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Upper Limb Prosthesis Control for High-Level Amputees via Myoelectric Recognition of Leg Gestures

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***Abstract*—Recognition of motion intent via surface electromyography (EMG) has become increasingly practical for prosthesis control, but lacking residual muscle sites remains a major obstacle to its use by high-level amputees. Currently, there are few approaches to upper limb prosthesis control for individuals with amputations proximal to the elbow, all of which suffer from one or more of three primary problems: invasiveness, the need for intensive training, and lacking functionality. Using surface EMG sensors placed on the lower leg and a natural mapping between degrees of freedom of the leg and the arm, we tested a noninvasive control approach by which high-level amputees could control prosthetic elbow, wrist, and hand movements with minimal training. In the current study, we used able-bodied subjects to facilitate a direct comparison between control using intact arm and leg muscles. First, we found that foot gestures could be classified offline using time domain features and linear discriminant analysis with accuracy comparable to an equivalent system for recognizing arm movements. Second, we used the target achievement control (TAC) test to evaluate real-time control performance in three and four degrees of freedom. After approximately 20 minutes of training, subjects tended to perform the task as well with the leg as with intact arm muscles, and performance overall was comparable to other control methods.**

***Index Terms*—electromyography, myoelectric control, gesture recognition, prosthesis control**

I. Introduction

UPPER limb loss affects an estimated $41,000$ individuals in the United States [1]. Particularly for those with amputations proximal to the elbow, the loss of one or both arms presents severe limitations in the ability to perform activities of daily living. Unfortunately, these high-level amputees have the fewest options for prosthesis control. Traditional body-powered prostheses that transfer motions of the shoulder through cables to the prosthetic joints have limited functionality, leading to high rates of rejection and abandonment [2]. Myoelectric control, where signals generated by muscle contraction are recorded from the surface of the skin, is becoming an increasingly practical technique for controlling advanced robotic arms [3]. Many techniques have been developed for prosthesis control via electromyography (EMG), but the typical assumption is that muscles of the forearm are available, as is the case with transradial or more distal amputations. High-level amputees, however, have few or no arm muscle sites at which to record EMG, so they are left with limited options for powered prosthesis control.

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This work proposes a new noninvasive approach to upper limb prosthesis control through myoelectric recognition of ankle and foot movements which map naturally to the elbow, wrist, and hand. Currently, the only approach offering truly intuitive myoelectric control of arm movements for individuals with amputations proximal to the elbow is targeted muscle reinnervation (TMR), a surgical technique in which nerves from the amputation site are relocated to other muscles of the body such as the pectoral muscles of the chest. This technique allows users to imagine moving the missing limb, producing muscle activations at the target site (e.g. the chest) that can be recognized as distinct gestures to control a prosthetic arm [4]. Despite the major advantages of TMR, eligibility for the surgery may be limited to those whose amputation occurred within the last 10 years [5], and a recovery time of several months in addition to extensive rehabilitation and EMG testing is required before operating a prosthetic arm [6]. While TMR presents a tremendous opportunity, some amputees who desire a functional prosthetic arm may not be willing to undergo surgery and the associated recovery and training time [7].

The idea of controlling an prosthetic arm with the lower limb has been sparingly studied for several decades. A range of techniques have been used, including measuring toe movement with strain gauges [8], measuring toe and foot movements with resistor strips [9], detecting foot movements with pressure sensors built into a shoe insole [10], and measuring foot movements with inertial measurement unit (IMU) sensors [11]. Each of these approaches involves a different mapping from lower limb movements to upper limb prosthesis function with different levels of intuitiveness. The IMU-based method of Resnik et al. [11] is one of the most comprehensive approaches to upper limb prosthesis control for high-level amputees, providing control of shoulder, elbow, and wrist movements as well as simple grasps. This is achieved by combining a number of techniques to create a complex system which requires significant training, in addition to requiring movement of both feet to control a single prosthetic arm. Despite the control complexity and the need to "re-zero" the IMU sensors after repositioning the body (e.g. standing to reclined sitting), users have reported positive experiences with using foot controls for prosthetic arm control [11].

We have developed a straightforward mapping between arm and leg gestures based on the alignment of the degrees of freedom of the ankle and the wrist. Additionally, we established a set of muscles in each limb which have analogous primary actions in order to facilitate comparison. First, we conducted an offline experiment in which subjects produced gestures with each limb, and we determined that leg gestures can be recognized accurately using techniques similar to those commonly used in prosthesis control studies. Second, we set up a simulated prosthetic arm control task—the target achievement control (TAC) test [12]—in order to evaluate real-time control capabilities of the system. Our goal was to explore electromyographic gesture recognition from lower leg muscles as an upper limb prosthesis control methodology. Our results indicate that using the leg to control a simulated prosthetic arm in up to four degrees of freedom works as well as an analogous setup on the intact arm of able-bodied subjects after just 20 minutes of classifier training and real-time control familiarization. This idea has the potential to offer prosthesis control performance to high-level amputees currently not achievable in such a short time by any other means.

II. Background

A. EMG-Based Gesture Recognition

Over the last several decades, classification of gestures based on electromyography recorded from residual muscles of the arm has become the predominant prosthesis control methodology. The approach is described generally in a review by Scheme and Englehart [13]. Briefly, raw EMG recordings from several muscle sites are split into short, often overlapping segments (typically less than 300 ms), a feature vector is extracted from each segment, and the feature vector is fed to a supervised classification algorithm as either a training instance of the gesture being performed or an unknown input requiring prediction. A typical classifier training procedure involves performing a set of gestures several times for several seconds each, producing many training instances for the classifier decision function to be created while requiring only a small amount of total time from the user. Afterward, the trained classifier can produce a gesture prediction when presented with a novel feature vector. If the length of the recording segment used to produce each feature vector is sufficiently small, this approach can give the illusion of real-time continuous control, where the user contracts the muscles as if to produce a gesture with the missing limb in order to command the prosthesis incrementally toward a desired posture. In addition to these pseudo-continuous control techniques, there has recently been a surge of interest in achieving simultaneous and continuous control of multiple degrees of freedom through techniques such as extracting muscle synergies [14] or regressing joint kinematics against EMG features [15]. While these methods could be useful for further evaluating the concept of controlling an upper-limb prosthesis with the leg, we use more thoroughly tested techniques for simpler system validation and evaluation of the core principle of recognizing leg gestures via surface EMG. Our gesture classification methods are overall comparable to several TMR studies [4], [16].

