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Neuromechanical Sensor Fusion Yields Highest Accuracies in Predicting Ambulation Mode Transitions for Trans-Tibial Amputees

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***Abstract*—Advances in battery and actuator technology have enabled clinical use of powered lower limb prostheses such as the BiOM Powered Ankle. To allow ambulation over various types of terrains, such devices rely on built-in mechanical sensors or manual actuation by the amputee to transition into an operational mode that is suitable for a given terrain. It is unclear if mechanical sensors alone can accurately modulate operational modes while voluntary actuation prevents seamless, naturalistic gait. Ensuring that the prosthesis is ready to accommodate new terrain types at first step is critical for user safety. EMG signals from patient's residual leg muscles may provide additional information to accurately choose the proper mode of prosthesis operation. Using a pattern recognition classifier we compared the accuracy of predicting 8 different mode transitions based on (1) prosthesis mechanical sensor output (2) EMG recorded from residual limb and (3) fusion of EMG and mechanical sensor data. Our findings indicate that the neuromechanical sensor fusion significantly decreases errors in predicting 10 mode transitions as compared to using either mechanical sensors or EMG alone (2.3±0.7% vs. 7.8±0.9% and 20.2±2.0% respectively).**

I. INTRODUCTION

Over 600,000 people are living with major lower limb amputation in the United States [1]. This number continues to grow as a consequence of traumatic incidents, recent military conflicts [2], but mainly due to the increase in the incidence of dysvascular disease. In fact, dysvascular disease accounts for 82% of limb loss discharges. Over, 70% of those amputations are below the knee [3]. This incidence rate is expected to nearly double by the year 2030 [1]. There is a pressing need to provide this diverse population of trans-tibial amputees with the best care and functional outcomes.

Ankle functionality is not only crucial for vertical support, but also for forward progression of the body especially during normal and fast walking speeds [4]. Ankle prostheses are currently the most effective means of restoring lost function following a trans-tibial amputation. Mechanically passive prostheses are able to provide vertical stability and can restore the natural gait for low-speed walking in a satisfactory way [5, 6]. However, these passive devices often require amputees to make extra movements with their trunk, pelvis and residual limb leading to high metabolic energy cost and unnatural gait [6, 7]. Recently, advances in actuator, transmission and battery technologies have extended the functionality of lower-limb prostheses beyond being passive devices to having powered joints [8, 9]. By enabling powered plantarflexion via timely application of joint torque at the toe-off, powered prostheses have the potential to restore natural gait and allow easy, metabolically efficient ambulation across diverse terrains. [6, 10-12].

Several control strategies have been developed for powered ankle prostheses. These include pre-programmed actuation patterns [8, 12] that rely on the periodic nature of the gait cycle, impedance-based control based on a neuro-muscular model of the foot-ankle complex [11, 13] and user motion-intent recognition control systems that use biological signals such as EMG along with the measure of ground interaction forces to adjust the operational mode of the device [14-15]. Ambulation over varying types of terrain – such as level ground vs. stairs - requires a different operational mode for joint torque delivery. To switch operational modes, the prosthesis must either automatically detect a change in ambulation mode or the user must manually "instruct" the prosthesis to engage the intended mode of operation. Manual instruction by the user severely limits performance of non-cyclic activities and smooth transitions throughout ambulation modes.

Automated ambulation mode detection has been achieved using machine learning algorithms such as pattern-recognition [15, 16]. Our group has recently shown that the fusion of residual limb EMG signals with the prosthesis mechanical sensor output leads to reliable detection of ambulation modes and joint control in a powered-knee prosthesis [16]. However, similar capability has not yet been shown for a powered ankle prosthesis. Additionally to date, evaluation of ambulation mode detection has been restricted to steady-state gate cycle within a mode, and has not been expanded to the detection of transitions among these modes [12]. Accurate initiation of an ambulation mode, or transition into/out of it, is equal in importance to "in-mode" operation for achieving safe and reliable control of a powered prosthesis: the prosthesis has to enter the appropriate operational mode prior to the first heel strike upon the new type of terrain.

The goal of our work was to evaluate the accuracy of detecting ambulation mode transitions using (1) mechanical sensor data only (2) EMG data only or (3) fusion of the two.

II. METHODS

A. Data Collection

Data were collected from 5 unilateral trans-tibial amputee subjects (4 male, average age: 36±7 years, amputated limb: 3 left and 2 right). All subjects were free of neuromuscular disorders and their amputations were all due to trauma

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(average time since amputation: 8.2±4 years). Northwestern University institutional review board approved the study protocol and informed consent was obtained from each subject prior to experimentation.

