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A Comparison of Direct and Pattern Recognition Control for a Two Degree-of-Freedom Above Elbow Virtual Prosthesis

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***Abstract*— Individuals with a transhumeral amputation have a large functional deficit and require basic functions out of their prosthesis. Myoelectric prostheses have used amplitude control techniques for decades to restore one or two degrees of freedom to these patients. Pattern recognition control has also been investigated for transhumeral amputees, but in recent years, has been more focused on transradial amputees or high-level patients who have received targeted muscle reinnervation. This study seeks to use the most recent advances in pattern recognition control and investigate techniques that could be applied to the majority of the transhumeral amputee population that has not had the reinnervation surgery to determine if pattern recognition systems may provide them with improved control. In this study, able-bodied control subjects demonstrated that highly accurate two degree-of-freedom pattern recognition systems may be trained using four EMG channels. Such systems may be used to better control a prosthesis in real-time when compared to conventional amplitude control with mode switching.**

I. Introduction

A myoelectric prosthesis is controlled using processed electromyographic (EMG) signals measured from the patient's residual limb. The EMG signal processing can be as simple as comparing the amplitude, or mean absolute values (MAV), of signals measured from a pair of agonist/ antagonist muscles or as complex as extracting patterns measured from multiple muscles [1]. The control method which provides the best functional outcome for each patient is the subject of ongoing research.

Individuals with high-level amputations have a great need for functional prostheses because of their vast functional deficits. Unfortunately, these patients have very few suitable muscles remaining from which to measure EMG signals. Kuiken *et. al*, developed a surgical technique, called targeted muscle reinnervation (TMR), that allows for simultaneous control of multiple degrees-of-freedom (DOF) in myoelectric prostheses [2]. This procedure is based on the transfer of residual nerves of amputees to 'spare' muscles in or near the residual limb that are no longer biomechanically functional as a result of the amputation. Post-surgery, individuals with a transhumeral amputation can either control a prosthesis with two DOF using conventional amplitude based direct-control or four DOF using pattern recognition [3]. Although the targeted reinnervation surgery is not difficult and is increasing in popularity, the vast majority of transhumeral amputees are not TMR recipients.

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Two-site direct control (DC) is a popular conventional myoelectric control method and works very well if EMG signals can be measured from physiologically appropriate agonist/antagonist muscles pairs. For example, in the context of transhumeral amputation, the MAV of the biceps and triceps muscles can be used to intuitively control elbow flexion and extension, respectively. A mode switch in the form of a mechanical switch or a muscle co-contraction is commonly used such that the same control sites can control a second DOF (hand-open and hand-close) but such systems are less intuitive to use. Williams [4] has provided an excellent, detailed summary of different conventional control options for upper limb amputees.

Pattern recognition systems do not require mode switches and are considered by many to be more intuitive methods to control two or more DOFs in comparison to direct control with mode switching. Hudgins [5] showed that transhumeral amputees were capable of producing repeatable EMG signal patterns for five discriminated motions with classification errors around 15%. These results were obtained by considering only the transient portions of the EMG signal from a single channel where one electrode was placed on the biceps and one electrode was placed on the triceps. All patterns were discriminated using an artificial neural network.

In addition to classification error, it is very important to characterize the patient's real-time control performance. Virtual environments are useful tools that allow researchers to quickly evaluate real-time control systems without the need for physical prostheses. Furthermore, simple assessment tests may be added to the virtual environment to quantify performances and enable comparisons between different control strategies. Simon *et. al* [6], developed a virtual environment performance metric termed the Target Achievement Control Test (TAC Test) which requires the subject to conform the virtual prosthesis to designated target postures and has been used to evaluate the performance of pattern recognition myoelectric control systems.

Recently, pattern recognition research has focused more on the transradial or TMR amputee with only a few studies reporting results for non-TMR transhumeral patients [7]. In this study, we evaluate the real-time performance of non-amputee subjects using similar muscle sites that would be available on a transhumeral amputee. Subjects controlled a virtual transhumeral prosthesis using both conventional amplitude and pattern recognition control.

II. METHODS

Six healthy non-amputee control subjects (Table I) participated in the study which was approved by the Northwestern University Institutional Review Board. The overall goal of the study was to compare one and two DOF control using EMG signals measured from the biceps and triceps with 1) a two-site direct control configuration with mode switching and 2) using pattern recognition. The study required two visits to complete. Configurations to control a single DOF were performed on one day and were performed by all six subjects. Configurations to control two DOFs were performed on a second day. Due to scheduling constraints, only four of the six subjects performed the second day's experiment.

