REAL-TIME PATTERN RECOGNITION OF FINGER MOVEMENTS USING REGENERATIVE PERIPHERAL NERVE INTERFACES AND IMPLANTED ELECTRODES

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ABSTRACT

Commercial myoelectric control systems using surface electromyography are unable to obtain consistent control signals for finger-specific motions because the desired signals are either obscured by more superficial muscles or non-existent due to the level of amputation. Intramuscular recording techniques and Regenerative Peripheral Nerve Interfaces (RPNIs) can potentially resolve each of these issues. Two persons with transradial amputations had bipolar electrodes surgically implanted into residual musculature and RPNIs. Participants used a low latency pattern recognition system to intuitively distinguish 7 individual finger postures with 100% online success and complete a functional task requiring multiple grasps with a commercially available prosthetic hand. A classifier with the same architecture was also used to distinguish movements in a simultaneous and proportional 2 degree of freedom control scheme. Both participants used this controller in real-time to complete a virtual target matching task with success rates of 99%.

INTRODUCTION

Traditional myoelectric prostheses for persons with upper-limb amputations are controlled by residual muscle activity via electromyography (EMG) recorded from the skin surface. Pattern recognition systems seek to provide users with intuitive control of wrist and hand functions. However, grip selection remains unintuitive as control is limited to simple open/close due to the lack of robust signals specific to finger movements [1]. Surgical interventions such as Targeted Muscle Reinnervation can create additional motor control sites [2] and more recent research has demonstrated the potential to extract specific motor inputs with signal decomposition [3]. Focusing on movement transitions has also allowed researchers to demonstrate more intuitive switching between a few grips [4]. However, without direct access to muscles that control fingers these techniques rely on algorithms to distinguish individual finger movements from subtle co-activations of prominent muscles or highly obscured deep muscle activity. Therefore, more work is needed to demonstrate that these techniques generalize outside of controlled tests. Given these challenges, it is also not surprising that pattern recognition is very sensitive to surface electrode placement [5]. Instead of attempting to resolve these issues with software alone, this study evaluates the use of intramuscular electrodes which can record large amplitude movement-specific EMG when implanted directly into finger flexors and Regenerative Peripheral Nerve Interfaces (RPNIs).

RPNIs are created by implanting the end of a severed peripheral nerve into a small, autologous free muscle graft. After reinnveration, electrodes implanted into RPNIs record highly specific and anatomically consistent EMG signals, which remain stable, allowing for precise control of individual fingers in humans for up to one year without requiring recalibration [6]. Previous work in able-bodied non-human primates has shown accurate tracking of digits, suggesting that control is intuitive as well as precise [7]. In this study, two participants with transradial amputations had bipolar recording electrodes surgically implanted into RPNIs and residual forearm muscles. The high-quality EMG signals recorded from the implants allowed a low latency pattern recognition system to predict individual finger movements and grasps in a virtual reality environment and during preliminary functional testing with a commercially available prosthetic hand. The high speed classifier also predicted movements in combination with a regression algorithm to provide 2 degree of freedom (DOF) position control of the index and middle-ring-small (MRS) fingers of a virtual hand to complete a dextrous target matching task.

METHODS

Two patients with transradial amputations, P1 and P2, had RPNIs surgically created on each of the median, ulnar, and radial nerves. P1 had one RPNI created on each nerve, while P2 had two RPNIs surgically created on the ulnar nerve, which had been subdivided into two fascicles, and one RPNI created on each of the median and radial nerves. Both participants provided written and informed consent and this study was approved by the Institutional Review Board at the University of Michigan. Eight pairs of bipolar electrodes (Synapse Biomedical, Oberlin, OH) were implanted into the ulnar and median RPNIs for both subjects as well as six and five residual muscles for P1 and P2, respectively. Although wrist movements were not a focus of this study, each subject had one electrode pair implanted in flexor carpi radialis (FCR). The remaining residual muscles were selected to target thumb, index, and small finger flexion and extension.

For 7 total experiment sessions, a Matlab xPC (Mathworks, Natick, MA) decoded EMG in real-time and controlled virtual [8] and physical (DEKA, Manchester, NH) prosthetic hands. Controllers were calibrated by having participants mimic 5-10 movement repetitions with their phantom limb while seated at a table. Training for virtual posture matching and functional grasps instructed participants to make discrete holds as opposed to gradual and intermediate movements for the continuous motor task. A Hidden Markov Model (HMM) was fit to training data and modelled transitions between latent states [9]. The underlying classifier, features, and processing windows were selected from other studies [6,7]. P1 performed preliminary functional tests where HMM output was directly mapped to pinch (Pi), point (Po), and hand close (HC), while rest (Re) predictions opened the DEKA hand (Figure 1). P1 and P2 also performed a pilot test that required them to precisely move the index and MRS fingers of a virtual hand to target positions (Figure 2). The controller for this task was a switching Kalman filter (KF) [10] with regression coefficients fit according to previous work [6,7] and an HMM to distinguish flexion of individual finger groups along with flexion and extension of both. Three performance metrics were evaluated per trial: acquisition time was the total time excluding a hold period, orbiting time was the time spent stabilizing around the target position, and path efficiency was defined as the distance ratio of a perfect 2D path to the actual path including orbiting (Table 1). These metrics were specifically chosen to evaluate the fine motor ability afforded by the intramuscular signals and controller.

