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A strategy for minimizing the effect of misclassifications during real time pattern recognition myoelectric control

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***Abstract*—Pattern recognition myoelectric control in combination with targeted muscle reinnervation (TMR) may provide better real-time control of upper limb prostheses. Current pattern recognition algorithms can classify movements with an off-line accuracy of ~95%. When amputees use these systems to control prostheses, motion misclassifications may hinder their performance. This study investigated the use of a decision based velocity profile that limited movement speed when there was a change in classifier decision. The goal of this velocity ramp was to improve prosthesis positioning by minimizing the effect of unintended movements. Two patients who had undergone TMR surgery controlled either a virtual or physical prosthesis. They completed a Target Achievement Control Test where they commanded a virtual prosthesis into a target posture. Participants showed improved performance metrics of 34% increase in completion rate and 13% faster overall time with the velocity ramp compared to without the velocity ramp. One participant controlled a physical prosthesis and in three minutes was able to create a tower of 1" cubes seven blocks tall with the velocity ramp compared to a tower of only two blocks tall in the control condition. These results suggest that using a pattern recognition system with a decision based velocity profile may improve user performance.**

I. Introduction

An individual with an upper limb amputation currently has the choice between using remaining joint motion to control a body-powered prosthesis or myoelectric signals from residual muscles to control an externally powered prosthesis. These control mechanisms, however, are slow and rarely become intuitive as the same movements or muscles signals are used to control different functions.

One type of advanced myoelectric control is through pattern recognition. For this signal processing technique, a computer program identifies an individual's intended movements by looking at the pattern produced by several channels of surface electromyography (EMG) [1]. After patterns are classified, a command signal is sent to a prosthesis. This control relies on the assumption that EMG patterns are repeatable within the same movement and distinct across different movements [2].

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Researchers have studied various pattern classification techniques with the goal to increase classification accuracy. Transradial amputees using pattern recognition systems with linear discriminant analysis, fuzzy logic, or artificial neural networks have off-line accuracies ranging from 92-98% [3-5]. Although no existing pattern recognition system is 100% accurate, they have been proposed for control of multifunctional myoelectric prostheses [3, 6].

A new surgical technique called targeted muscle reinnervation (TMR) [7, 8] was developed to make the control of myoelectric prostheses more intuitive. In TMR surgery, residual nerves that originally innervated muscles of the amputated limb are transferred to alternative muscles that are no longer biomechanically functional. The reinnervated muscle serves as a biological amplifier for the amputated nerve signal. Surface electrodes can then record EMG signals from the reinnervated muscles.

With the signal processing technique of pattern recognition in combination with TMR surgery, an individual's muscle-amplified neural signals control physiologically appropriate functions in the prosthesis [9]. TMR surgery provides a richer data set for pattern recognition control and can be used on individuals with higher amputations. This control strategy has recently demonstrated to be useful for real-time control of an upper limb prosthesis with a mean classification accuracy of 88% for patients who had undergone TMR surgery [9]. Even with high system accuracies, there still are misclassifications where the pattern recognition system predicts the wrong motion. These unintended movements may cause users to become frustrated, drop items they are manipulating, and/or be unsuccessful at a task they are trying to complete.

We have developed a way to minimize the effect of unintended movements. Based on previous work described by Hudgins et al [10], we implemented a decision based velocity profile that limits the speed of any motion when there is a change in decision from the classifier. Motion speed could then increase, or ramp up, to 100% of the original proportional speed (determined by the mean absolute value of EMG channels) as more and more same class decisions are made. Furthermore, the velocity ramp took less time to ramp back up to speed if only a few different class decisions were made. Constraining the speed of new motion classes with a ramp does not change the decision output from the classifier but limited the motion effect. This strategy may prove beneficial because many of the misclassifications happen at the onset or transition of motions. This method also initially limits the speed of intended movements but could provide an advantage as this may increase users' fine control of a prosthesis.

