Myoelectric Neural Interface Enables Accurate Control of a Virtual Multiple Degree-Of-Freedom Foot-Ankle Prosthesis

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***Abstract*—Technological advances have enabled clinical use of powered foot-ankle prostheses. Although the fundamental purposes of such devices are to restore natural gait and reduce energy expenditure by amputees during walking, these powered prostheses enable further restoration of ankle function through possible voluntary control of the powered joints. Such control would greatly assist amputees in daily tasks such as reaching, dressing, or simple limb repositioning for comfort. A myoelectric interface between an amputee and the powered foot-ankle prostheses may provide the required control signals for accurate control of multiple degrees of freedom of the ankle joint. Using a pattern recognition classifier we compared the error rates of predicting up to 7 different ankle-joint movements using electromyographic (EMG) signals collected from below-knee, as well as below-knee combined with above-knee muscles of 12 trans-tibial amputee and 5 control subjects. Our findings suggest very accurate (5.3±0.5%SE mean error) real-time control of a 1 degree of freedom (DOF) of ankle joint can be achieved by amputees using EMG from as few as 4 below-knee muscles. Reliable control (9.8±0.7%SE mean error) of 3 DOFs can be achieved using EMG from 8 below-knee and above-knee muscles.**

I. INTRODUCTION

There are over half a million people in the United States alone living with a major lower limb amputation [1]. In addition to traumatic incidents and recent military conflicts, dysvascular disease is the largest cause, accounting for 82% of lower limb loss discharges. Over 70% of those amputations are below the knee [2]. As this incidence rate is expected to nearly double by the year 2030 [1], there is a pressing need to provide the diverse population of trans-tibial amputees with accessible, affordable best care and functional outcomes.

Over the past decade, foot-ankle prostheses have evolved beyond passive feet and energy storing devices to having actuated powered joints [3, 4]. Currently, powered foot-ankle prostheses have only one actuated joint that provides powered plantarflexion at the toe-off during walking [7-6]. This serves to restore natural gait and reduce metabolic costs associated with prosthesis use. Although restoration of natural gait and stability are the fundamental purposes of a foot-ankle prosthesis, there are additional functions of the foot that are integral to daily activities. Volitional repositioning of the foot for comfort and aesthetic reasons, repositioning to assist with dressing, and powered plantarflexion to raise one while reaching up are just some examples. Functionality of the emerging powered foot-ankle prostheses could be extended to accommodate some of these additional actions. To do so successfully, however, requires a reliable neural interface between the amputee and the prosthesis.

For upper limb prosthetics, surface EMG signals have proven to be a reliable means of achieving volitional control over multi-degree of freedom (DOF) prosthetic arms [8-10]. Recently, our group successfully demonstrated the effectiveness of using EMG signals from the residual leg musculature to control a powered knee prosthesis [11]. To date, however, the ability to control a multiple DOF foot-ankle prosthesis by trans-tibial amputees has not been demonstrated. Instead, research into the control of powered foot-ankle prostheses has focused on reliable detection of ambulation modes [7,12,13]. Herr et. al. have utilized the EMG signals from below-the knee (BK) muscles of amputees to engage the “stair-descent” mode of the BiOM Powerfoot [14]. More recently, our group has evaluated the use of EMG signals in conjunction with mechanical sensor data of the prosthesis to detect 10 types of ambulation mode transitions with high accuracy (Manuscript detailing this work is currently in review). As the integration of EMG signals into control strategies for powered foot-ankle prostheses continues, the feasibility of implementing EMG-based volitional control over these prostheses needs to be evaluated.

The goal of this work was to determine if EMG from BK muscles of amputee’s residual limb can be used to accurately control foot flexion, rotation and in/eversion of a powered, multi DOF foot-ankle prosthesis. Although such devices are currently not in existence, findings of this work offer significant design considerations for the next generation of powered foot-ankle prostheses.

II. METHODS

A. Data Collection

12 unilateral trans-tibial amputee subjects (6 male; Average age: 45±14 years; Amputated limb: 8 left) and 5 able-bodied control subjects (2 male; Average age: 29±5 years; Limb used: 2 left) participated in the study. All subjects were free of neuromuscular disorders and all amputations were due to trauma (Average time since amputation: 13±9 years). Northwestern University institutional review board approved the study protocol and informed consent was obtained from each subject prior to experimentation.

