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Real-Time Myoelectric Decoding of Individual Finger Movements For a Virtual Target Task

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Abstract— **This study presents the development of a myoelectric decoding algorithm capable of continuous online decoding of finger movements with the intended eventual application for use in prostheses for transradial amputees. The effectiveness of the algorithm was evaluated through controlling a multi-fingered hand in a virtual environment. Two intact limbed adult subjects were able to use myoelectric signals collected from 8 bipolar electrodes to control four fingers in real-time to touch and maintain contact with targets appearing at various points in the flexion space of the hand. In these tasks, subjects achieved accuracies of 94% when target regions extended ± 11.5° about a target angle and 81% when the target region extended only ± 5.75° about the target angle. The real-time virtual system provides a practical and economic way to develop and train algorithms and amputee subjects using dexterous prostheses.**

I. Introduction

There has been an increasing amount of research directed toward myoelectric control of individual fingers for robotic and prosthetic devices. Control of multi-fingered prostheses is of particular importance, especially to transradial amputees, as these devices are gradually becoming more widely available. From initial investigations in using electromyography (EMG) for classifying individual finger flexions and extensions [1-3] to continuous regression of the position of one or more fingers [4-7], researchers have acknowledged the growing need for controlling these artificial multi-fingered dexterous hands.

Much of the past work in myoelectric decoding has been performed using offline experimental paradigms [1-4, 8]. In other words, subjects were attempting to generate myoelectric control signals without any feedback as to whether or not the proper movement was being decoded. There is some concern whether these decoding algorithms developed and benchmarked in offline situations will translate well to real-time online control scenarios. Indeed, the translation of algorithms developed offline for use in online applications is difficult to test. Many of these algorithms attempt to decode movements that are beyond the performance capability of most widely-available prosthetic end effectors.

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Some researchers have recently demonstrated success with real-time control. Shenoy et al. [9] were able to achieve myoelectric control of a 4 degree of freedom robotic arm for completing complex tasks. Meanwhile, other researchers have resorted to the use of virtual limbs. Sebelius et al. [6] have presented some preliminary results for regressing finger positions of a virtual model for the performance of various movements. Also, Hargrove et al. [10] attempted a task-based approach by requiring users to use EMG signals to complete a virtual clothespin task.

In this study, we combined continuous decoding of finger position from EMG signals with a virtual prosthetic to evaluate controllability in an online setting. In particular, we investigate whether or not intact limbed subjects could exert control over individual fingers of this virtual prosthesis in target touching tasks that require both active movement as well as sustained contractions at various locations in the flexion space of the fingers.

II. Methods

A. Data Acquisition

Two healthy normal limbed adults participated as subjects in this experiment. Eight bipolar Ag/AgCl electrodes from Myotronics-Noromed (Kent, WA) were placed on the subject's right forearm approximately two inches below the elbow. The electrodes were arranged such that they were equally spaced in a ring without particular concern as to

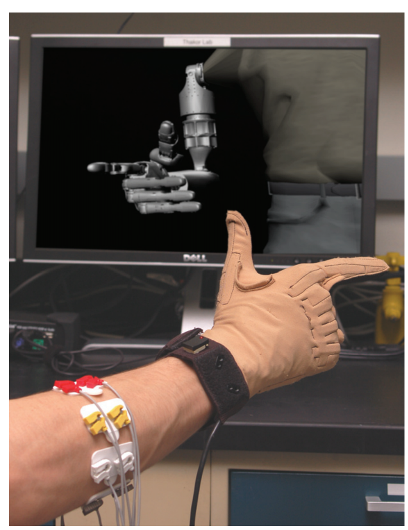

Fig. 1. A subject demonstrates control of the virtual prosthesis through use of the CyberGlove while EMG signals are simultaneously recorded.