Only recently have real-time performance metrics been used to assess the real-time pattern recognition control and function of multifunction prostheses [9]. Existing real-time performance metrics prompt users to move a multifunctional virtual prosthesis through its full range of motion and quantify motion completion time and motion completion rate [9]. We developed a new virtual test to further quantify performance and evaluate the usability of a pattern recognition system with a decision based velocity ramp. In the Target Achievement Control (TAC) Test, users moved a virtual prosthesis to a target posture. Performance metrics included motion completion time, motion completion rate, and overall test time. The results suggest that a pattern recognition system with a velocity ramp can improve performance of a multifunctional prosthesis.

II. Methods

A. Participants

Two patients who had undergone TMR surgery participated in this study: one male participant (S1) with bilateral shoulder-disarticulations and one female participant (T4) with left transhumeral amputation. Both patients used a myoelectric prosthesis and had experience with pattern recognition systems. Participants gave written informed consent to participate in these studies.

B. EMG and Pattern Recognition Configuration

Nine bipolar EMG electrodes were placed on the skin over the reinnervated muscles. Four electrodes were placed on the clinical sites used for each patient's myoelectric prosthesis. The additional five electrodes were distributed to cover the remaining reinnervated muscle area. The EMG signals were amplified and high pass filtered (cutoff frequency of 80 Hz for Participant S1 and 20 Hz for Participant T4). Data was sampled at a frequency of 1 kHz and processed in real-time using custom Matlab programs.

Participants trained the system to recognize nine motion classes. The classes included elbow flexion, elbow extension, wrist flexion, wrist extension, forearm supination, forearm pronation, hand opening, one hand grasp, and no movement. Subjects were prompted with a demonstration of each movement and asked to perform the movement at a comfortable level of effort. Each contraction was held for three seconds with a three second delay between prompted movements. Movements were repeated five times for a concatenated total of 15 seconds of data for each class.

The pattern recognition system segmented the EMG data from each channel into a series of 150 ms analysis windows with a 50 ms window increment. Four time domain features (mean absolute value, number of zero crossings, waveform length, and number of slope sign changes) were extracted from the EMG data each analysis window. After all nine motion classes were trained, a linear discriminant analysis classifier was used to predict user commands and control a prosthesis. The threshold and gain of each motion class were configured such that participants could achieve full dynamic range of that class (i.e. they could produce a muscle contraction that resulted in either a small output signal which would operate the prosthesis motors at minimum velocity or a larger output signal which would operate motors at maximum velocity). After all motions were configured, three more repetitions of each movement with three second durations were collected to test the classifiers' accuracy.

C. Decision Based Velocity Ramp

In the control condition, output speed of the selected motion class was determined by the mean absolute value of the nine EMG signals in conjunction with thresholds and gains. In the experimental condition, a decision based velocity ramp was applied at the end of all other signal processing to limit the motion class' speed when there was a change in class decision. The velocity ramp used in this experiment was a linear function and described by (1).

$$\begin{matrix} Ramped \\ Output \\ Speed \end{matrix} = \frac{Motion\ Class\ Specific\ Counter}{Ramp\ Length} * \begin{matrix} Desired \\ Speed \end{matrix} \qquad (1)$$

Ramp length equaled 40 and desired speed was the user's proportional speed determined by the mean absolute value of EMG channels. Class specific counters increased by one if the newest motion decision was the same as the previous decision and decreased by eight (or 20% of the ramp length) when there was a change in class decision. Each counter's minimum was zero and maximum was equal to the ramp length. The velocity ramp limited the output speed of a class after a decision change occurred. The ramped output speed increased to saturation of 100% of the desired speed as more and more same class decisions were made. Figure 1 shows the relationship between the desired speed, ramped output speed and counter of a wrist flexion movement.

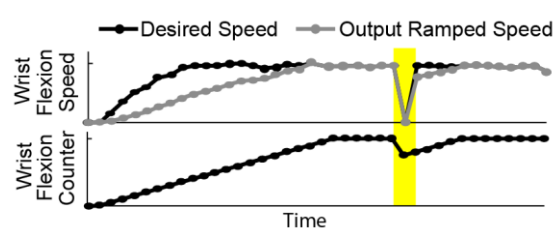

Fig 1. Movement speed and counter of a wrist flexion movement versus time. The black line represents desired speed, grey line represents ramped speed, and dots represent individual decisions. The wrist flexion counter decreases (yellow shaded region) indicating that a decision other than wrist flexion was produced.