A. Direct Control

For the direct control configuration, one pair of electrodes was placed on the muscle belly over the short head of the biceps and one pair of electrodes was placed on the muscle belly over the medial head of the triceps. EMG signal testing was performed according to clinical best practices and the electrodes were relocated if either signal was contaminated by a substantial amount of muscle crosstalk. The gain of each channel was set to a convenient value and all data were bandpass filtered (20-500 Hz) and sampled at 1000 Hz using a Delsys-Bagnoli-16 EMG amplifier system. The MAV of each signal was computed over 250 ms windows, which was updated each 50 ms. A dual-site differential direct proportional control system [4] was configured by setting appropriate gains and thresholds with the assistance of a prosthetist according to clinical best practices. A co-contraction switch was used to toggle between the DOFs during TAC Tests that required control over two DOFs.

B. Pattern Recognition

For the pattern recognition configuration, the same channels of the direct control configuration were used. Two additional pairs of electrodes, were placed on the upper arm between the direct control sites but were not targeted over specific muscles. Previous work by Hudgins [5] suggested that EMG signal patterns produced by elbow flexion/extension and humeral rotation in/out produce repeatable patterns suitable for pattern recognition. Pattern recognition data were collected using computer-guided sessions which displayed pictures of the motions subjects were required to perform. Subjects were instructed to make repeatable, medium force contractions to the best of their ability; however, no feedback was provided. Eight repetitions of each motion were collected in a non-randomized order and each motion was held for 3 s, with 2 s of rest between motions. This protocol is very similar to training data collections used previously to configure pattern recognition systems for both transradial and TMR amputee patients and resulted in 12 s of data to train the classifier and 12 s of data to test the classifier. The pattern recognition controller used four time-domain features (mean absolute value, waveform length, number of zero crossings, and number of slope sign changes) extracted from 250 ms window, updated each 50 ms, and a linear discriminant analysis (LDA) classifier. This control scheme has been thoroughly described in the literature [2, 8] and performs similarly to other, more computationally intensive, non-linear methods [9].

The pattern recognition control system was trained for three scenarios. Firstly, the system was trained to recognize only one DOF: elbow flexion/extension. Secondly, the system was trained to recognize only one DOF: humeral rotation in/out. Thirdly, the system was trained to recognize two DOFs: elbow flexion/extension and humeral rotation in/out.

C. Real-time Testing

The TAC Test is a virtual environment test that requires subjects to conform a virtual prosthesis into a set of designated postures. Test complexity defined the minimum number of DOFs required to reach each posture. For this study, a series of postures were used with test complexities equal to 1 (i.e. either elbow flexion, elbow extension, humeral rotation in, or humeral rotation out was required to reach the target posture) and 2 (e.g. both elbow flexion and humeral rotation in was required to reach the target posture).

For TAC tests of complexity 1, the subjects had 15 s to successfully reach the target posture and remain within the target for 2 s. For the TAC tests of complexity 2, the subject was allowed 30 s to successfully reach the target posture and remain in the target for 2 s. An outline of the target posture was provided to the subject and the virtual prosthesis changed from beige to green when it was within the target area (Fig 1) plus or minus 5 deg.

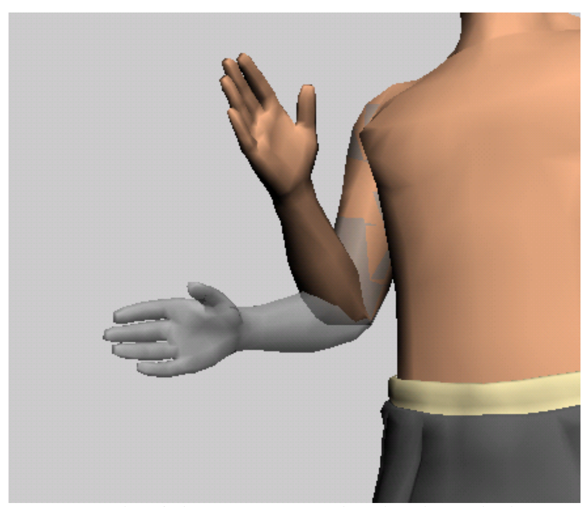

Fig 1: Example of the TAC Test. The virtual prosthesis must be conformed to the target posture outlined in grey. The prosthesis will change color when it is in the approriate locatoin.

A TAC Test of complexity 1 was comprised of 24 repetitions (12 along each direction of the degree of freedom) presented in a random order to the subject. A TAC Test of complexity 2 was comprised of 48 repetitions (six repetitions of every possible combination of the two DOFs) presented in a random order.

TABLE I. DEMOGRAPHICS OF TESTED SUBJECTS.