RESULTS

P2 controlled a virtual hand in real-time to match a cue hand and select 7 postures: thumb, index, ring, and small finger flexion, fist, finger abduction, and rest. The HMM issued an incorrect prediction transitioning to the cue on 8.64% of trials, however P2 was able to quickly recover from these errors and hold the cued posture for 1 second with a 100% success rate. P2’s average latency between the onset of new EMG activity and a successful hold was 311±31.2ms. Total trial time including reaction and hold was 1.73±0.03s on average (mean±s.e.m, n=73 trials across 3 sessions).

P1 controlled the DEKA hand with a HMM and completed a reach and place task (Figure 1) with an average time of 18.39±2.77s (mean±s.t.d, n=5 trials). Real-time accuracy was calculated by comparing the instructed grips for interacting with each object to the HMM commands output to the hand. Most misclassifications occurred when using the point grip during the button press, which was found to be a result of moderate index flexor activation.

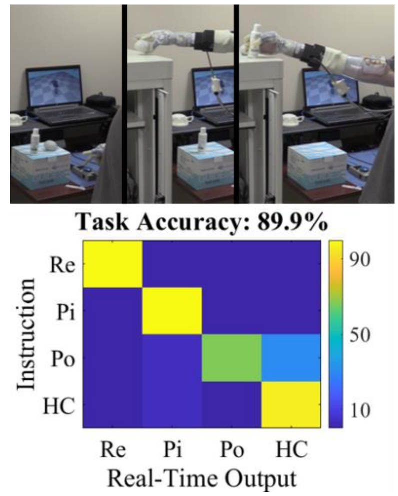

Figure 1: P1 performing the reach and place task which required three separate grips: point to press a timer button, pinch to move a ball, and hand close to move a bottle. P1 was instructed to start the timer, place both items on the shelf, bring the items back to the table, and stop the timer. Real-time accuracy was calculated across 5 trials.

P1 and P2 both used the switching KF to perform the dextrous 2 DOF target matching task which evaluated fine motor performance. The virtual task required them to navigate to 9 precise finger positions and remain within a tolerance window of ±13% flexion for 0.5-1s. Both subjects completed the task with success rates of 99%. On average P2 could not manage to move to target positions as directly as P1, evidenced by lower path efficiency and higher acquisition times despite comparable orbiting times (Table 1). This indicates that the P1 was better able to use the control algorithm to independently make fine movements.

Table 1: Dextrous 2 DOF Target Task Metrics

Participant	**Successful Trials (n)**	**Metric (mean±s.e.m.)**		
		Acquisition Time (ms)	***Orbiting Time (ms)***	***Path Efficiency (%)***
P1	100	871.8±77.4	190.5±72.0	74.2±2.5
P2	109	1025.7±82.3	141.2±51.3	63.2±2.5

Figure 2: P2 performing the dextrous 2 DOF target matching task by simultaneously and precisely matching the positions of the virtual index and MRS fingers (*grey*) which she had position control over to their cued positions (*blue*). The cue turned green to indicate successful positioning of the fingers.

DISCUSSION

This study demonstrated that electrodes surgically implanted into residual muscles and RPNIs allow pattern recognition of individual finger movements and functional grasps. The HMM did not require lengthy integration windows, allowing P2 to quickly recover from errors and complete the 7 posture virtual task with low average latency and a perfect success rate. P1 was also able to use the HMM and the DEKA hand to perform a task that required interacting with objects at multiple elevations. The common misclassification noticed during this preliminary functional test could be the result of subconscious muscle activity to stiffen the index finger for a button press. Similar phenomena have been noted by other groups and a variety of strategies exist to prevent such errors in future work [2,4]. The HMM implementation used a Naïve Bayes classifier to model latent states. However, it is likely that many classifiers could provide comparable performance due to the high amplitude and anatomical specificity of intramuscular EMG [6].

P1 and P2 also piloted a 2 DOF controller and performed a dextrous target matching task with similar near perfect success rates. P2's slightly lower average orbiting time may have been an artefact of a lower required hold time than P1. The larger discrepancies in other metrics suggest that for P2 either the HMM was not as effective in suppressing undesired movements or the movement distinctions were less intuitive. Strategies that blend trajectories of a switching KF may mitigate these issues [11]. The 2 DOF target task assessed fine motor control of independent finger groups. With commercial myoelectric systems using surface EMG, users rely on features of prosthetic hands such as compliant joints or internal controllers to substitute fine actuation for a gross motor command. Providing users with direct fine motor control of their prostheses will increase confidence over a broader range of activities, particularly as research in sensory feedback mechanisms progresses. Long term goals of this research are to increase the number of DOF and precision of finger control and incorporate precise control of wrist movements into a fully dextrous controller.

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