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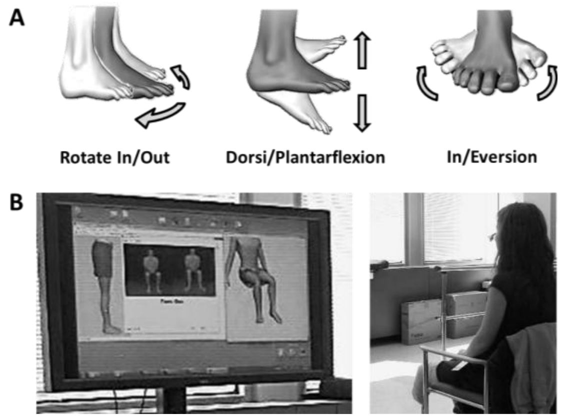

Fig.1 Subjects were prompted to complete 3 classes of ankle movements: ankle rotation, flexion and in/eversion (A). Experimental setup showing an amputee subjected seated in front of a video prompt (B). EMG data was recorded during execution of each motion.

Amputee subjects were instructed to sit comfortably in a chair such that their residual limb rested freely, pointing toward the floor. The residual limb was free of any prosthesis or prosthetic equipment. Likewise, control subjects were asked to sit comfortably in a chair such that their feet were raised above the floor to provide full range of ankle flexion. While seated in this posture, both amputee and control subjects were asked to perform 7 different movement classes (MC): medial rotation of the foot (*rotate in)* and lateral rotation of the foot (*rotate out*) (or adduction/abduction), ankle *dorsiflexion* and ankle *plantarflexion,* ankle *eversion* and ankle *inversion* (or ankle pronation/supination), and a relaxed (or *no motion*) class (Fig 1A).

Movement prompts were provided as photos with brief text descriptions on a video screen (Fig 1B). In response to these prompts, control subjects moved their intact foot while amputee subjects contracted their residual limb muscles to emulate movement of their missing limb. Each contraction lasted 3s and was repeated 8 times yielding 24 seconds of data for each movement class, including the *no motion* class. An additional set of data – *no motion KFE* - was collected in which only amputee subjects were asked to perform knee flexion and extension while keeping their below-knee (BK) muscles relaxed. This data was collected to be used as a proxy for the *no motion* movement class in offline classification analysis to evaluate classifier sensitivity to leg movement.

Eight leg muscles – 4 (BK) and 4 above-knee (AK) - from either the amputated side or control subjects' preferred side were targeted for electrode placement: *Tibialis Anterior (TA), Peroneus Longus (PL), Gastrocnemius Lateralis (GL), Gastrocnemius Medialis (GM), Vastus Medialis (VM), Vastus Lateralis (VL), Rectus Femoris (RF) and Biceps Femoris (BF).* Muscles were localized by palpation and Ag/AgCl self-adhesive surface EMG electrodes (Bio-Medical Instruments) were used to acquire EMG signal. Prior to electrode placement, the skin at each recording site was cleaned with rubbing alcohol and conductive gel was applied. Inter-electrode distance was 20-30mm center to center. EMG signals were sampled using a custom 16-bit data acquisition system at 1kHz and high-pass filtered at 20Hz to reduce motion artifact.

B. Data Analysis

Recorded EMG data was filtered offline using a 2^{nd} order Butterworth band-pass filter (20Hz to 450Hz) and then segmented into 250ms windows with 50ms of overlap [15]. Time domain (TD) and autoregressive (AR) features were extracted from the EMG signal windows. The TD feature set included *mean absolute value*, *zero crossings*, *slope sign changes*, and *waveform length*. The AR feature set included the six coefficients of a 6^{th} order AR model, which was selected based on previous related work [16]. The extracted features were used to train a pattern recognition classifier to evaluate the ability of subjects to control a virtual multiple DOF foot-ankle prosthesis. Linear discriminant analysis (LDA) was chosen for pattern recognition control because it is computationally efficient and its accuracy is comparable to other classification techniques [11,13,17].

4 types of classifiers were trained: a 1-DOF classifier included *no movement*, *dorsiflexion* and *plantarflexion* movement classes, a 2-DOF classifier included the 1-DOF classifier movement classes as well as medial and lateral ankle *rotation*, and a 3-DOF classifier included all the movement classes that subjects performed in this study (Fig. 1A). The fourth classifier – 3-DOF-Kn – was analogous to the 3-DOF classifier, with the exception that, the *no movement* motion class was comprised of equal amounts of *no movement* and *no movement KFE* motion data.

15 fold cross validation was used to evaluate offline classification error yielding n=180 classification results for the 12 amputee subjects and n=75 classification results for the 5 control subjects. For each fold, 18s of data per movement class, for all considered classes was used to train the classifier. Classifier was tested on the remaining 6s of data per movement class for all considered classes. Offline classification was done using data either from BK muscles only or from both BK and AK muscles. Classification results from each fold were pooled across all folds and across all subjects, per subject group. Outliers were removed from pooled data and were defined as mean±2.5SD. Statistical tests were done using either a 1 or 2-way ANOVA (Bonferroni correction a=0.001) where appropriate.

