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Pattern Recognition Control Outperforms Conventional Myoelectric Control in Upper Limb Patients with Targeted Muscle Reinnervation

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Abstract **Pattern recognition myoelectric control shows great promise as an alternative to conventional amplitude based control to control multiple degree of freedom prosthetic limbs. Many studies have reported pattern recognition classification error performances of less than 10% during offline tests; however, it remains unclear how this translates to real-time control performance. In this contribution, we compare the real-time control performances between pattern recognition and direct myoelectric control (a popular form of conventional amplitude control) for participants who had received targeted muscle reinnervation. The real-time performance was evaluated during three tasks; 1) a box and blocks task, 2) a clothespin relocation task, and 3) a block stacking task. Our results found that pattern recognition significantly outperformed direct control for all three performance tasks. Furthermore, it was found that pattern recognition was configured much quicker. The classification error of the pattern recognition systems used by the patients was found to be 16% ±(1.6%) suggesting that systems with this error rate may still provide excellent control. Finally, patients qualitatively preferred using pattern recognition control and reported the resulting control to be smoother and more consistent.**

I. Introduction

Pattern recognition has been proposed as an alternative to conventional amplitude-based control, also referred to as direct control, for several decades. The primary benefit of pattern recognition is it provides an intuitive mapping of physiologically appropriate muscle contractions to the corresponding prosthesis movements. This is achieved by using a classifier to discriminate electromyographic (EMG) signal features measured from an arbitrary number of residual limb muscles into a discrete number of movement classes [1]. Several studies are available in the literature that quantify the performance of pattern recognition control systems in terms of classification error, with many implementations producing classification errors of less than 10% [2]. However, the relationship between classification error and functional performance remains unclear. Furthermore, pattern recognition systems have not yet been accepted by the clinical community leading to questions regarding a need to change focus in the direction of research efforts towards systems better suited for simultaneous multifunction control [3].

Conventional amplitude based control has received wide-spread clinical adoption. The most popular implementation, termed direct control, requires placement of electrode pairs over agonist-antagonist muscles [4]. The muscles must be independently controlled and the resulting EMG signals free from muscle crosstalk. Estimates of the EMG amplitudes are then compared to preset thresholds to determine what user intends to make a motion. Direct control is usually limited to controlling a single degree of freedom due limited available control muscles on the residual limb. A mode switch may be used to control additional degrees of freedom, however, this adds cognitive burden to the user and reduces the intuitiveness of the overall system.

Targeted muscle reinnervation (TMR) is a surgical technique that restores physiologically appropriate electromyographic (EMG) signals to high-level upper-limb amputee patients. The TMR procedure is growing in popularity and excellent functional outcomes have been achieved direct control techniques [5]. Pattern recognition has been suggested as an alternative control method because the reinnervation results in rich EMG signal patterns that can be reliably and voluntarily elicited by the patients [6].

There have been few previous studies that have directly compared the performance of pattern recognition to direct control [7, 8]. The first study found improved performance using pattern recognition control but was very limited because only control subjects were tested within a virtual environment. Preliminary functional comparisons between direct control of single degree of freedom hand with passive wrist rotation to a six degree of freedom multifunction arm system showed better performance using the direct control system in a single subject case study [8]. It was suggested that the patients limited experience with pattern recognition, compensatory body movements when using the direct control system, and desire to demonstrate control of all degrees of freedom of the device may have biased the results in favor of direct control. Subsequent testing of transradial amputee subjects have found that mixed results when variables were controlled for [9].

In this contribution, we directly compare the functional performances of TMR amputee patients controlling a physical prosthesis between pattern recognition to direct control during three simple performance tasks. Our findings

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suggest that pattern recognition provides significantly improved results for this amputee subpopulation.

II. Methodology

Four individuals (1 male with a shoulder disarticulation, 2 males and 1 female with a transhumeral amputation) who received TMR surgery more than 3 years prior to the experiment completed the study. All patients had extensive at-home experience using a conventional myoelectric-controlled prostheses. The patients reported on average, using the prosthesis daily for approximately two hours. The subjects also had significant within-lab experience (estimated at tens of hours over the last three years) using pattern recognition-controlled prostheses.

