Real-Time Evaluation of a Myoelectric Control Method for High-Level Upper Limb Amputees Based on Homologous Leg Movements

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***Abstract*— Electromyography-based gesture classification methods for control of advanced upper limb prostheses are limited either to individuals with amputations distal to the elbow or to those willing to undergo targeted muscle reinnervation surgery. Based on the natural similarity between gestures of the lower leg and the arm and on established methods in electromyography-based gesture classification, we propose a noninvasive system with which users control an upper limb prosthesis via homologous movements of the leg and foot. Eight inexperienced able-bodied subjects controlled a simulated robotic arm in a target achievement control (TAC) task with command of up to four degrees of freedom toward targets requiring one motion class. All subjects performed the task with analogous electromyography recording configurations on both the leg and the arm (as a benchmark), achieving slightly better performance with leg control overall. Only a brief demonstration of the arm-leg gesture mapping was necessary for subjects to perform the task, establishing the minimal training time required to begin using the control scheme. Our findings indicate that electromyography-based recognition of leg gestures may be a viable noninvasive prosthesis control option for high-level amputees.**

I. Introduction

A fundamental problem in myoelectric upper limb prosthesis control is the lack of muscle sites available for determination of the user's movement intentions. In some cases, as in shoulder disarticulation, there are no residual arm muscles remaining at all. The gap between functionality of prostheses available to individuals with low-level and high-level amputations is widening with the emergence and advancement of electromyography (EMG)-based gesture recognition techniques for prosthesis control [1], which is reliant on recording EMG from a collection of residual muscles. Prosthesis rejection and abandonment rates are highest among high-level amputees [2], even though this group would seemingly benefit the most from reliable control of a highly functional prosthetic arm.

The only existing technique offering intuitive upper limb prosthesis control for high-level amputees is targeted muscle reinnervation (TMR), a surgical procedure in which efferent nerves from the residual limb are relocated to other muscles, such as the pectoralis muscles in the chest. With some recovery and training (approximately a year), prosthesis control can be achieved using EMG-based gesture recognition techniques commonly used for low-level amputees [3]. Despite its advantages, TMR is an invasive procedure which some amputees may not be willing to undergo [4].

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Another control scheme for high-level amputees, developed for the DEKA arm, uses foot-mounted inertial measurement unit (IMU) sensors to detect movements about the ankle which map to various prosthesis functions. This technique is noninvasive, but only a few movements are recognized by the IMU sensors, so both feet are used to control a single arm. This results in a non-straightforward mapping from leg movements to prosthesis action, and intensive training (~ 20 hours) is needed. Despite this, many amputees trained in the use of this control scheme responded positively and found the interference with walking acceptable [5]. Other types of foot controllers have been proposed sparsely over the last several decades [6]–[8], but none have offered capabilities comparable to TMR or the IMU-based foot controller.

In this study, inexperienced able-bodied subjects used leg gestures, recognized by current standard techniques in surface EMG-based gesture recognition [1], to control a simulated robotic arm in real time. They also performed the task using an analogous recording configuration on the arm for comparison. The target achievement control (TAC) test [9] was used to evaluate real-time performance in controlling the arm with three and four active degrees of freedom (DOF) to 1-DOF targets. The results suggest that upper limb prosthesis control via EMG-based recognition of leg gestures may be a viable noninvasive option for high-level amputees, requiring little user training.

II. Methods

A. Mapping Between the Arm and Leg

The idea of controlling an upper limb prosthesis with movements of the lower leg is based on the natural mapping between the degrees of freedom of the two limbs, shown in Fig. 1. All degrees of freedom are in alignment assuming a posture in which the foot is flat on the ground and the arm is held out with the palm facing down and the shoulder abducted. One modification of the strict mapping is that foot adduction/abduction can represent elbow flexion/extension instead of radial/ulnar deviation, as control of the elbow is more important for high-level amputees. In this study, the elbow of the simulated arm was controlled with radial/ulnar deviation in the arm configuration and foot adduction/abduction in the leg configuration.