The features used in the current study are mean absolute value (MAV), waveform length (WL), number of zero crossings (ZC), and number of slope sign changes (SSC)—all simple time-domain features [17]. Despite their simplicity, these features have been shown to represent the information in raw EMG signals quite well. Many features have been investigated in the context of EMG-based gesture recognition [18] and while some features can lead to higher classification accuracies (e.g. autoregressive coefficients, sample entropy, fractal length), the more complicated features tend to increase computational load and/or introduce parameters to optimize. While computational complexity is becoming less of an issue with increasingly powerful embedded processors, the introduction of more parameters to adjust makes system evaluation more complex, especially at such an early stage in development.

Linear discriminant analysis (LDA) was used for supervised classification of the feature vectors. LDA is a classic statistical classification technique that, like the time-domain features described above, is simple but effective for EMG-based gesture recognition, as shown by many studies using the combination of LDA with time domain features [4], [19]–[21]. The objective of LDA is to find a subspace in which separation between classes is maximized. It has a closed-form solution, even for the case of more than two classes [22], so it is straightforward to implement and efficient to compute.

B. Mapping Between the Arm and Leg

Our control scheme is based on the natural alignment of the degrees of freedom of the wrist and the ankle, as shown in Fig. 1. Specifically: forearm pronation/supination maps to foot eversion/inversion, wrist extension/flexion maps to dorsiflexion/plantarflexion, and radial/ulnar deviation maps to foot adduction/abduction. In addition to movements about the wrist and ankle, there are analogous movements of the fingers and toes. While hallux extension (corresponding to thumb extension) can be performed independently of the lesser toes and recognized with the methods used here [23], the lesser toes are not readily controlled independently so they are grouped together in flexion/extension (corresponding to open hand/closed fist). In addition, independent hallux flexion may be limited or impossible, so hallux extension in combination with lesser toe flexion could potentially serve as an alternative to the closed hand command, such as hook grip. For high-level amputees, elbow flexion/extension is likely a more important degree of freedom than radial/ulnar deviation. In this case, foot adduction/abduction serves as a suitable analog without significantly impacting the intuitiveness of the mapping, as it is often aligned with elbow flexion/extension depending on the angle of shoulder abduction.

In addition to establishing a set of analogous gestures, we utilized a mapping between forearm and lower leg muscles. It is common in EMG gesture recognition studies to arrange the sensors in a ring around the forearm, as this arrangement is suitable for the largest subset of patients with an amputation distal to the elbow and it facilitates a simple and repeatable electrode positioning procedure [13]. We found in preliminary testing that with sensors placed circumferentially around the lower leg (approximately one third the distance from the medial condyle of the tibia to the medial malleolus), toe movements were essentially unrecognizable. To solve this

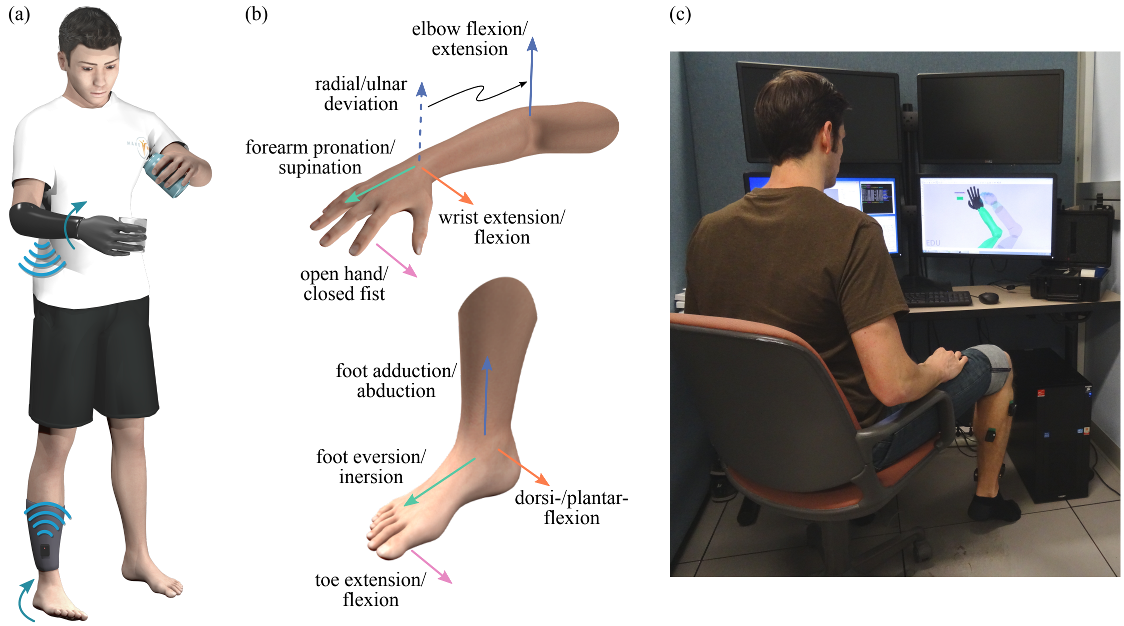

Fig. 1. Overview of the proposed control scheme. (a) The goal of this work is develop a noninvasive yet easy-to-use control scheme which could enable individuals with transhumeral or more proximal amputations to control a powered prosthetic arm. (b) Control is based on a mapping between the degrees of freedom of the ankle and the wrist. Arrows indicate the axes of rotation for each degree of freedom and colors indicate the mapping between upper and lower limb degrees of freedom. Radial/ulnar deviation and foot adduction/abduction were used to represent elbow flexion/extension in this study. (c) The proposed control scheme was evaluated in real time with a simulated prosthetic arm using the target achievement control (TAC) test.