As a result of all the TMR surgery, all patients had 4 independent control sites (2 reinnervated sets of agonist/antagonist muscle pairs) over which 4 bipolar pairs of EMG electrodes could be placed for direct control as described by the clinical electrode configuration in [10]. These physiologically appropriate reinnervated sites were used to control elbow flexion/extension and hand open and close degrees of freedom. All patients also had control of wrist supination and pronation. The method of wrist rotation control was similar to their conventional myoelectric prosthesis (selected by the clinical team responsible constructing the patients' daily use prosthesis). One transhumeral patient had a 5^{th} independent control site resulting from his TMR surgery which he used to control wrist rotation; a 'fast' muscle contraction (short, high amplitude contraction) caused the wrist to pronate and a 'slow' muscle contraction (slower, graded muscle contraction) caused the wrist to supinate. Two patients used a mode switch, implemented through a mechanical switch or muscle co-contraction, so they could switch from opening and closing the hand (shoulder disarticulation patient) or from flexing and extending the elbow (transhumeral patient) to pronating and supinating the wrist. The final transhumeral patient used a linear transducer (i.e. body-driven cable) to operate the wrist. The direct control system gains and thresholds [4] were configured by a certified prosthetist to match the settings used with the patients' daily use prosthesis.

Four additional pairs of electrodes were placed on the patients' residual limbs to cover the areas between the TMR control sites for the pattern recognition control system. The control system was comprised of time-domain features and auto-regressive coefficients classified by a linear discriminant analysis classifier. This feature set and classifier combination has been well researched and shown to classify EMG data from TMR locations with low classification errors [6]. Features were extracted from 250 ms analysis windows and classifications were updated at every 50 ms [11]. The velocity of the desired movement was computed using a simple proportional control algorithm smoothed by a decision-based velocity ramp to condition the output of the pattern recognition system [12]. The pattern recognition was trained using a previously described auto-calibration routine during which patients mimicked pre-programmed movements of the prosthesis [13]. The routine was configured such that approximately 6 seconds of EMG data were collected for each movement. The entire pattern recognition algorithm was implemented on a custom embedded system and mounted on the prosthesis.

Figure 1. TMR patient with a transhumeral amputation performing clothespin relocation task using the embedded pattern recognition control system.

Patients completed three different real-time performance tests with each system: 1) a blocks and box test (number of 1-inch blocks moved over a barrier in two min) [5], 2) a block stacking test (number of blocks stacked in three min) [12], and 3) a clothespin relocation test (time to move three clothespins) [14]. Three trials of each test were completed. Tests were performed in two separate, randomized-order sessions (conventional control or pattern recognition). Following testing, subjects provided qualitative feedback about each control system. The classification error rate was also computed for three of the four patients. In addition, the time taken to configure each control system was recorded.

A statistical analysis was completed using ANOVAs with the real-time performance metrics as the response variables, control type and trial number as fixed factors, and subject as a random factor.

III. Results

Patients showed significant (ANOVA, $p<0.05$) performance improvements across all tasks while using the pattern recognition compared to conventional control (Figure 2). The trial number was not found to be significant. Approximately 15 minutes was required to configure the prosthesis control system for direct control in comparison to approximately 5 minutes for pattern recognition. This time did not include time taken for electrode placement as the locations had been previously identified. Patients moved 40% more blocks and the stacked towers were 59% higher using the pattern recognition control system. The clothespin relocation times task was completed in 25% less time when using the pattern recognition control system. The average classification error rates for the pattern recognition systems were 16.3% (standard deviation1.6%).

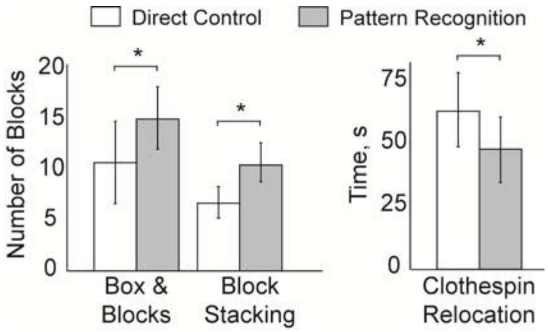

Figure 2. Average performance measures for patients using conventional control and pattern recognition. Asterisks indicate significant differences ($p<0.05$) between control conditions.