Although high-level amputees would not be able to use arm muscles for gesture classification, we tested able-bodied subjects in order to record EMG from an analogous set of muscles of the arm and leg (Table I). Each muscle pair has a similar primary action on the corresponding limb to keep the two different configurations as comparable as possible. The

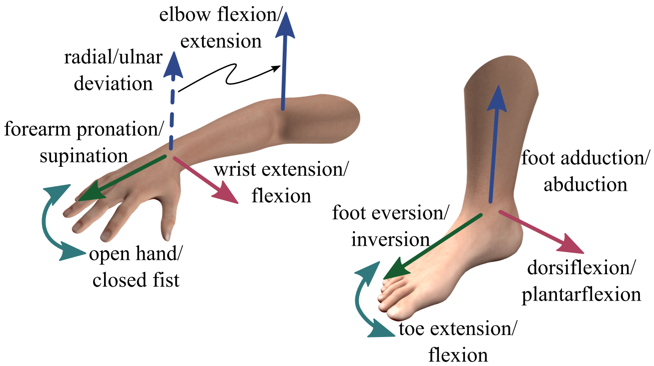


Fig. 1: Alignment of the degrees of freedom of the arm and leg. Foot adduction/abduction can map to either radial/ulnar deviation or elbow flexion/extension.

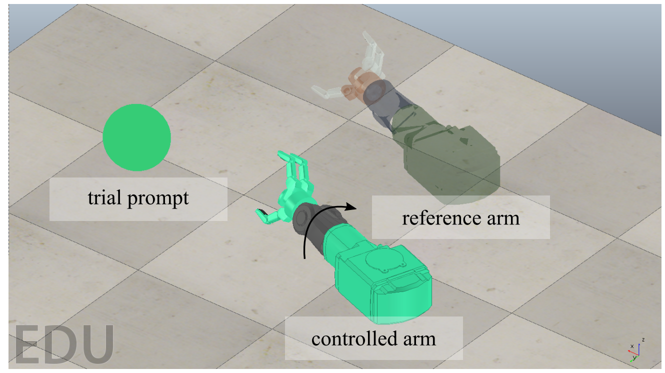


Fig. 2: TAC test environment simulated with V-REP. The subject is being prompted to supinate the forearm.

TABLE I: Muscles Used for Gesture Recognition

		Muscle	Primary Action
Arm	A	extensor carpi radialis longus	wrist extension
	B	pronator teres	forearm pronation
	C	flexor carpi radialis	wrist flexion
	D	extensor pollicis longus	thumb extension
	E	extensor digitorum	finger extension
	F	flexor digitorum superficialis	finger flexion
Leg	A	tibialis anterior	dorsiflexion
	B	peroneus longus	foot eversion
	C	gastrocnemius lateralis	plantarflexion
	D	extensor hallucis longus	hallux extension
	E	extensor digitorum longus	lesser toe extension
	F	flexor digitorum longus	lesser toe flexion

leg muscle sites chosen were verified to produce sufficient offline classification accuracy of the movements in Fig. 1 in a previous study [10].

B. Experiment Setup

Eight able-bodied subjects with no myoelectric control experience participated in the study: five male, six right hand dominant (interface was reversed for left-handed subjects), ages 20–23. All subjects were informed of and consented to procedures approved by the Institutional Review Board at UC Davis (protocol #251192).

Twelve disposable Ag/AgCl center snap electrodes (ConMed 1620) were placed in bipolar pairs on muscles listed in Table I with approximately 2.5 cm spacing and were connected to Motion Labs Systems Y03 differential amplifiers ($\times$300 gain, 100 dB bandwidth from 15 Hz to 2 kHz). The amplifiers were powered by a custom power supply board and connected to a Measurement Computing USB-1608G data acquisition unit (16-bit). Signals were sampled at 5120 Hz in 50-sample segments, bandpass filtered with a fourth order digital Butterworth filter between 8 Hz and 512 Hz, then downsampled to 2560 Hz.

Subjects remained seated throughout the session and removed footwear during the leg control portion. They performed each gesture four times for three seconds in randomized order to generate classifier training data. In all cases, the subjects were prompted with an image of the corresponding arm gesture. The middle two-second section of each recording was extracted for processing, and these portions were segmented into 150 ms windows with 100 ms overlap. The popular time domain feature set was extracted from each window (mean absolute value, waveform length, slope sign changes, and zero crossings) [11], and linear discriminant analysis (LDA) was used to classify gestures throughout the study.