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

problem, the muscles contributing to extension and flexion of the toes were targeted. For a fair comparison between the arm and leg configurations, we decided to target specific muscle sites in both cases. Although fewer EMG gesture recognition studies apply sensors to specific muscle sites, there is at least some work to serve as a reference for our arm gesture recognition results [4], [24]. The muscles used and their primary actions are listed in Table I.

III. METHODS

We conducted two experiments to test the idea of using EMG-based gesture recognition for upper limb prosthesis control. First, nine able-bodied subjects (four male and five female, 18 to 23 years old, eight right-hand and one left-hand dominant) participated in an offline classification experiment which was designed solely to determine how well current standard techniques in upper limb gesture recognition apply to the leg. Based on the results of this study, eight separate able-bodied subjects (four male and four female, 18 to 21 years old, all right-hand dominant) performed a target achievement control (TAC) task [12] in order to evaluate these methods for real-time control of a simulated prosthetic arm. In both studies, participants performed the task seated with EMG sensors on the leg in addition to a benchmark setup on the arm for comparison—able-bodied subjects facilitated this within-subjects design. All subjects were informed of and consented to procedures approved by the Institutional Review Board at UC Davis (protocol #251192).

A. Offline Classification Experiment

In the offline experiment, a custom data acquisition and graphical user interface program was created to display a photograph of the prompted gesture being performed, a horizontal sliding bar for prompting the user when to transition from rest to the desired gesture final position and back to rest, and an indicator of the progress through the current cycle. Six pairs of disposable Ag/AgCl center snap electrodes (ConMed 1620) were placed with approximately 2.5 cm spacing over the muscles listed in Table I. A reference electrode was placed over the olecranon (arm configuration) or the medial malleolus (leg configuration). The electrodes were connected to Motion Labs Systems Y03 differential amplifiers ($\times$300 gain, 100 dB CMRR, -3 dB bandwidth from 15 Hz to 2 kHz), and the resulting EMG signals were sampled at 8 kHz by a Measurement Computing USB-1608G data acquisition unit (16-bit) and recorded directly to disk for offline analysis.

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All subjects produced the gestures shown in Fig 1 with the dominant arm and the dominant leg while EMG signals from the muscle sites listed in Table I were recorded. Each trial lasted six seconds and subjects were prompted to perform the pictured gesture for three seconds of the trial. Each gesture was performed three times per cycle in randomized order. Eight cycles made up the experimental session. First, sensors were placed on the arm (arm configuration) and four consecutive cycles of wrist/hand gestures were performed. Then sensors were placed on the leg (leg configuration) and participants completed four cycles of ankle/foot gestures

Before recording arm gestures, subjects viewed each of the arm/hand gesture images they would be seeing throughout the session and practiced each gesture several times. During recording, subjects sat in a chair with the dominant hand resting on a table. For the leg configuration, footwear was removed to ensure consistent conditions (note that the foot gestures can be performed with shoes on assuming the toe box is not overly restrictive). Subjects then viewed the same arm/hand gesture images, but here they were asked to produce the *lower limb* movements they thought should naturally correspond to the pictures of *upper limb* movements displayed. Any confusion with respect to a given gesture mapping was discussed with the researcher and verbally clarified (typically little clarification was needed) and each gesture was practiced several times. Subjects sat with their knees bent to a 90-degree angle and their feet flat on the ground. They were instructed to keep at least some part of the foot in contact with the ground while performing the gestures.

The raw data was conditioned with a digital fourth-order Butterworth bandpass filter with cutoff frequencies at 10 Hz and 450 Hz, then downsampled to 2 kHz. The conditioned data was then segmented into 150 ms windows with 50 ms overlap. Segments between 1 and 1.5 seconds of each recording were labeled as instances of the rest class (to avoid having trials in which the user simply rests the entire time), and segments between 2 and 4 seconds were labeled with the prompted gesture class. Although the participants were prompted to hold the gesture between 2 and 5 seconds, there was some variability in the actual onset and offset timing for each trial. It was found that participants often anticipated the prompts, and the portion of the recordings between 2 and 4 seconds generally captured the static portion of most recordings in addition to some of the dynamic onset and offset segments. The four time-domain features were calculated for each channel (mean absolute value, waveform length, slope sign changes, and zero crossings), and linear discriminant analysis (implemented by scikit-learn [25]) was used to evaluate offline classification accuracy.

The classification accuracies presented were obtained by splitting the data into training and testing sets based on *whole cycles* rather than trials or instances (individual recording segments). This simulates how the classifier might perform (on average) in a realistic setting in which the training always occurs as a separate occasion from system use. For each limb configuration, the four cycles of the given set were split into all possible combinations of two cycles for training and two cycles for testing. An LDA classifier was built for each and their results were concatenated. The average classification accuracies presented reflect the number of correct classifications divided by the total number of testing instances. Three different gesture sets were analyzed: the "full" gesture set including all eight gestures in Fig. 1 plus the rest class, the full gesture set with radial/ulnar deviation or foot adduction/abduction removed ("no elbow"), and the full gesture set with forearm pronation/supination or foot eversion/inversion removed ("no forearm"). An ANOVA was carried out with limb and gesture set as fixed factors and participant as a random factor. Significance was set at $\alpha = 0.05$.