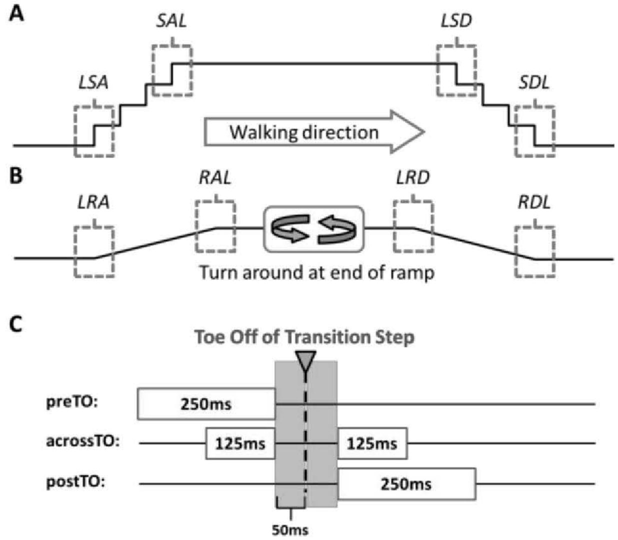

Fig. 1. 8 walking mode transitions for (A) stairs and (B) ramp. The stairs used in the study were a continuous structure as indicated in A. The ramp used in the study was a single incline ramp 2.36m long terminating in a raised level platform. (C) 3 types of 250ms epoch used for classification.

Subjects were fit with commercially available powered ankle-foot prosthesis: BiOM [9] (Fig. 2D; manufactured by iWalk, Bedford, MA). The BiOM was either fit to the subject's existing, prescribed, socket or a custom socket was created for the subject by our clinical staff. Prior to the experimental trials and following the initial fitting, the BiOM's functional parameters (e.g. stiffness, damping, torque gain, etc.) were tuned to suit each subjects' preference in accordance to the manufacturer-recommended tuning procedure. Successful tuning was confirmed by each subject's ability to walk naturally over level ground without extraneous trunk, pelvic or residual limb movement as judged by a trained physical therapist.

Subjects were instructed to walk at a comfortable, self-selected pace over 3 types of terrains: level ground, 4 uniform stairs (18cm rise, 23.5cm run) and a 2.36m long 10^{o} incline/decline ramp (Fig. 1). In addition to ambulation over these 3 types of terrains, a single *baseline (B)* trial was recorded for each subject during which subjects comfortably stood upright without moving for 15 seconds.

Walking over the 3 terrains required subjects to make a total of 8 ambulation mode transitions. A single stair walking trial comprised subjects transitioning from level ground walking to ascending the set of stairs (*LSA*), transitioning onto level ground from stair ascent (*SAL*), walking over the level platform and transitioning into stair descent (*LSD*) and transitioning back to level ground from stair descent (*SDL*) (Fig. 1A). A single ramp walking trial yielded 4 analogous ambulation mode transitions: Subjects transitioned from level ground to ramp ascent (*LRA*) and then from ramp ascent onto the level surface of of the elevated platform (*RAL*). Subjects proceeded to walk to the end of the platform (~3m), turned around and walked back along the platform from which they transitioned into ramp descent (*LRD*) and then from ramp descent back onto level ground of the floor (*RDL*). Subjects performed 12 trials of each type of ambulation mode transition, as well as 12 trials of ambulation over level ground.

EMG data and mechanical sensor data from the BiOM (ankle moment, 3-axis IMU, pitch velocity, ankle angle, and gait phase indicator [9]) were collected during all trials. IR light-beam sensor output was synchronously recorded with EMG and BiOM sensor data during walking trials. Each trial was videotaped for offline analysis and validation.

Four leg muscles from the amputated side were targeted for EMG data collection: *Tibialis Anterior (TA), Peroneus Longus (PL), Gastrocnemius Lateralis (GL), and Gastrocnemius Medialis (GM).* To ensure patient comfort and reduce the motion artifact due to motion of electrode poles relative to skin during walking, we used a novel gel liner system with embedded EMG electrodes to collect and record EMG signals from the below-knee (BK) muscles (Fig. 2) [17].

