. Stubblefield, R. D. Lipschutz, B. A. Lock, and T. A. Kuiken, “Improved myoelectric prosthesis control using targeted reinnervation surgery: A case series,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 16, no. 1, pp. 46–50, Feb. 2008.

[18] L. A. Miller and S. Swanson, “Summary and recommendations of the academy’s state of the science conference on upper limb prosthetic outcome measures,” JPO J. Prosthetics Orthotics, vol. 21, no. 9, pp. P83–P89, 2009.

[19] A. Murgia, P. Kyberd, and T. Barnhill, “The use of kinematic and parametric information to highlight lack of movement and compensation in the upper extremities during activities of daily living,” Gait Posture, vol. 31, no. 3, pp. 300–306, 2010.

[20] J. He, D. Zhang, N. Jiang, X. Sheng, D. Farina, and X. Zhu, “User adaptation in long-term, open-loop myoelectric training: Implications for EMG pattern recognition in prosthesis control,” J. Neural Eng., vol. 12, no. 4, p. 046005, 2015.

[21] C. Chicoine, A. Simon, and L. Hargrove, “Prosthesis-guided training of pattern recognition-controlled myoelectric prosthesis,” in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), San Diego, CA, USA, Sep. 2012, pp. 1876–1879.

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