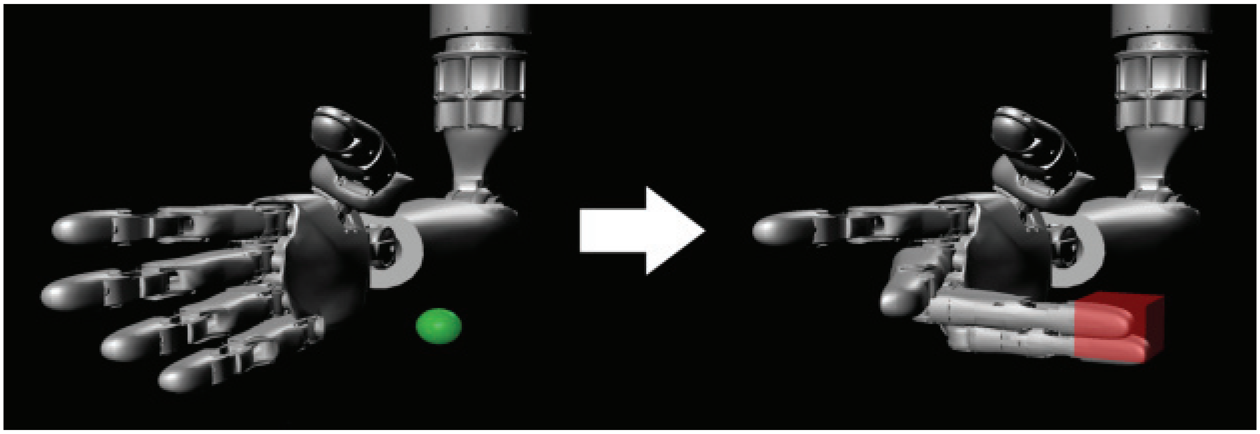

Fig. 2. Screenshots of the virtual model. On the left, the hand is in a resting position when a green target is presented in the space accessible to the ring and little fingers. On the right, the user has contacted the target, which has changed to a red cube to reflect that it is being contacted by the virtual hand.

aligning them with any muscular or anatomical features. A single unipolar Ag/AgCl electrode placed on the *olecranon* served as a reference. An Immersion (San Jose, CA) CyberGlove was also worn by each subject on the same limb as the electrodes during the initial portion of the experiment.

Each pair of myoelectric signals from a given bipolar electrode was passed through a differential Otto Bock (Duderstadt, Germany) pre-amplifier resulting in eight differential EMG signals. These signals were routed through a custom-built isolation box and a National Instruments (Austin, TX) SCC-68 I/O connector device which was interfaced to a National Instruments NI6040E data acquisition card connected to personal computer configured as an xPC Target for real-time signal processing.

B. Virtual Model

The virtual model was constructed within the framework of the Virtual Integration Environment (VIE) [11] produced at the Johns Hopkins Applied Physics Laboratory. The VIE consists of a Simulink model (The Mathworks, Inc. Natick, MA) containing blocks representative of the signal inputs, data acquisition, signal analysis, physical control and plant blocks of the virtual limb. The xPC Target running the VIE received the isolated sampled EMG signals as input and returned joint angles for desired joints of the virtual limb as output. Outputs from the VIE were visualized in MusculoSkeletal Modeling Software [12] (MSMS).

The MSMS was used for presentation of the virtual limb to the subject. The virtual limb was adjusted so that the elbow was fixed at a 90 degree flexion and the wrist was fixed in a neutral fixed position. Fingers on the virtual prosthesis were capable of 30 degrees of extension and 90 degrees of flexion about the metacarpophalangeal (MCP) joint relative to the rest position. The index, middle, and ring fingers as well as the thumb were all capable of independent motion about their respective MCP joints. The little finger was tethered to match the motion of the ring finger and was incapable of independent movement. Figure 2 illustrates the resting position of the virtual hand as well as the perspective available to the subject throughout the experiment. Models in the VIE were constructed such that the MSMS limb was capable of switching between myoelectric and CyberGlove control as needed.

C. Target Presentation

A single trial began with the presentation of a Virtual Target, represented as a green sphere located on the palmar side of the virtual hand. Each target was within reach of only one finger at a time and its location was chosen from 1 of 8 equidistantly spaced positions throughout the range of flexion of each finger. The Virtual Target's location corresponded to a particular degree of flexion of a particular finger's MCP joint. Given 4 fingers capable of independent movement and 8 potential locations per finger, shown in Figure 3, targets could appear in a total of 32 locations.