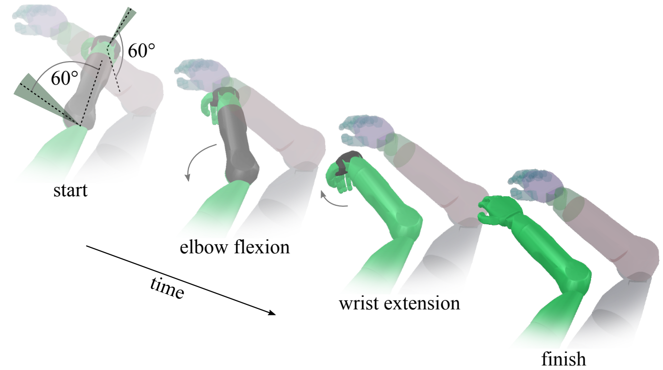

Fig. 2. Progression of a 2-DOF TAC test trial depicted using serial screenshots of the V-REP interface. A translucent, multi-colored "reference arm" was shown to the subject to display the resting (target) posture. Each DOF involved in the trial was initially displaced by 60 degrees and the task involved bringing the arm back to the resting posture with ± 10-degree tolerances in each joint. Arm segments corresponding to joints outside the target were colored grey and turned green when the joint reached the target.

B. Target Achievement Control Experiment

In the second study, eight subjects performed the target achievement control (TAC) task [12] with analogous EMG sensor configurations on the arm and the leg—six Delsys Trigno wireless EMG sensors were placed in the same locations as in the offline experiment. Two additional subjects participated in the experiment, but they seemed to have trouble fully understanding the nature of velocity control and were dismissed after struggling to complete any TAC test trials. Overall, the signal processing and gesture classification techniques were similar to those of the offline experiment. The EMG signals were sampled at 2 kHz and a fourth-order Butterworth bandpass filter with cutoff frequencies of 10 Hz and 500 Hz was used to condition the recordings. Data was acquired in 216 ms windows with 108 ms overlap. Time domain features and linear discriminant analysis were used to classify the gestures. A decision-based velocity ramp controller [16] was applied to the stream of LDA classification decisions to help attenuate the effect of misclassification. The joint velocities output by the controller were then directly applied to a model of the Modular Prosthetic Limb (MPL) [26] simulated in the V-REP [27] simulation environment, shown in Fig. 2. The software written to implement the TAC test experiment is available online [28].

Subjects produced classifier training data for the TAC test trials similarly to the methods used in the offline experiment,

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and the instructions during this portion of the experiment were the same. Four repetitions of each gesture were performed in randomized order. Subjects were prompted to perform the gesture at 2 seconds into the trial and hold the gesture for three seconds. The section of each recording from 2.5 seconds to 4.5 seconds was used as training data. In this experiment, the rest class data came from separate trials rather than the beginning portion of non-rest trials.

After the classifier was trained, the online portion of the test began. An example TAC test trial is illustrated in Fig. 2. During TAC test trials, a translucent "reference arm" was shown just above the "controlled arm" to demonstrate the neutral posture (joints at zero degrees). At the beginning of a trial, the controlled arm disappeared while it moved into the target posture, which consisted of either: a single joint movement by $60°$ (1-DOF target), or a two-joint movement by $60°$ each (2-DOF target). The controlled arm then reappeared in the offset posture, and an indicator changed color to prompt the user to begin moving the controlled arm to back to the neutral posture. Segments of the arm corresponding to the controlled joints (elbow, forearm, wrist, and hand) changed color depending on the state of the joint—if the joint moved to a position within the tolerance of the target joint angle, the arm segment changed from grey to green. Once the controlled arm remained within the tolerance angle of the target for all joints for a dwell period of 2 s, or if the target could not be achieved within 20 s, the trial ended. The tolerance angle was set to $10°$. Joint limits were set at $\pm 80°$ with respect to the neutral posture. The averages of the top 10 mean absolute value features from the training data for each class were used to calculate boost values [16] for the decision-based velocity ramp controller such that the maximum output velocity for a given joint would be $100°$/s, and joint velocities were explicitly limited to this velocity.

The experiment consisted of two sessions, one for each limb configuration, separated by at least 24 hours. Half of the subjects started in the arm configuration and the other half started in the leg configuration, but tests for differences between these groups were not included in the statistical analyses. After generating classifier training data (about five minutes), subjects were given approximately 10 minutes of guided practice controlling the simulated prosthetic arm in order to become familiar with the nature of pattern recognition control and the simulation environment. Subjects controlled the arm with three and four active degrees of freedom. In the 3-DOF active condition, subjects controlled forearm pronation/supination, wrist extension/flexion, and open hand/closed fist (i.e. no elbow flexion/extension). In the 4-DOF active condition, control was augmented with elbow flexion/extension. Subjects practiced with two repetitions of every possible target requiring only one motion class (1-DOF targets) with 3-DOF active control. They then moved on to two repetitions of every possible 1-DOF target with 4-DOF active. After practice, subjects alternated between blocks of 3-DOF and 4-DOF active conditions, where each block consisted of one repetition of every possible 2-DOF target (includes all 1-DOF targets). Subjects were told before each block whether or not control of elbow flexion/extension would be enabled. In total, subjects completed 4 blocks with 3-DOF active ($4 \times 18 = 72$ trials) and 3 blocks with 4-DOF active ($3 \times 32 = 96$ trials). The exact same procedure was carried out in the second session, but with the other limb configuration. The "no forearm" condition from the offline classification experiment was not used in the target achievement control experiment.

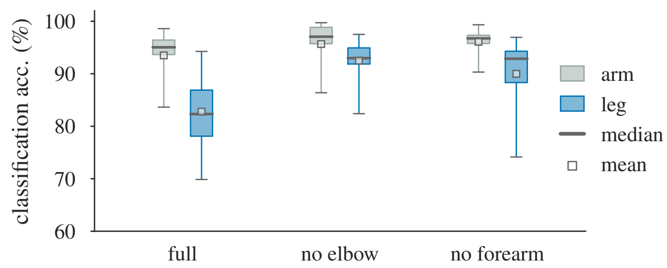

Fig. 3. Classification accuracy for the nine subjects averaged across gesture classes in the offline experiment. Three gesture sets were analyzed: full, the full gesture set without elbow flexion/extension (no elbow), and the full gesture set without forearm pronation/supination (no forearm).