III. RESULTS

A. Offline classification accuracies

Lowest mean classification errors were achieved when using all EMG muscles sites with a 1-DOF classifier for both control and amputee subjects (0.2±0.1% SE and 4.7±0.5% SE, respectively). Highest classification errors resulted from using BK EMG only with a 3-DOF classifier for both control and amputee subjects (6.1±0.6% SE and 15.6±0.8% SE, respectively). Classification error significantly increased with the complexity of the classifier across both amputee and control subjects ($p<0.001$, f=0.86

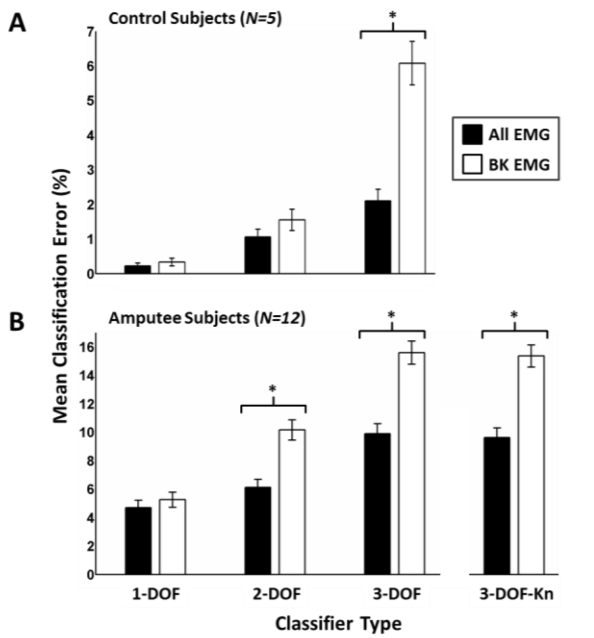

Fig.2 Mean offline classification errors of 4 classifiers for 5 control subjects (A) and 12 amputee subjects (B). Classification errors of classifiers trained on data from BK muscles (white bars) and on data from both BK and AK muscles (black bars). Error bars represent 1 standard error. Asterisks and horizontal brackets indicate statistically significant differences between the means of the highlighted groups.

and f=0.07 respectively, 2-way ANOVA excluding comparison of 3-DOF-Kn) (Fig. 2).

With respect to muscle sites used (BK EMG vs. All EMG), classification error was not significantly affected when using a 1-DOF classifier for both amputee and control subjects (p=0.49 and p=0.39, respectively, 1-way ANOVA). However, in amputee subjects, using all EMG sites instead of just the BK EMG sites yielded significantly lower classification errors for the 2-DOF and 3-DOF classifiers (p<0.001, f=0.2, 2-way ANOVA) for both classifier types) (Fig. 2B). For control subjects, using all EMG sites instead of only BK EMG sites resulted in significantly lower classification errors only for the 3-DOF classifier and not for the 2-DOF classifier (p<0.001 and p=0.21, respectively, 1-way ANOVA) (Fig. 2A).

Classification errors of the 3-DOF-Kn classifier closely resembled those of the 3-DOF classifier. Statistically, there was no difference in the mean classification errors for the two types of classifiers for both the BK EMG and all EMG conditions (p=0.78, f=0.98, 2-way ANOVA). For both the 3-DOF and the 3-DOF-Kn classifiers, however, using all EMG muscle sites instead of only BK EMG sites resulted in significantly lower classification errors (p<0.001 f=0.98, 2-way ANOVA). The majority of misclassifications were similar between the 3-DOF and the 3-DOF-Kn classifiers as well (Fig. 3). *In\Eversion* were misclassified most frequently as *Dorsi\Plantarflexion* (and vice versa) for both types of classifiers when all EMG muscles sites were used. When using BK EMG data, frequency of misclassifications of the remaining motion classes increased. Notably: *plantarflexion* was misclassified as *inward rotation* 7.5% of the time and *dorsiflexion* was misclassified as *inversion* 10.5% of the time, on average.