For a given trial, the Virtual Target was assigned a threshold around it called the *target region*. During a trial, if the MCP joint angle of the appropriate finger fell within this region, the finger was considered to be touching the target. Contact was reflected in the virtual environment by changing the target from a green sphere to a red cube as can be seen in Figure 2. The size of the target region was

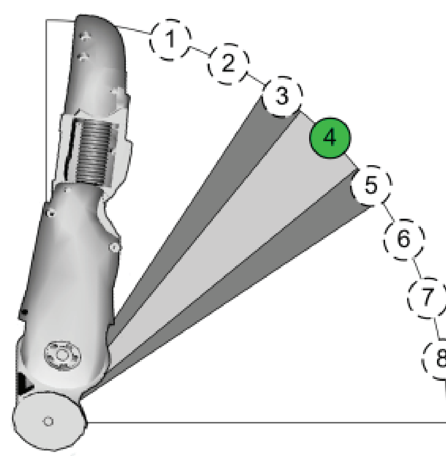

Fig. 3. Diagram showing a top down view of a finger of the virtual limb with locations of potential targets. A sample active target is highlighted in green. Corresponding difficult and easy target regions are shown shaded in light and dark gray, respectively.

modulated to alter the difficulty of a series of trials. For this study, two difficulties were presented: an 'easy' mode in which the target region extended ± 11.5° about the target angle, and a 'difficult' mode in which the target region extended ± 5.75° about the target angle.

Following the target presentation, the subject attempted to cause the appropriate finger of the virtual limb to move into and remain within the target region. A trial was considered successful if the user maintained the virtual finger's position within the target region continuously for 750 milliseconds. The subject was given up to 15 seconds to attempt to successfully complete a trial at a given target location.

D. *Experimental Protocol*

Subjects initially participated in a training session in which they used the CyberGlove to control the virtual hand while EMG signals were recorded from the same arm. During this session, targets were presented at four locations for each finger with each target position being repeated five times. This session generated a set of training data as well as established a control trial block for comparison against later trials in which subjects exhibited myoelectric control.

Following the initial training session, the signal processing block of the VIE was updated for myoelectric control. Subjects participated in four additional trial blocks in which they controlled the virtual hand using myoelectric signals. In each trial block, as in the training session, the subject was presented with targets appearing at four locations for each finger with five repetitions each for a total of 80 trials per trial block. The first two of these blocks were performed in 'easy' mode and the latter two blocks were performed in the 'difficult' mode. All Virtual Target positions were utilized equally throughout these trial blocks.

E. *Signal Processing*

The amplified differential EMG signals were sampled at 1000 Hz and band passed between 5 and 500 Hz. These signals were windowed using a sliding rectangular window with a 200 ms width and 25 ms slide size. The waveform length and mean absolute value of each channel were extracted from each window and passed as input to an artificial neural network with a single hidden layer of tan-sigmoidal neurons and an output layer of linear neurons. The network was trained on CyberGlove and EMG data collected during the control trial. The artificial neural network's output represented the intended joint angle of each of the 4 joints and was smoothed with a 6 point running average.

Smoothed outputs from the trained neural network represented the intended MCP joint angle for each finger of the virtual prosthetic limb. These outputs were then used as input for the control and plant blocks of the VIE model. The output from these blocks represented the actual finger angles of the virtual limb, which were used for comparison against the target region at each instant during a trial and formed the basis for determination of whether or not contact was being made with the Virtual Target.

III. RESULTS

Initial data were quantified and summarized based on the subject's ability to successfully complete a particular trial as well as the time to completion. These results were collected for both myoelectrically controlled trial blocks as well as the initial trial block controlled by the CyberGlove. Tables I and II summarize the overall success rate for each finger and each difficulty in terms of trial completion time as well as accuracy in terms of successfully completed trials.

TABLE I
MEAN TIME TO TRIAL COMPLETION (SECONDS)

	Control	Easy	Difficult
Overall	2.095 ± 0.700	2.945 ± 2.322	4.302 ± 3.217
Index	2.095 ± 0.712	3.587 ± 2.647	5.496 ± 3.841
Middle	2.114 ± 0.758	2.135 ± 1.163	3.609 ± 2.582
Ring/Little	2.276 ± 0.590	2.218 ± 1.188	4.131 ± 2.962
Thumb	1.895 ± 0.701	3.976 ± 3.149	4.242 ± 3.349

TABLE II
MEAN ACCURACY BASED ON TRIAL DIFFICULTY

	Control	Easy	Difficult
Overall	100%	94.06%	81.56%
Index	100%	88.75%	71.25%
Middle	100%	100%	95%
Ring/Little	100%	96.25%	87.50%
Thumb	100%	91.25%	72.50%

The mean time to completion of successful trials across all three variables of difficulty level, the Virtual Target location and active finger is displayed in Figure 4.