Performance metrics for the TAC test include completion rate, completion time, and path efficiency [12]. Completion rate is the percentage of trials successfully completed before the trial timeout. 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 Euclidean 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. For each performance metric, an ANOVA was performed with subject as a random factor and target degrees of freedom (minimum number of movement classes needed to reach a target—either 1 or 2), active degrees of freedom (number of degrees of freedom controllable by the subject—either 3 or 4), and limb configuration (either arm or leg) as fixed factors. The significance threshold was set at $\alpha = 0.05$.

IV. Results

A. *Offline Experiment*

Classification accuracies for each gesture set in the two limb configurations (arm and leg) are shown in Fig. 3. An ANOVA found significant effects of limb ($p < 0.001$) and gesture set ($p \ll 0.001$), as well as a significant interaction between the two ($p = 0.003$). Most notably, there was a significant increase in classification accuracy in the leg configuration when removing either the foot adduction/abduction classes ("no elbow") or the foot eversion/inversion classes ("no forearm") from the full gesture set. Differences between the arm and leg configurations were significant across all gesture sets, though the classification accuracy in the leg configuration with the full gesture set was especially low.

While gesture set augmentation with additional gesture classes generally results in reduced classification accuracy, such a large difference was not found in the arm configuration. This can be largely explained by Fig. 4, which shows the confusion matrix averaged across subjects for the leg configuration and the full gesture set. Four off-diagonal cells are annotated,

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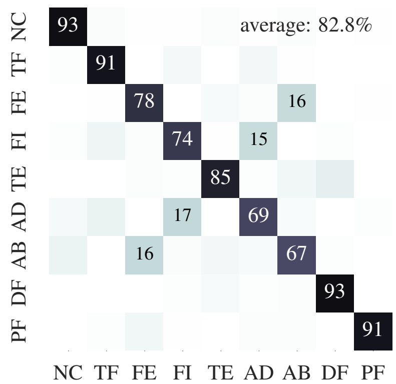

Fig. 4. Confusion matrix showing the classification accuracy for each gesture class in the full gesture set in the leg configuration. Abbreviations: NC (no contraction), TF (toe flexion), FE (foot eversion), FI (foot inversion), TE (toe extension), AD (foot adduction), AB (foot abduction), DF (dorsiflexion), PF (plantarflexion).

corresponding to the misclassification of foot adduction as foot inversion (and vice versa) as well as the misclassification of foot abduction as foot eversion (and vice versa). This failure to accurately discriminate adduction/inversion from abduction/eversion was a primary consideration in the TAC test experiment design.

B. TAC Test

1) TAC Test Performance Metrics: TAC test performance in the arm and leg configurations are shown in Fig. 5. With 3 active degrees of freedom, subjects performed remarkably similarly in the arm and leg configurations. Performance in the leg configuration dropped, however, when elbow control was enabled (4-DOF active). This is reflected in completion rate but not completion time or path efficiency because the latter two metrics are only computed for successful trials, and in the trials that were successful, subjects tended to perform well with the leg configuration. Furthermore, this difference can be almost entirely explained by a single subject's inconsistent performance with 4-DOF active control in the leg configuration. Unlike the other two subjects dismissed during the session, this subject seemed to only have difficulty with the leg configuration with elbow control enabled.

For completion rates, the number of active degrees of freedom was a significant factor ($p = 0.009$) as well as the number of target degrees of freedom ($p \ll 0.001$). There were also significant interactions between limb and number of active DOFs ($p = 0.033$) and number of active DOFs and number of target DOFs ($p = 0.008$). Similarly, for completion time, active DOFs was significant ($p < 0.001$) as well as target DOFs ($p \ll 0.001$). Furthermore, the interactions between limb and active DOFs ($p = 0.001$) and between limb and target DOFs ($p = 0.008$) were significant. The three-way interaction between limb, active DOFs, and target DOFs was also found to be significant ($p = 0.012$). For path efficiency, active DOFs ($p < 0.001$) and target DOFs ($p \ll 0.001$) were found to be significant main effects and the interaction between limb and active DOFs was also significant ($p = 0.008$).

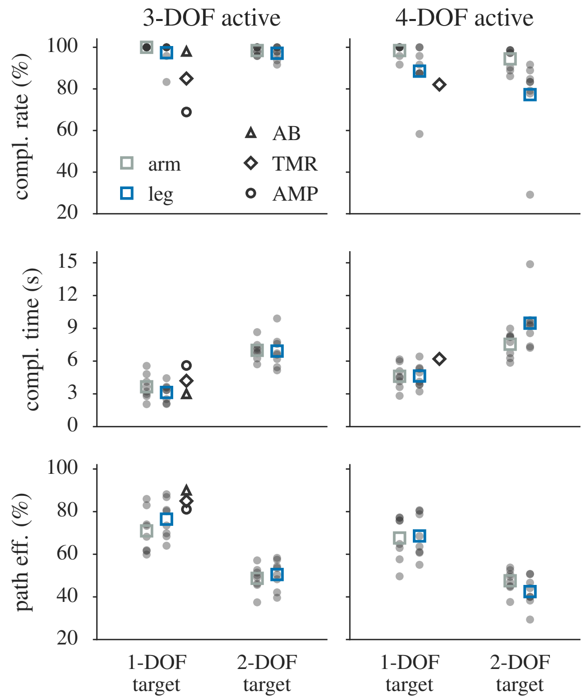

Fig. 5. Subject performance in the target achievement control task. Each subject's performance is shown with a translucent grey dot, and across-subject means are indicated as squares. Completion time and path efficiency correspond only to successful trials. Data from comparable studies are also shown near the corresponding configurations: AB (inexperienced able-bodied subjects with sensors on the arm [16]), TMR (experienced TMR subjects [16], [29]), AMP (experienced amputees with sensors on the residual limb [12]).