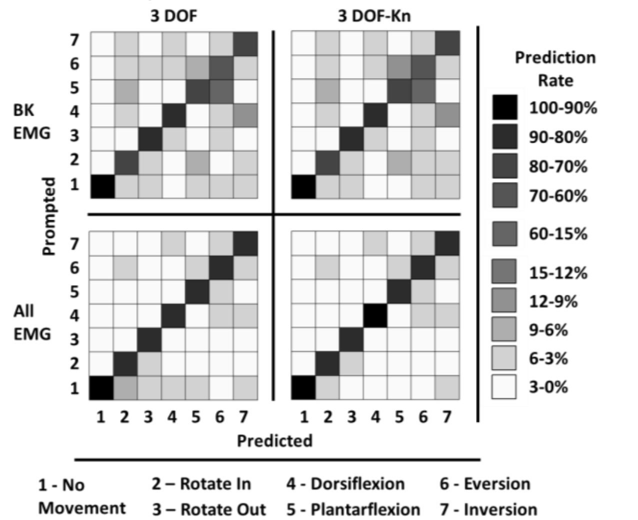

Fig.3 Percentages of accurate motion predictions per prompted motion class shown as confusion matrices for the 3-DOF and the 3-DOF-Kn classifiers. Darker squares indicate higher accuracy prediction rates, whereas lighter squares represent lower accuracy prediction rates.

IV. Discussion

This study demonstrated that it is possible to achieve accurate control of as many as 3 DOFs of the ankle joint for trans-tibial amputee patients using an EMG-based neural interface. Higher classification errors were observed when decoding 3 DOF movements for both the amputee, and the control subjects. The 3-DOF classifier differed from the 1-DOF and the 2-DOF classifiers in that it included the foot *eversion* and *inversion* movement classes. These two motions are complex tri-planar movements and their biomechanics include abduction/adduction and dorsiflexion/plantarflexion [18]. As such, this compound motion may prove difficult for the classifier to separate because muscles used by other motion classes are also active (*Tibialis anterior* and *peroneus longus*). Consistent with this notion, we observed that the more common motion misclassifications were between *plantarflexion* and *eversion*, *dorsiflexion* and *eversion*, and *dorsiflexion* and *inversion* (Fig. 3). *Eversion/inversion* movements of the ankle serve primarily to provide stability during the stance phase of the gait cycle by stiffening the foot as well as contouring to the walking terrain. These functions may be adequately compensated by the rigidity of the prosthesis during walking and therefore powered eversion/inversion of the prosthesis may not be a priority for device design.

The overall higher classification errors of the amputee subject group as compared to the control subject group are likely due to such physiological differences as lack of proprioceptive feedback, reduced residual musculature and altered motor command strategies as a consequence of limb loss [19]. None of the subjects have trained or practiced the motions they were asked to perform as part of the study. It is reasonable to consider that, with additional training, classification errors would decrease. Future work will evaluate this hypothesis.

For the amputee subjects, aside from the 1 DOF control, lower classification errors were achieved when combined data from both the BK muscles and AK muscles was used. This phenomenon was also observed for the control subjects, but only with the 3-DOF classifier. A possible explanation for this observation may have to do with the postural control of one's limb in a non-weight bearing posture. *In/Eversion* of the foot transmits forces up the kinetic chain of the limb and causes medial/lateral translation of the knee [18]. It is possible that AK muscles co-contract to stabilize the subject's limb. As *in*/*eversion* rely on BK muscles that are used for other motions as well, the additional activation of the AK muscles may lead to more accurate segregation of motion classes by the classifier. In amputee subjects, accurate classification of ankle *rotation* (2-DOF classifier) also benefits from the combined use of BK and AK muscles. In this instance, the lack of foot fails to counterbalance the residual motion of the amputee's limb as the result of contractile effort to produce ankle *rotation* and amputees may also be relying on AK muscle activation to stabilize their limb. Additionally, recent findings by our group have also shown that AK muscles contribute to ankle movements in amputees [11]. Future work should further examine contribution of AK muscles to ankle control in trans-tibial patients.

A key finding of this study is that overall leg motion, which is not related to ankle motions studied, did not degrade classifier performance. This finding is demonstrated by the fact that classification errors of the 3-DOF-Kn classifier were statistically indifferent from those of the 3-DOF classifier for amputee subjects (Fig. 2B). This finding implies that AK muscle activity due to limb repositioning would not affect the accuracy of ankle motion control. Other variables such as changes in socket pressure due to limb repositioning should also be evaluated.

Currently, there is only 1 powered foot-ankle prosthesis that is available on the market: BiOM Powerfoot (iWalk, Bedford, MA). This device has 1 actuated DOF – *dorsi/plantarflexion*. Whether additional DOFs will be incorporated into future designs of this and other powered foot-ankle prostheses remains to be seen and the potential added complexity and increased cost of the device needs to be considered to avoid limiting patient access to this treatment. As of now, our control strategy can accurately predict volitional *dorsiflexion* and *plantarflexion* using just the BK muscles.

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