D. Performance Tests

After familiarization with the virtual environment, participants completed a virtual test in an ABAB (or BABA) format. Condition A was the control, and Condition B was the experimental condition of pattern recognition with the decision based velocity ramp. Participants performed a

TABLE I. TACT PERFORMANCE METRICS

		Participant S1		Participant T4	
		Control	Velocity Ramp	Control	Velocity Ramp
All trials:	Completion Rate (%)	56.3 ± 5.1	92.2 ± 3.3	65.6 ± 16.5	71.9 ± 10.8
	Total Time (s)	178.2 ± 15.4	139.2 ± 15.7	173.2 ± 19.6	165.7 ±21.7
Successful trials only:	Completion Time (s)	6.0 ± 1.1	6.1 ± 0.9	6.6 ± 0.4	6.46 ± 1.0

Target Achievement Control (TAC) Test five times per condition to quantify performance with and without the velocity ramp. An outline of a target posture appeared on the screen (Fig 2) and participants were instructed to move the virtual arm to the target posture and remain there for two seconds. Subjects received visual feedback that they reached the target within an acceptable tolerance (10 degrees for S1 and 20 degrees for T4). Each target posture only required one motion to achieve (e.g. wrist flexion) but all other trained motions were active in the classifier.

Participants could complete the test the fastest if they were able to control the virtual arm in such a way that they only produced the necessary motion (e.g. wrist flexion). However, if they overshot the target posture (e.g. produced wrist flexion for too long) or produced an incorrect class decision (e.g. wrist pronation), it would cause unnecessary movements that needed to be corrected for (e.g. wrist extension or wrist supination, respectively) to achieve the target posture. The test consisted of two repetitions of eight target postures with a trial timeout length of 15 seconds.

Participant S1 also performed a block stacking task with an experimental multifunction prosthesis with and without the velocity ramp. He used a 7 degree of freedom arm developed by Johns Hopkins University Applied Physics Laboratory and collaborators. Three additional electrodes and one additional degree of freedom, humeral rotation, were included. S1 was already familiar with operating this prosthesis and was instructed to stack as many 1” cubes on top of one another in three minutes.

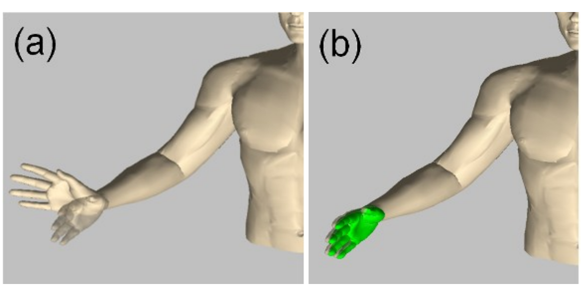

Fig 2. Target Achievement Control (TAC) Test. a) Participants were instructed to move the virtual arm into a target posture indicated by the transparent outline of an arm. b) The virtual hand changed color when the target posture was achieved.

III. RESULTS

A. Classification Accuracy

Average classification accuracy over all nine trained movements was 94.0% ± 9.2% for participant S1 and 87.7% ± 8.4% for participant T4.

B. Virtual Prosthesis Performance Metrics

Averaged performance metrics for each participant with and without the velocity ramp are summarized in Table 1. The total average time to complete all 16 postures of TACT was approximately 22% (S1) and 5% (T4) faster for the velocity ramp than for the control. Overall completion rates for individual participants are shown in Fig 3. The amount of trials participants were able to successfully complete increased by 63% (S1) and 10% (T4) for the velocity ramp compared to the control.

Performance metrics for only successful trials do not show differences between conditions. The average time to complete a TACT trial successfully during both conditions was approximately 6s (S1) and 6.5s (T4). Average non-zero virtual joint speeds were 99.5º/s (S1) and 140.6º/s (T4).