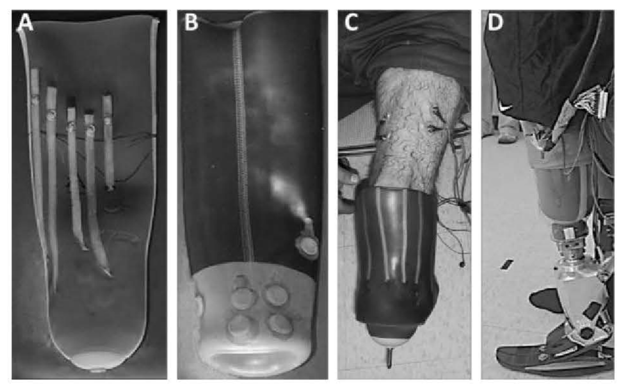

Fig. 2. Custom fabricated gel-liners with embedded EMG electrodes. Electrode leads exit the gel liner and travel along the outer surface of the liner (A) to conventional stainless steel snaps for connectivity with EMG data acquisition unit. Electrode poles are embedded within the gel layer of the liner and protrude through the layer to comfortably contact the subject's skin (B). Subjects wore these liners in place of their take-home liners (C) and the liners were used along with a subject's socket for attachment to the BiOM powered ankle prosthesis (D).

B. Data Analysis

EMG signals were sampled using a custom 16-bit data acquisition system at 1kHz and high-pass filtered at 20Hz to reduce motion artifact. Data from the following 8 mechanical sensors (Mech) of the BiOM was sampled at 500Hz and used in the analysis: *prosthesis vertical acceleration, pitch angle, pitch velocity, velocity angle, accelerometer vertical and linear axes and angular acceleration in the sagittal and vertical planes.* Both the EMG and Mech data from each of the 12 trials were segmented into 3 groups of 250ms epochs (Fig 1C): 250ms epoch occurring 50ms before the toe-off (TO) of the mode transition step, 250ms epoch occurring 50ms after the TO of mode transition step, and 250ms epoch comprised of two 125ms, each positioned 50ms prior and post the TO of the mode transition step. We imposed the 50ms padding on

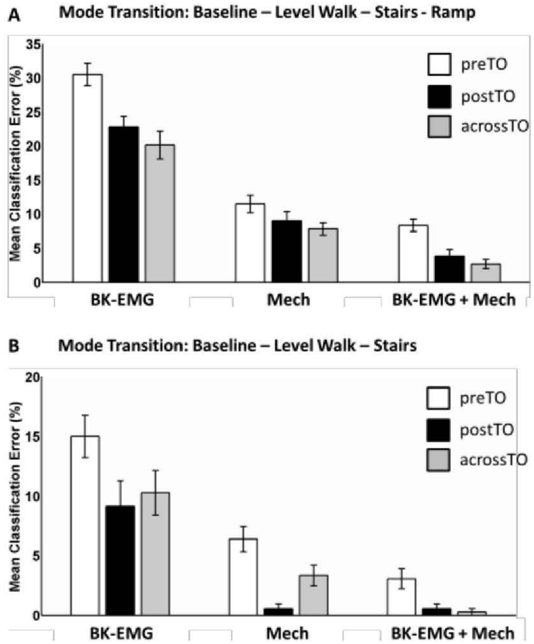

Fig.3 Mean offline classification error of 10 mode transitions (A) and 6 mode transitions (B) using BK-EMG data only, Mech data only, and BK-EMG with Mech data. Results are shown for three different time windows used in the analysis: 250ms prior to TO of mode transition step (white bars), 250ms following the TO of mode transition step (black bars) and 250ms centered on the TO of the mode transition step (grey bars). Error bars represent 1 standard error.

either side of the TO to prevent inclusion of the signal motion artifact in our analysis. EMG data was filtered offline using a 2^{nd} order Butterworth band-pass filter (20Hz to 450Hz). A boxcar smoothing algorithm (25ms window) was applied to the recorded Mech data.

Linear discriminant analysis (LDA) was used for classification of ambulation mode transitions [16,19]. LDA data windows were 250ms without overlap. *Mean absolute value*, *zero crossings*, *slope sign changes*, and *waveform length* time-domain (TD) features were extracted from the EMG data [18]. *Mean* and *standard deviation* TD features were extracted from the Mech data. 12 fold "leave-one-out" cross validation was used to evaluate classification error.

III. RESULTS

A. *Offline classification accuracy of all mode transitions*

Across all subjects, the lowest mean error in predicting all 8 (*LSA, SAL, LSD, SDL, LRA, RAL, LRD, RDL*) walking mode transitions along with *B* and *L* conditions was 2.3% (Fig 3A). This was achieved using the fusion of EMG signals from the 4 below-the-knee (BK) muscles and the 8 Mech sensors, using a 250ms time window that spanned the TO of the mode transition step (Fig 3). Highest mean classification error of 30.5% resulted from using only BK-muscle EMG during the time window preceding the TO of the mode transition step. 2-way ANOVA indicated that classification errors achieved from using the three types of data windows (*preTO*, *postTO* and *acrossTO*) are significantly different from each other ($p<0.01$). Additionally, classification errors achieved from using the three types of data sources (BK-EMG only, Mech only and fusion of BK-EMG and Mech) are significantly different from each other ($p<0.01$).