C. Real-Time Control

The target achievement control (TAC) test was used to evaluate real-time control performance [9]. The TAC test has the advantage of providing realistic visual feedback for control of an arbitrary number of degrees of freedom, where cursor-to-target tasks are generally limited to two or three degrees of freedom. The arm (ABB IRB140) and hand (BarrettHand) were simulated in V-REP [12], as shown in Fig. 2. At the beginning of each trial, a translucent “reference arm” moved into the target posture, then an indicator changed color to prompt the user to begin moving the controlled arm to the target. Segments of the arm corresponding to the controlled joints (elbow, forearm, wrist, and hand) changed from grey to green if the joint moved to a position within the tolerance of the target joint angle. Once the controlled arm remained within $\pm 10^\circ$ tolerance of the target angle (60°) for all joints for a dwell period of 2 s, or if the target could not be achieved within 15 s, the trial ended. Joint limits were set to 10° beyond the target (plus tolerance) to allow for overshoot. A decision-based velocity ramp controller with a ramp length of 10 (500 ms) was used to help attenuate undesired movements due to misclassifications [13]. The top 10 mean absolute value features for each class from the training data were averaged to obtain the boost values for the controller such that the maximum output velocity for a given joint would be 100°/s.

Half of the subjects started the session in the arm configuration and the other half started in the leg configuration. Both configurations were tested in a single session. Subjects were given approximately 10 minutes of guided practice controlling the simulated prosthetic arm before starting the first recorded cycle in order to become familiar with the nature of pattern recognition control and the simulation environment. In each limb configuration, subjects performed two different TAC test tasks. In the first condition, six motion classes were used to train the classifier (3-DOF active) and every possible target was repeated four times in randomized order (24 trials). The active DOFs included forearm pronation/supination, wrist extension/flexion, and open hand/closed fist. In the second condition, elbow flexion and extension were added to the classifier (4-DOF active) and every possible target was repeated 3 times (24 trials). In both cases, the target posture involved a single movement (1-DOF target), though erroneous activation of other degrees of freedom and overshoot required correction. The distinction between these two conditions is especially important for the leg configuration, as we have found that classification accuracy can be heavily affected by the inclusion of the foot adduction and abduction gestures.

D. Analysis

Classification accuracy was obtained by leave-one-out cross validation with whole recording trials as the unit of train/test splitting (data from a single recording was never split into training and testing sets). TAC test performance metrics include completion rate, completion time, and path efficiency [9]. Completion rate is the percentage of trials successfully completed before the trial timeout (15 s). Completion time is the amount of time from movement initiation to the moment the target is entered for the last time on a successful trial. Path efficiency is the straight-line distance to the final arm position divided by the cumulative distance travelled by the arm to get to the target, measured in joint angle space (100% efficiency is achievable with 1-DOF targets). An ANOVA was performed for each performance metric with subject as a random factor and number of active DOFs (3 or 4) and limb (arm or leg) as fixed factors. The significance threshold was set at $\alpha = 0.05$. Significant factors prompted follow-up paired t-tests repeated for each level of the factor.

III. Results

A. Classification Accuracy

A summary of the results is given in Fig. 3. Average classification accuracy was generally higher than 90%, except in the leg configuration with 4-DOF active. An ANOVA showed that number of active DOFs was a significant factor ($p = 0.003$), and post-hoc t-tests indicated a significant decrease from 3-DOF to 4-DOF for both the arm and the leg configurations ($p = 0.017$ and $p = 0.012$ respectively). Although limb was only a marginally significant factor ($p = 0.050$), there does seem to have been a systematic drop in classification accuracy in the leg configuration, especially in the 4-DOF case.

B. Real-Time Performance

Completion rate similarly decreased in the 4-DOF active case for both limb configurations ($p = 0.005$ for arm, $p = 0.023$ for leg). ANOVA failed to show limb to be a significant factor ($p = 0.155$), though completion rates

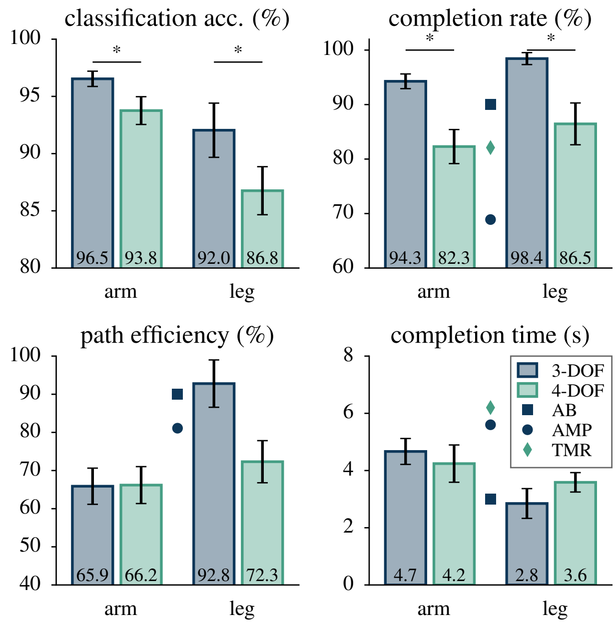
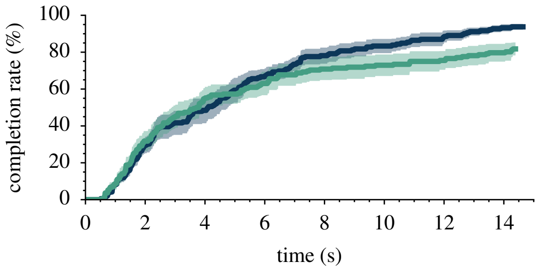