Although not shown in Fig. 5, we tracked initiation time (time from presentation of the target to first non-rest class output), but found it to be essentially constant (~ 1.2 s) across all conditions except a slight systematic increase for 2-DOF targets. This increase was likely due to subjects deciding which of the two gestures should initiate the trial. No difference was found between the arm and leg configurations.

2) Trial Completion Timing: As in previous TAC test studies, we examined the number of trials completed at incrementally increasing artificial cutoff times, known as the cumulative completion rate (Fig. 6). Below the cumulative completion rate curves, we also show a kernel density estimate of the distribution of all completion times (for all subjects) in order to show the time at which subjects tended to complete the trials for the different conditions. For both the arm and leg configurations and across 3-DOF active and 4-DOF active cases, it is clear that 2-DOF targets tend to take longer to reach than 1-DOF targets (as expected with serial control). In the 3-DOF active case, the completion curves are nearly identical, with a slightly faster initial rise in the leg configuration for 1-DOF targets. With four active degrees of freedom, subjects tended to complete 1-DOF target trials roughly as quickly in both the arm and leg configurations, though there was more subject variability and an overall lower percentage of trials completed. With 2-DOF targets, this difference was amplified, and the curve for the leg configuration climbs steadily over the entire 20-second trial duration without a sharp initial increase. The density estimate shows a general grouping of

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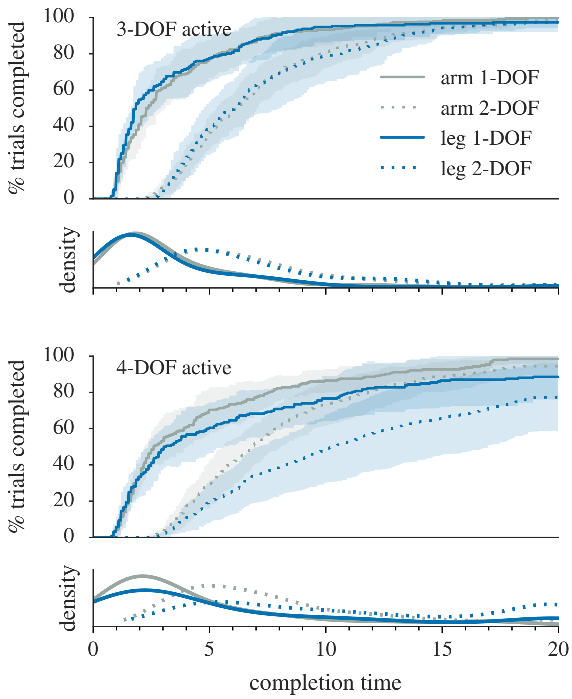

Fig. 6. Cumulative completion rate: the percentage of trials completed across the range of completion times. Kernel density estimates of completion rates are plotted below to highlight the time at which most of the trials were completed for each condition.

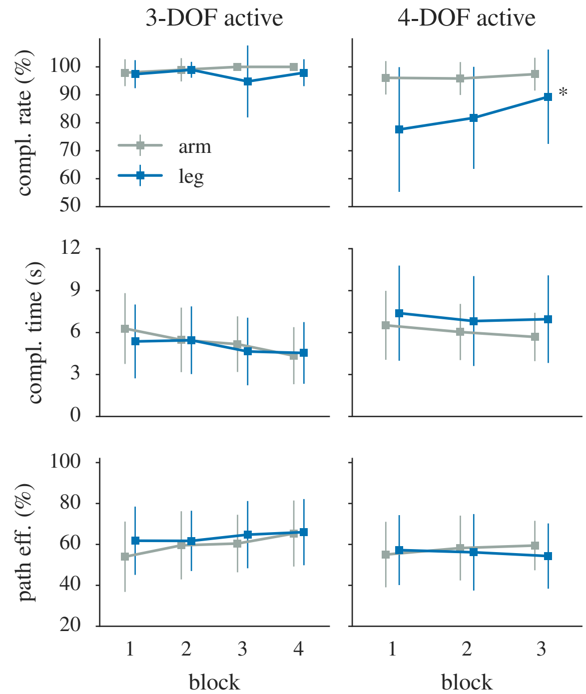

Fig. 7. Subject performance in the target achievement control task across trial blocks. Each point is the mean over subjects and target DOFs, and error bars indicate standard deviation of the mean across subjects. Only completion rate in the leg configuration with 4-DOF active showed a significant change over the session (marked with *).

trial completion times around 6 seconds and another grouping just before trial termination (20 seconds).

3) Improvement Over Time: In order to investigate whether or not subjects improved performance over time, we analyzed each of the TAC test metrics split into the blocks from the experiment design (each block contains all possible 1-DOF and 2-DOF targets in the given number of active degrees of freedom). This is shown in Fig. 7. Although target DOF was a significant factor in all three metrics, each block contained a randomized ordering of 1-DOF and 2-DOF targets, and similar changes over time were observed for both 1-DOF and 2-DOF targets. From Fig. 7, there is a clear, albeit slight, increase in completion rate in the leg configuration with 4-DOF active. The large variance across subjects is caused primarily by the single low-performing subject. A repeated measures t-test with Bonferroni correction confirmed that the completion rate in block 3 was significantly higher than in block 1 ($p = 0.013$), though the differences between blocks 1 and 2 as well as blocks 2 and 3 were not found to be significant.

4) Comparison to Other Studies: Our results with 3-DOF active control toward 1-DOF targets are compared to the results of similar studies in Fig. 5. Note with caution, however, that every study using the TAC test uses slightly different parameters, including trial cutoff time, target distance (with respect to maximum joint angular velocity), and target size (joint angle tolerance). Most notably, the comparable studies used a 15-second cutoff time (compared to 20 seconds for our study), but Fig. 6 shows that the final five seconds account for only a small portion of the successful trials. Performance in the arm configuration is well-matched to similar studies with inexperienced able-bodied subjects [16], validating the end-to-end operation of our experimental procedures, hardware, and software. Interestingly, performance in the leg configuration in this condition (3-DOF active, 1-DOF target) was overall on par with the benchmark arm configuration and sometimes slightly better. We attribute this to a challenge some subjects faced in the arm configuration in commanding the arm to rest without inadvertently pronating. This did not seem to heavily impact performance, though path efficiency was somewhat reduced compared to the leg configuration as well as the other comparable studies. In contrast, movements with 3-DOF active in the leg configuration were notably fast and accurate. Compared to amputees using residual muscles of the forearm [12] as well as a set of six TMR patients [16], our 3-DOF control results are favorable. While we tested only able-bodied subjects, we hypothesize that amputees with intact legs will perform just as well as able-bodied subjects, however this must be validated in a future study.