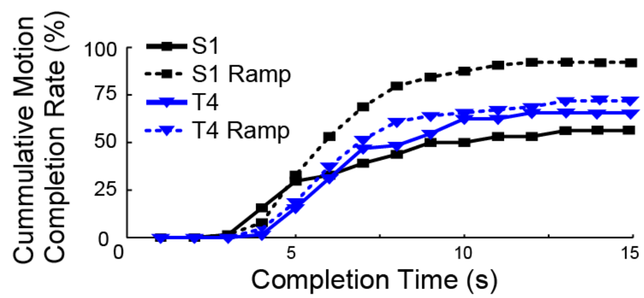

Fig 3. TAC Test motion completion rates. Solid lines represent the control condition and dotted lines represent the system with the velocity ramp. A higher task completion rate was achieved with the velocity profile for both participants.

C. Physical Prosthesis Performance Metrics

While using 7 degree of freedom prosthetic arm to stack a tower of 1” cubes, participant S1 built a higher tower with the velocity ramp. In three minutes he built a tower of seven blocks with the velocity ramp compared to a tower of two blocks in the control condition. No blocks fell during the condition with the velocity ramp, whereas six blocks were unsuccessfully placed on the tower and fell during the control condition. These cubes were knocked over or off because of inadvertent movements caused by misclassifications. For the ramped system, S1 was allowed to continue stacking until the tower collapsed, resulting in a tower of 13 blocks built in seven minutes (Fig 4).

IV. DISCUSSION

This study presented a strategy of improving prosthesis positioning by minimizing the effect of misclassifications of real time pattern recognition myoelectric control. Average classification accuracies of 94% and 88% from the current

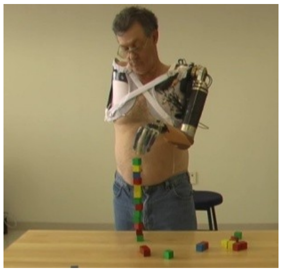

Fig 4. Participant S1 performing the block stacking task during the experimental condition with the velocity ramp.

study were similar to previous results on amputees who had undergone TMR surgery [9]. A decision based velocity ramp was used to slowly ramp up motion speed as consecutive same class decisions were made, thereby reducing the amplitude of unintended motions. Accurate motion classifications were also subject to the decision based velocity ramp and therefore decreased the initial speed of intended motions. **Decreasing initial speed of all movements did not adversely affect users' performance and may have lead to more fine control of the multifunctional virtual prosthesis.** Users had a 34% higher completion rate with the velocity ramp compared to trials without the velocity ramp. When users were successful at TAC Test trials, on average they finished with ~equal completion times with and without the velocity ramp. This result further supports the idea that limiting initial speed of all movements due to the velocity ramp did not negatively affect performance. Both participants reported less frustration during trials with the velocity ramp.

The velocity ramp parameters chosen in this study may not have been optimal. The ramp length value of 40 decisions for the virtual task was determined through pilot studies. This value provided a relatively short period of time for the speed to initially ramp up to 100% of the desired speed but still minimized the effect of several inaccurate classifications in a row. The 20% ramp down counter length was chosen to allow for less time to ramp up to speed if only a few different class decisions were made. Additional testing is necessary to determine if choosing a different of ramp up or down length could further improve user performance. Even with a sub-optimal ramp and short training periods, users still completed more trials with the velocity ramp.

Limited speed should not be confused with increased system delay. Shorter system delays can increase system usability [11] but with a velocity ramp users are still getting visual feedback about what class they are in with the only difference that the movement has a decreased amplitude. Therefore the system delay is the same for the pattern recognition system with and without velocity ramp.

This study also suggests that the virtual test (TAC Test) may be a useful tool to quantify differences in control mechanisms without the initial need for a physical prosthesis. Although this test cannot measure functional outcomes, users get practice in performing repeatable muscle contractions. TAC Test also may allow users to become more familiar at controlling a multifunctional prosthesis in a goal-oriented way. Both participants showed increases in performance metrics with the velocity ramp as measured by the TAC Test. Participant S1 also demonstrated increases in performance while using a physical prosthesis as measured by the cube stacking task.

V. Conclusion

We have developed two useful mechanisms for pattern recognition with myoelectric control. First, adding a decision based velocity ramp to a pattern recognition system limits the speed of any motion when there is a change in decision from the classifier. Results suggest that using this new technique to minimize the effect of unintended movements may improve performance. Second, TAC Test may be a useful virtual test to quantify performance differences throughout time as both users learn to better control multifunctional prostheses and developers design new controllers.

Acknowledgement

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