Fig. 3: Summary of results averaged across participants. Error bars indicate standard error of the mean. Results from comparable studies are also shown: AB (inexperienced able-bodied subjects with sensors on the arm, 3-DOF active [13], [14]), AMP (experienced amputees with sensors on the residual limb, 3-DOF active [9]), TMR (experienced TMR subjects, 4-DOF active [15]).

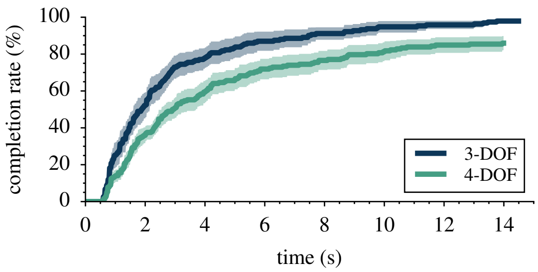
in the leg configuration were slightly higher overall. Path efficiency was somewhat low (compared to similar studies) across all cases except in the leg configuration with 3-DOF active. This interaction between limb and number of active DOFs was significant ($p = 0.037$). No significant differences were found for completion time. Fig. 4 shows the completion rate calculated at artificial trial cutoff times. In the leg configuration with 3-DOF active, there was a notably rapid increase in completion rate over the first four seconds. Otherwise, cumulative completion rate curves were similar across all conditions.

IV. Discussion

Most studies using the TAC test to measure performance of prosthesis control schemes use a task with 3-DOF active and 1-DOF targets, with a few including multi-DOF targets [16], [17] and only one including four active DOF [15]. It is somewhat difficult to directly compare results between studies because of differences in subject type (able-bodied, amputees, TMR patients), levels of experience with myoelectric control, recording setup, and TAC test parameters. We selected our methods for gesture classification and TAC test parameters to facilitate comparison with other studies, a few of which are shown in Fig. 3. Note that we do not expect arm amputees with intact legs to show significantly different performance from able-bodied subjects, in contrast to the drop in performance typically found in myoelectric control work. However, cortical reorganization following amputation



(a) Arm configuration



(b) Leg configuration

Fig. 4: Cumulative completion rates averaged over participants. Filled areas represent ± 1 standard error of the mean.

and the effects of prosthesis use may lead to differences [18].

The main result from this study is that the real-time performance in the leg configuration is as good as and sometimes better than in the arm configuration. One of the concerns we initially had was that performance in the leg configuration would drop along with classification accuracy with the foot adduction/abduction gestures included (4-DOF active). Since this work aims specifically to help high-level amputees, it is necessary to evaluate performance with elbow control included, and the 3-DOF and 4-DOF conditions were used to explicitly test for the effect of the added gesture classes. While the drop in performance moving to 4-DOF is not too different from the arm configuration, it is worth noting that some subjects struggled to actuate the elbow correctly while others did not. The effect on performance may have been reduced to some extent by experience with 3-DOF active before moving on to 4-DOF. Regardless, we have found that feedback is a vital part of effectively using the foot adduction and abduction gestures for control, at least for inexperienced subjects.

Subjects tended to be more efficient in the leg configuration, and we note anecdotally that several subjects had some difficulty in the arm configuration with low levels of muscle activity being classified as forearm supination. Despite the use of a decision-based velocity ramp controller, these misclassifications resulted in the need to correct the arm position with forearm pronation. These corrective motions had an inflating effect on both the completion time and path efficiency metrics in the arm configuration. In contrast, subjects exhibited notably fast and accurate movements with 3-DOF active in the leg configuration.

Overall, our results show promise for myoelectric upper limb prosthesis control via leg movements. Future work should address practical issues that may arise from this approach, such as the effect of standing. So far, this control scheme compares favorably to the few options currently available to high-level arm amputees by offering balance between high functionality and minimal user training.