Control with 4-DOF active does not seem to be commonly studied, so there is little to compare our results to in this condition. One study involving two TMR patients [29] implemented 4-DOF active control, and the patients achieved substantially different completion rates (92.2% and 71.9% with a velocity ramp controller). The average is indicated in Fig. 5. While performance with 4-DOF active dropped in the leg configuration, all but one of our subjects surpassed 85% completion rate, with two completing 100% of the 4-DOF active/1-DOF target trials with the leg. Control in four degrees of freedom with 2-DOF targets has, to our knowledge, not been tested elsewhere. Strong conclusions should not be drawn from these comparisons, but they serve to validate the system overall, especially in light of the fact that our subjects started with no myoelectric control experience and produced these results after less than one hour, including setup ($\sim$ 20 minutes), classifier training ($\sim$ 5 minutes), and real-time control familiarization ($\sim$ 10 minutes). This is in contrast to the time for recovery, rehabilitation, and training involved with targeted reinnervation surgery.

While we cannot directly compare quantitative control performance of the proposed system to the IMU-based controller of Resnik et al. [11], we can address the functionality provided by each. As demonstrated, the current EMG-based system can provide fairly reliable control of three degrees of freedom, and most subjects obtained good performance with four degrees of freedom. In addition, hallux extension has been investigated previously as a potential gesture for controlling a secondary grip [23]. The IMU-based controller provides all of these functions, and some instantiations add the ability to cycle through six different grips (via mode switch) as well as directly control the direction of hand movement via coordinated actuation of the elbow and shoulder (endpoint control). These additional features come at the cost of increased control complexity, however, as they overload foot movements to command different functions depending on the current control mode, and typically a single arm is controlled using both feet. It is worth noting that this kind of mode switch could be added to the current EMG-based controller while remaining under control via a single leg (as opposed to both feet). In addition, we have demonstrated that EMG can be used to detect several toe movements [23], which the IMU system cannot do.

V. Discussion

The results of the offline classification study (Fig. 4) showed that inclusion of foot inversion/eversion in addition to adduction/abduction in the gesture set can be problematic, at least with the current sensor configuration and signal processing/classification techniques. We speculate that this was caused by three factors. First, there is biomechanical coupling between the movements misclassified for one another. For example, foot adduction is a somewhat difficult gesture to produce without also inverting the foot to some extent—the more natural movement for the foot is supination, which is a triaxial movement comprised of simultaneous adduction, inversion, and plantarflexion. A similar argument can be made for pronation. Users could potentially improve distinguishability of these two gesture pairs with practice, and Fig. 7 provides indirect evidence that this may occur within a single session. Second, the sensor configuration used was not heavily optimized and could potentially be improved, though the arm configuration was also non-optimized. Finally, users received no feedback during the offline experiment, so misclassifications occurred without subjects taking corrective action. Our motivation for including 4-DOF active control in the TAC test experiment was to determine if real-time visual feedback could help subjects produce the gestures with fewer misclassifications. While performance using the leg control scheme indeed dropped with elbow control enabled, this seems to be driven primarily by a single subject performing especially poorly. This may have been caused by an inability to adapt during the familiarization period or anomalous sensor preparation. The problems this poorly performing subject faced, however, were also observed by the researchers during testing of other subjects, albeit to a much lesser extent. Control of the elbow seemed to involve one of two problems: it was either difficult to avoid actuating the elbow unintentionally, or it was difficult to avoid actuating other joints while controlling the elbow. The two dismissed subjects understood the arm-leg mapping from the beginning, but despite producing the correct movements, they could not generate a reliable stream of classification decisions. This seems to indicate that, while high classification accuracy is not necessary for real time performance, especially low classification performance can make the system difficult to use. Future work should investigate alternative electrode configurations and gesture training procedures to improve performance in recognizing lower leg gestures via surface EMG.

The slight improvement over the session in the leg configuration with 4-DOF active (Fig. 7) could be due to several factors. First, subjects could be learning overt strategies for completing trials in order to overcome poor classification performance. Two specific strategies we identified during testing were: avoiding problematic gestures when possible, and waiting to correct for errant movements at the end of a trial rather than stopping the primary movement to fix issues before moving on. The latter strategy was especially beneficial to completion rate for subjects that had difficulty with unintentionally flexing the elbow. Second, subjects could be learning to improve classification performance itself by producing more distinguishable gestures. In future experiments, a final post-training classification accuracy assessment could be used to detect the presence or absence of this effect. Finally, the subjects could be learning the mapping from the leg to the arm. While we cannot definitively discount this as a potential factor, the lack of change in completion time and path efficiency seems consistent with strategy learning as opposed to mapping learning. That is, subjects learned to complete trials more often, but they could not do so more quickly or more efficiently. If subjects were able to reliably produce a stream of classification decisions but were confused as to which gesture to produce, improvements in the latter would lead to lower trial completion times with more direct trajectories.