Subject No.	Gender	Arm Tested	Trial Subject
1	M	Right	Control
2	M	Right	Control
3	F	Right	Control
4	M	Right	Control
5	F	Right	Control
6	M	Right	Control

The pattern recognition performance was quantified in terms of classification error – the percentage of motions incorrectly identified by the classifier. TAC Test performance metrics are presented in terms of completion time, completion rate and path efficiency. Completion Time is the time that takes the subject to complete the test. Path efficiency is the shortest path to the target divided by the total distance traveled by the virtual prosthesis. The less corrections made, the more efficient the path. Completion rate is the number of trials achieved divided by the total number of trials.

III. RESULTS

The pattern recognition classification errors for the pattern recognition control systems investigated as part of this study were all very low. Pattern recognition classifiers configured to control only elbow flexion and extension had, on average, errors of less than 1% (±0.5), and classifiers configured to control only humeral rotation had errors of less than 5% (±4). Systems configured to control both DOFs had errors of less than 6% (±3). When controlling only a virtual elbow, there was no difference in subject performance between direct control and pattern recognition (Table II). Subjects took a longer time to complete tests using pattern recognition when they were controlling for humeral rotation instead of elbow flexion and extension.

TABLE II. PERFORMANCE METRICS FOR 1 DOF CONTROLLERS.

Control	Completion Time (s)	Path Efficiency (%)	Completion Rate (%)
Elbow flex/extend DC	1.6 ± 0.4	91.0 ± 2.0	100 ± 0.0
Elbow flex/extend PR	1.3 ± 0.3	87.7 ± 3.3	100 ± 0.0
Humeral rotation PR	3.8 ± 1.4	60. 3 ± 11.7	95.1 ± 7.6

The TAC test results yielded by using a system configured to recognize two DOFs show longer completion times, lower path efficiencies, and lower completion rates (Table III) than compared with using a system configured to recognize only one DOF.

TABLE III. PERFORMANCE METRICS FOR 2 DOF CONTROLLERS.

Control	TAC Test Complexity	Completion Time (s)	Path Efficiency (%)	Completion Rate (%)
DC	1	3.0 ± 0.7	76.4 ± 4.6	91.8 ± 13.1
PR	1	3.6 ± 0.8	60.2 ± 10.1	89.6 ± 10.9
DC	2	11.1 ± 1.1	57.6 ± 8.0	84.5 ± 14.9
PR	2	7.4 ± 1.0	64.4 ± 8.1	95.3 ± 2.0

IV. DISCUSSION AND CONCLUSION

Several interesting points can be made when considering the control systems configured to control only a single DOF. Unsurprisingly, it should be noted that either pattern recognition or direct control can be used to reliably control elbow flexion/extension in real time. Subjects were able to quickly position the virtual prosthesis into all postures. The humeral rotation motions were also accurately discriminated by the pattern recognition system and reliably controlled in real-time when only a single DOF classifier was trained to recognize these motions. Subjects had more difficulty and higher classification errors when controlling the humeral rotation DOF but still were able to successfully complete over 95% of the motions on average. Subjects reported that performing elbow flexion and extension contractions felt more natural then performing humeral rotation contractions.

When considering systems configured to control two DOFs, it is interesting to contrast the performance of a TAC Test complexity of 1 with a TAC Test complexity 2. When controlling both the elbow and humeral rotation in a two DOF virtual prosthesis, performance is dependent upon the complexity of the task presented. Tests that involve performing only one motion to reach the target show minimal differences between using direct control and pattern recognition (Table III). This difference may be in part due to the fact that with direct control, users only had to perform the co-contraction switch half of the time. Tests that involve performing two motions to reach the target required use of this co-contraction switch during all direct control trials.

Completion times were approximately two times longer during TAC Tests of complexity 2 compared to a complexity of 1 for the pattern recognition system train to recognize two DOFs. This result is intuitive when considering that pattern recognition is currently limited to sequential control. The TAC tests of complexity 2 were almost three times longer than tests of complexity 1 for the direct control configuration. This suggests that a large portion of the trial was spent mode switching. Qualitatively, subjects reported a strong dislike of mode switching.

Our classification results support the work of Hudgins [5] and extends them to show that the system can be controlled in the presence of real-time feedback in order to complete a task. In this study, able-bodied subjects provided our preliminary evidence of success with a two DOF pattern recognition system using muscle sites that would be available on a transhumeral amputee.

Transhumeral amputees are in much greater need of control over a hand in comparison to humeral rotation – although both are very important to activities of daily living. In this experiment, we investigated humeral rotation because of previous success in extracting repeatable EMG signal patterns [5]. Commercially available prosthesis do not support actuated humeral rotation. Instead, in a clinical implementation we would re-map the humeral rotation commands to open or close a hand. This control scheme would eliminate the need for mode switching but would require that patients think about performing humeral rotation to operate their hand. We plan to complete these experiments with transhumeral amputees in order to extend our findings. We expect that the improvements made in pattern recognition control over the past decade may be applied to non-TMR transhumeral amputees to improve their functional performance.

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