References

[1] E. Scheme and K. Englehart, "Electromyogram Pattern Recognition for Control of Powered Upper-Limb Prostheses: State of the Art and Challenges for Clinical Use," *J. Rehabil. Res. Dev.*, vol. 48, no. 6, pp. 643–660, 2011.

[2] E. Biddiss and T. Chau, "Upper-Limb Prosthetics: Critical Factors in Device Abandonment," *Am. J. Phys. Med. Rehabil.*, vol. 86, no. 12, pp. 977–987, 2007.

[3] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted Muscle Reinnervation for Real-time Myoelectric Control of Multifunction Artificial Limbs," *JAMA*, vol. 301, no. 6, pp. 619–628, 2009.

[4] S. M. Engdahl, B. P. Christie, B. Kelly, A. Davis, C. A. Chestek, and D. H. Gates, "Surveying the Interest of Individuals with Upper Limb Loss in Novel Prosthetic Control Techniques," *J. Neuroeng. Rehabil.*, vol. 12, no. 53, pp. 1–11, 2015.

[5] L. Resnik, S. L. Klinger, K. Etter, and C. Fantini, "Controlling a Multi-Degree of Freedom Upper Limb Prosthesis Using Foot Controls: User Experience," *Disabil. Rehabil. Assist. Technol.*, vol. 9, no. 4, pp. 318–329, 2014.

[6] D. Graupe, "Control of Upper-Limb Prostheses in Several Degrees of Freedom," *Bull. Prosthet. Res.*, pp. 226–236, 1974.

[7] C. C. Luzzio, "Controlling an Artificial Arm with Foot Movements," *Neurorehabil. Neural Repair*, vol. 14, no. 3, pp. 207–212, 2000.

[8] M. C. Carrozza, A. Persichetti, C. Laschi, F. Vecchi, R. Lazzarini, P. Vacalebri, and P. Dario, "A Wearable Biomechatronic Interface for Controlling Robots with Voluntary Foot Movements," *IEEE/ASME Trans. Mechatronics*, vol. 12, no. 1, pp. 1–11, 2007.

[9] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Target Achievement Control Test: Evaluating Real-Time Myoelectric Pattern Recognition Control of a Multifunctional Upper-Limb Prosthesis," *J. Rehabil. Res. Dev.*, vol. 48, no. 6, pp. 619–627, 2011.

[10] K. R. Lyons and S. S. Joshi, "A Case Study on Classification of Foot Gestures via Surface Electromyography," in *Annu. Conf. Rehabil. Eng. Assist. Technol. Soc. Am.*, (Denver, CO), pp. 1–5, 2015.

[11] B. Hudgins, P. Parker, and R. N. Scott, "A New Strategy for Multifunction Myoelectric Control," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, 1993.

[12] E. Rohmer, S. P. N. Singh, and M. Freese, "V-REP: A Versatile and Scalable Robot Simulation Framework," in *2013 IEEE/RSJ Int. Conf. Intell. Robot. Syst.*, pp. 1321–1326, 2013.

[13] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "A Decision-Based Velocity Ramp for Minimizing the Effect of Misclassifications During Real-Time Pattern Recognition Control," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 8, pp. 2360–2368, 2011.

[14] L. H. Smith, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Determining the Optimal Window Length for Pattern Recognition- Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 2, pp. 186–192, 2011.

[15] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "A Strategy for Minimizing the Effect of Misclassifications During Real Time Pattern Recognition Myoelectric Control," in *Proc. IEEE Eng. Med. Biol. Soc. Conf. (EMBC)*, (Minneapolis, MN), pp. 1327–1330, 2009.

[16] M. Ortiz-Catalan, B. Håkansson, and R. Brånemark, "Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 756–764, 2014.

[17] A. J. Young, L. H. Smith, E. J. Rouse, and L. J. Hargrove, "A Comparison of the Real-Time Controllability of Pattern Recognition to Conventional Myoelectric Control for Discrete and Simultaneous Movements," *J. Neuroeng. Rehabil.*, vol. 11, no. 5, pp. 1–10, 2014.

[18] M. Lotze, W. Grodd, N. Birbaumer, M. Erb, E. Huse, and H. Flor, "Does Use of a Myoelectric Prosthesis Prevent Cortical Reorganization and Phantom Limb Pain?," *Nat. Neurosci.*, vol. 2, no. 6, pp. 501–502, 1999.