Our decision to employ the gesture classification methods (LDA and time domain features) and real-time evaluation task (TAC test) commonly used in targeted muscle reinnervation studies was primarily driven by the desire to maintain comparability between our work and the only other high-functionality myoelectric prosthesis control approach for high-level amputees (i.e. excluding mode-switch control). Our results seem to indicate that these techniques are compatible with leg muscles and movements, so it seems likely that more recent advances in intent recognition from arm muscles could also benefit this upper limb prosthesis control idea. For example, a common problem in myoelectric control is the limb

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2018.2807360, IEEE Transactions on Neural Systems and Rehabilitation Engineering

position effect [30]. Weightbearing and changing leg position (e.g. sitting, standing, lying down, etc.) could be regarded as similar to the limb position effect, and techniques designed to overcome this issue could potentially be applied to obtain accurate recognition of leg gestures in different positions [31]. Furthermore, it could be beneficial to use automatic gesture onset and offset detection methods to segment the recordings used to train the classifier. This would produce a richer data set by including segments of dynamic as well as static contraction for each gesture class [32].

However, since the leg is different from the arm in many ways—musculature, dexterity of control, types of muscle fibers—future work should treat it as such in order to more thoroughly evaluate its control output capacity. Recording surface EMG from the leg is commonly used in a number of clinical and research settings, such as motor coordination (gait analysis), sport science, and neurological disease. In the context of gait analysis, for example, the rich temporal information in EMG signals may be used in combination with joint angle measurements to detect abnormalities in muscle activations during the gait cycle [33]. Leg EMG is also used in lower limb prosthetics research, which has recently been taking advantage of leg EMG as an additional sensor for improved control over other active devices which work only with "kinesthetic" and "proprioceptive" sensors [34]. There has also been some recent work using supervised classification of leg movements for volitional control of lower limb prostheses in non-weight-bearing situations [35], [36]. Interestingly, Hargrove et al. found that a small number of lower leg movements (plantarflexion/dorsiflexion and external/internal tibial rotation) can be recognized with EMG sensors placed only on upper leg muscles in both able-bodied subjects and transfemoral amputees [36]. Optimization efforts specifically for control using leg EMG could target the persistent problem of confusion between inversion/adduction and eversion/abduction. It is also worth noting that using surface EMG to record from the extrinsic toe extensors and flexors has, to our knowledge, not been done before. More experience is needed to ensure reliable and clean recording from these muscles, especially in developing methods for daily application by a non-expert (i.e. the prosthesis user).

While the basis of this work is on the natural mapping between upper and lower limb movements, there have been several studies suggesting that, with training, performance with a nonintuitive mapping from EMG to interface action can approach that of a more intuitive mapping [37], [38]. These results are interesting, but it remains unclear if or how they extend to control in more than two degrees of freedom. It is likely that the training time required to match performance with a nonintuitive mapping increases along with increased control complexity. There seem to be no obvious benefits to forcing the use of a nonintuitive mapping when an intuitive one is available, though perhaps the mapping discovery process promotes a deeper understanding of the system and is beneficial to the user's ability to adapt to perturbations or nonstationarities. One of the goals of this study was to minimize training time needed to begin functional control of a prosthetic arm, and maintaining a mapping that can be rapidly learned was the primary factor in working toward this goal.

One potential avenue for expanding on this work is to consider hybrid controllers utilizing multiple modalities, such as combining EMG and inertial measurements. In these control schemes, the benefits of each sensor modality can be used to improve intent recognition and/or to control distinct aspects of the robot's motion [39]. While EMG is a somewhat noisy sensor modality, the advantages of detecting toe movements and not necessarily requiring recalibration following changes in foot orientation or loading could make it a valuable component of such a hybrid system. Furthermore, EMG recordings capture control signals "upstream" of end effector states that other sensors like IMUs or foot switches measure, hence containing potentially much richer information. For example, surface EMG signals can be decomposed into motor unit action potentials [40], giving access to neural commands which are difficult or impossible to measure once the "musculoskeletal filter" [41] has applied and the limb has interacted with the external world. EMG signals from antagonistic pairs of muscles could also be used to infer properties like joint stiffness, which is not possible to measure via joint movement alone without applying known external forces. Ultimately, however, measuring both neural drive and kinematic parameters would enable better stiffness estimation than either measurement alone. Signal processing and machine learning techniques for myoelectric control continue to progress toward detecting subtler and more fluid user intentions, making EMG a promising sensor modality despite the ability to reliably measure limb movements or forces directly using other sensors.

One of the benefits of targeted reinnervation is that, in addition to efferent neural pathways for output of control signals that map intuitively to prosthesis function, some sensory feedback is restored as a result of the surgery. Indeed, specific surgical techniques for enhancing the quality of this restored somatosensory feedback have been developed [42]. This presents an exciting opportunity to provide dense anatomically relevant feedback, which is a critical step toward sensorimotor integration of prosthetic limbs [43]. With our proposed control scheme and mapped feedback signals (e.g. mapped tactile feedback to the toes corresponding to prosthetic fingers), it would be interesting to investigate the potential for cortical reorganization associated with limb substitution for both feedback and control.

Although ambulation would interfere with the ability to use the leg for upper limb prosthesis control, many activities of daily living (ADLs) that require the use of both arms are performed in a stationary position, such as eating at a table, washing dishes, or folding laundry. Furthermore, the use of both arms while walking often involves one or both arms being held in a static posture, such as carrying a box. Transitioning between standing and walking can be detected automatically, and this could trigger the arm to lock in place. Regardless of the solutions to these practical issues, there will always be a trade-off between the merits of the control capabilities achieved and the burden of the system's intrusiveness. This trade-off is not unique to our system, as all prosthesis control interfaces have benefits and drawbacks. While many of the practical concerns associated with a foot-based controller have been addressed by Resnik et al. for their controller based on inertial measurement unit sensing of foot movements [11], we are interested in addressing them for our system by developing techniques specifically optimized for the application, testing the system with amputees and conducting usability studies, and eventually testing with physical robotic arms or prostheses. There does not exist a single system that will work for everyone, but our findings represent a first step toward adding another option to the limited pool of techniques for high-level upper limb amputees to control a powered prosthetic arm.

Acknowledgment

We would like to thank the subjects who participated in the experiments. We also thank the editors and anonymous reviewers for their comments and suggestions.

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