B. *Offline classification accuracy excluding ramp*

Across all subjects, the lowest mean error in predicting 4 (*LSA, SAL, LSD, SDL*) walking mode transitions along with *B* and *L* was 0.3% (Fig 3B). This was again achieved using the fusion of EMG signals from the 4 below-the-knee (BK) muscles and 8 Mech sensors, using a 250ms time window that followed the TO of the mode transition step (Fig 3). Similarly low classification errors were achieved when using the 250ms time window spanning the TO of the mode transition as well as using only Mech sensor data (0.6% and 0.6%, respectively, Fig 3B). Highest mean classification error of 15% resulted from using only BK-muscle EMG, using the time window preceding the TO of the mode transition step. 2-way ANOVA indicated that classification errors achieved from using the three types of data windows (*preTO*, *postTO* and *acrossTO*) are not significantly different from each other ($p=0.19$). However, classification errors achieved from using the three types of data sources (BK-EMG only, Mech only and fusion of BK-EMG and Mech) are significantly different from each other ($p<0.01$).

IV. DISCUSSION

This analysis of mode transition data collected from 5 trans-tibial amputees demonstrated that the use of neuromechanical sensor fusion can discriminate among 10 different types of terrain transitions with a very low error rate of 2.3%. Data from only mechanical sensors yields higher error rates of 7.8% while data from only EMG sensors yields error rates in the 10%+ range. The observation that the fusion of Mech and EMG data leads to best performance may be explained by the notion that EMG signals leverage the amputee's anticipation of the upcoming terrain type, while Mech sensor data captures the kinematics during the transition onto a new terrain type. When considering ambulation over level ground, stairs and ramps, this notion is supported by our findings that using a 250ms window spanning the TO event of the mode transition step resulted in significantly lower classification errors. Second-lowest errors were achieved when using a time window that followed the TO event.

Based on our clinical experience with trans-tibial amputees and as evidenced by previous studies [5], ambulation over lower grade ramps such as the one used in this study, resembles ambulation over level ground in terms of kinematic requirements (although with a small shift in ankle angle). We, therefore, performed additional analysis in which we removed transitions associated with ramps (Fig. 3B). Results of this analysis indicated that using only the Mech data can yield nearly the same classification performance (0.6% error) as the use of Mech and EMG data together (0.3%). When using Mech data alone, this negligible classification error is achieved when with the *postTO* time window. Mechanical sensors yield significantly more consistent signals than the EMG sensors and this consistency can reliably reflect the drastic dynamic changes in foot trajectory as related to ambulation mode transitions.

It could certainly be argued that the use of Mech data alone does not impose a great penalty on the accuracy of classification as compared to the use of both EMG and Mech data, especially in the case when ramp transitions are not considered. It is important to consider, however, that accurate function of a lower-limb prosthesis is directly linked to patient safety and as such, any improvement in functional performance further reduces risk of fall or injury. There is also another vital benefit to using EMG signals in conjunction with the mechanical sensor data: a neuromuscular interface enables the patient to voluntarily actuate the prosthesis outside of walking to perform other activities such as reaching up via raising oneself up on their toes or simply repositioning their foot for comfort [19].

Lowest classification error resulted from using the time window that spans the TO of the mode transition step. A possible explanation for this finding is that such a window benefits from both the anticipatory nature of the biological signal and the reactive nature of the mechanical signal. Future analysis of the data will evaluate this hypothesis. The 250ms time window following the TO also yields accurate classification, however, the remaining time prior to the next heel strike may not be sufficient to smoothly transition the prosthesis into the proper operational mode. For real-time, online implementation, the LDA classifier can make an accurate decision regarding the ambulation mode of the upcoming step within the 250ms of the window spanning the TO. Since this time window extends only 125ms beyond the TO event, there would be sufficient time to adjust the parameters of the powered prosthesis in a smooth manner to accommodate the upcoming HS.

One limitation of our methodology is that we utilized a novel means of collecting EMG data, using a liner with embedded EMG electrodes. Although not conventional, this method has been used successfully in other instances for collection of EMG data from lower limb amputees as described by Lipschutz et. al. [17]. This novel approach avoids discomfort experienced by amputees stemming from conventional, rigid electrodes pressing into sensitive areas of the amputee's residual limb.

The findings of this study indicate that neuromechanical sensor fusion used with a pattern recognition-based classifier can accurately predict the onset of as many as 10 different ambulation mode transitions. The demonstrated approach is computationally efficient and can be expanded to enable voluntary control of the prosthesis by the amputee.

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