Qualitatively, subjects preferred using the pattern recognition control system. They reported it to be more intuitive to control, smoother to operate with better proportional control, and more consistent in its performance. They also reported that the conventional control setup performed equivalently to their daily use prosthesis.

IV. Discussion

The TMR procedure has resulted in significant and clinically relevant performance improvements when used with direct myoelectric control systems [14]. Furthermore, TMR patients have successfully demonstrated use of pattern recognition controlled advanced prosthesis prototypes [15]. However, this is the first study to directly compare the performance of pattern recognition systems to direct control systems using a physical prosthesis with TMR patients. The results suggest that pattern recognition significantly ($p<0.05$) outperforms direct control for all of the performance tasks tested in this experiment. Perhaps equally as important in clinical deployment of pattern recognition systems is the indication of faster clinical configuration. This has far-reaching effects in the patients' rehabilitation process and the practioners economic planning; an increased proportion of funded time can be dedicated to functional development instead of system configuration.

The relationship between pattern recognition classification error and functional performance remains unclear. While early work found only a weak correlation between classification error and functional performance [16], more recent studies have found a stronger correlation between these variables during experiments conducted within virtual environments [11, 17]. This work demonstrates that systems with classification errors of 16% result in control systems that outperform direct control. The classification accuracy for one of the subjects could not be computed because the file was not properly saved by the microcontroller. This anomaly was corrected for the other three subjects. Less accurate systems may still provide acceptable control. Many such feature set and classifier combinations are capable of generating these accuracies [2].

Current implementations of pattern recognition systems are limited to seamless sequential control to achieve tasks that require movements of more than one degree of freedom. Some preliminary work has shown that pattern recognition systems may be extended simultaneously classify multiple degree of freedom movements [18]. Other signal processing approaches [19, 20] have been developed to specifically allow for simultaneous and proportional control of movements but have yet to be thoroughly tested with amputee patients using physical prostheses. In fact, TMR with direct control allows for simultaneous control of the elbow with a wrist or hand [14]. Even though patients could simultaneously control these movements with direct control, our results showed that the seamless sequential pattern recognition system provided better functional results. Thus, while multifunction simultaneous and proportional control systems are worthy end-goals, the limitation of pattern recognition to seamless sequential control should not be perceived as a limiting factor in its clinical adoption.

Pattern recognition systems do not directly provide a proportional control estimate. Rather, a secondary algorithm is used to compute estimate the proportional control speed. Proposed secondary algorithms may be a simple as using the average power across each channel [21], or more advanced using the predicted class as prior information allowing for automatic and class specific normalization of each movement prosthesis movements [22]. Qualitatively, all patients tested in our functional tests perceived the proportional control of the pattern recognition system to be better than that of the direct control. They reported the control to be 'smoother' and 'more consistent' allowing them to operate the prosthesis with more confidence.

It should be noted the performance tests may not be representative of activities of daily living; however, we feel they are more representative of functional performance than virtual environment tasks. Furthermore, the tasks were selected because they require use of all three degrees of freedom that were under voluntary control of the patient (clothespin relocation task), and required both gross (box and blocks) and fine (block stacking task) control of movements. Each task required that subjects use the prosthesis in closed loop with visual feedback. Further work is required to perform clinically validated outcome measures for both direct and pattern recognition control.

V. Conclusion

Pattern recognition performance has traditionally been quantified in terms of classification error but few studies have quantified, or even demonstrated, functional control using pattern recognition controlled devices. There are many reasons for this including: ease and cost efficiency of performing experiments within virtual environments, convenience of testing with control subjects, and no commercially available of pattern recognition controlled prostheses. In this contribution, we showed that pattern recognition systems significantly outperformed direct control systems for TMR amputees when completing simple performance tasks required using a multi-degree of freedom prosthesis. Furthermore, pattern recognition systems were significantly faster to configure and patients preferred using the pattern recognition systems despite inherent limitations associated with pattern recognition. Thus, we conclude that pattern recognition should be considered as a viable clinical alternative until more advanced simultaneous proportional control systems are developed.

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