IV. DISCUSSION

As reflected in Tables I and II, subjects were able to control the virtual hand to contact Virtual Targets located at a majority of locations with overall accuracies of 94.06% when the target region extended ± 11.5° about the target angle. When this region was decreased to ± 5.75° subjects still achieved 81.56% accuracy. Performance times approach those achieved in the control trial block with successful trials taking less than 5 seconds each across all difficulty levels.

Since the threshold during these trials represented almost a quarter of the range of flexion of the fingers, subjects occasionally completed trials by pure chance that the correct finger was already within the target range when the target was presented. This was most noticeable for targets appearing in locations nearest the hand's resting position.

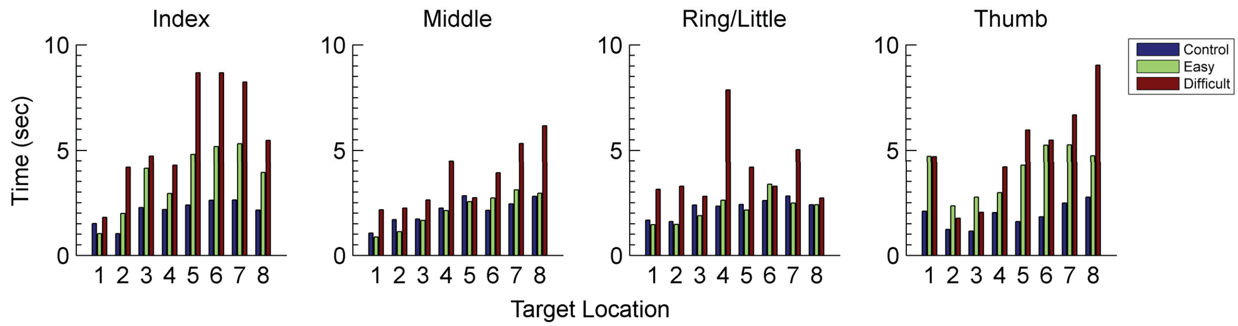

Fig. 4. The average time to completion of successful trials based on finger, difficulty mode and target position. Targets are numbered based on their relative proximity to the resting position of the hand. The relative difficulty of control of each finger can also be seen from larger mean completion times for the thumb and index finger.

As Figure 4 illustrates, targets further away from the resting position were generally harder to hit, particularly for the thumb and index finger. This is likely due to the location of these targets being mapped to the extreme upper end of the dynamic range of the subject's EMG signals. Succeeding on trials in which the target appeared in positions 7 or 8, which are most distal from the resting position, required the subject to exert and sustain a near-maximal contraction for the appropriate fingers, which proved difficult.

There were two principle causes for missed trials: difficulty reaching targets at the maximal end of the range of flexion and small oscillations in the virtual fingers causing difficulties sustaining a particular angle of flexion. Subjects typically exhibited having a better degree of control at positions nearer to rest, indicating that achieving and maintaining near-maximal muscular contractions may be an issue to consider in the future. One solution may be to train the neural network so that the virtual fingers saturate at full flexion before maximal muscle contraction is reached. This will ideally make the fingers of the virtual prosthesis easier to control throughout their entire range of motion.

Ultimately, the results are a positive indicator of the likelihood of being able to construct functional and intuitive control schemes for myoelectric control of individual fingers. Further investigations involving transradial amputees will be necessary to evaluate the true effectiveness of these algorithms.

V. Conclusion

We have presented results that show able-limbed subjects can successfully exert fine motor control over a virtual hand model. Though these results are promising, further investigation is warranted to examine the performance by amputees. In addition, there is much to learn about the manner in which a person learns to control this virtual device and the change in performance across multiple trials. For now, the experimental setup provides a quick and efficient manner of testing various myoelectric control schemes in objective-based tasks. Of additional importance is the flexibility of the model to be expanded to other online setups, paving the way for rapid development and online testing of a myriad of myoelectric control schemes.

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