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Analysis of using EMG and mechanical sensors to enhance intent recognition in powered lower limb prostheses

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Abstract

Objective. The purpose of this study was to determine the contribution of electromyography (EMG) data, in combination with a diverse array of mechanical sensors, to locomotion mode intent recognition in transfemoral amputees using powered prostheses. Additionally, we determined the effect of adding time history information using a dynamic Bayesian network (DBN) for both the mechanical and EMG sensors. *Approach.* EMG signals from the residual limbs of amputees have been proposed to enhance pattern recognition-based intent recognition systems for powered lower limb prostheses, but mechanical sensors on the prosthesis—such as inertial measurement units, position and velocity sensors, and load cells—may be just as useful. EMG and mechanical sensor data were collected from 8 transfemoral amputees using a powered knee/ankle prosthesis over basic locomotion modes such as walking, slopes and stairs. An offline study was conducted to determine the benefit of different sensor sets for predicting intent. *Main results.* EMG information was not as accurate alone as mechanical sensor information ($p < 0.05$) for any classification strategy. However, EMG in combination with the mechanical sensor data did significantly reduce intent recognition errors ($p < 0.05$) both for transitions between locomotion modes and steady-state locomotion. The sensor time history (DBN) classifier significantly reduced error rates compared to a linear discriminant classifier for steady-state steps, without increasing the transitional error, for both EMG and mechanical sensors. Combining EMG and mechanical sensor data with sensor time history reduced the average transitional error from 18.4% to 12.2% and the average steady-state error from 3.8% to 1.0% when classifying level-ground walking, ramps, and stairs in eight transfemoral amputee subjects. *Significance.* These results suggest that a neural interface in combination with time history methods for locomotion mode classification can enhance intent recognition performance; this strategy should be considered for future real-time experiments.

Keywords: lower limb prostheses, EMG signal processing, sensor fusion, biomedical signal classification

(Some figures may appear in colour only in the online journal)

1. Introduction

Myoelectric interfaces have been clinically deployed for decades for powered upper limb prostheses [1] but have yet to be clinically implemented for lower limb prostheses. Currently most amputees use mechanically passive prostheses that do not require advanced controllers. In recent years prostheses with onboard computers [2, 3] and motorized joints [4–6] have become available. Control of these devices could potentially be augmented by adding neural information. Electromyography (EMG) has been proposed as a control signal for lower limb prostheses for decades, even for mechanically passive devices [7, 8] and has primarily been studied for use in computerized prostheses with variable damping or in powered (motorized) devices. Many different strategies have been employed using EMG-based approaches. Non-weight-bearing control, similar to myoelectric control of upper limb prostheses [9, 10], has been accomplished through signal processing techniques applied to EMG from isometric contractions to reposition a knee or ankle [11–13]. Although effective for static contractions, these strategies are not suitable for use during ambulatory tasks where EMG signals are non-stationary. Direct proportional control using EMG information has been applied to lower limb prostheses in various ways including controlling the amount of plantarflexion torque at pushoff [14, 15], for powered ankle orthosis assistance [16–18], and for control of knee torque [19] and knee equilibrium set points [20]. These strategies may help to augment specific functions such as the amount of powered plantar flexion during walking or the amount of extension torque during stair ascent. Unfortunately, EMG signals are noisy and may be difficult to use for directly controlling a powered prosthesis during all phases of different locomotion modes (e.g. level-ground walking, stair ascent, etc).

EMG has been used in multiple studies to identify locomotion modes such as level-ground walking, standing, sitting, and ascending/descending stairs and ramps [21–25]. Discriminating locomotion modes is an important function as current powered transfemoral prostheses require users to stop and use a key fob or perform an unnatural movement (such as rocking on the prosthesis) to switch between locomotion modes. Ideally, prostheses should be capable of transitioning between locomotion modes automatically, seamlessly, and naturally (i.e. requiring no unnatural body movements). Thus, rather than using EMG to directly control a prosthesis, the approach in this study was to use EMG as a high-level controller to recognize amputee locomotion mode in combination with a lower-level state machine that uses mechanical sensors on the prosthesis [26, 27] to render appropriate torques (or impedances) for each mode. Most studies that use EMG to determine locomotion mode use EMG as the only control input [21–25]. Similarly, previous studies such as Varol 2010 [28] have used only a set of mechanical sensors for intent recognition purposes. Mechanical sensors are typically embedded on computerized lower limb prostheses for lower-level control and are easier to implement than an EMG interface. Thus, a key research question is whether EMG combined with data from these mechanical sensors provides additional value.

A few studies have considered using both mechanical sensors and EMG sensors for locomotion mode recognition [29–31]. Farrell 2011 [30] and Huang 2013 [29] were primarily interested in reducing the number of features and sensors used for intent recognition. Huang 2011 [31] used EMG from the residual limb together with mechanical sensors on a passive prosthesis and found that the EMG added considerable information to that provided by the mechanical sensors. However, this finding was limited in that the mechanical sensor set comprised only a 6-DOF load cell. In the current study, an array of different mechanical sensors, including kinematic, kinetic, and inertial sensors, were used in combination with residual limb EMG to determine the relative contribution of each sensor type. Additionally, the number and location of EMG channels necessary for accurate intent recognition was determined.

Previous studies using EMG for intent recognition have been conducted on non-amputee subjects [24, 25] or amputee subjects using mechanically passive devices [21–23, 29–31]. A key difference between powered and passive prostheses is that powered devices change mechanical properties between different locomotion modes. For a powered prosthesis, the change in impedance parameters must occur directly *before* the transitions, thus, if a transition is to occur seamlessly, the intent recognition system must correctly *predict* upcoming locomotion modes, rather than *estimate* the current mode. If a transition is not performed correctly, the powered device may generate an incorrect gait profile, misclassifications may propagate and the user is at high risk of falling. Additionally, the EMG signals generated when using a powered device may be substantially different than those from a mechanically passive device; thus the relative contributions of mechanical and EMG sensors may be different than on a passive device such as in [31]. For this study, the authors analyzed the contribution of EMG and mechanical sensors to intent recognition both during transitions between locomotion modes (transition error) and during steady-state ambulation (steady state error) in transfemoral amputees using an experimental powered prosthesis.

Due to the non-stationary nature of EMG signals during the gait cycle, phase dependent approaches are necessary [21] to effectively use pattern recognition–based intent recognition techniques for locomotion mode identification. Typically, features are calculated over the previous 100–500 ms data window [21, 28, 31]. This small snapshot of the gait cycle is used to identify the locomotion mode, and the time history of the signals is either ignored or used through a majority vote strategy, which simply filters the output based on the previous stream of decisions. For example, if a five-count majority vote is used, a transition will not occur until at least three of the previous five overlapping windows agree upon a new locomotion mode. However, it may be beneficial to capture the sequence of the time history of signals. In preliminary work [32], we introduced a new strategy using a dynamic Bayesian network (DBN) to incorporate the patterns of gait information over the entire stride in order to account for the non-

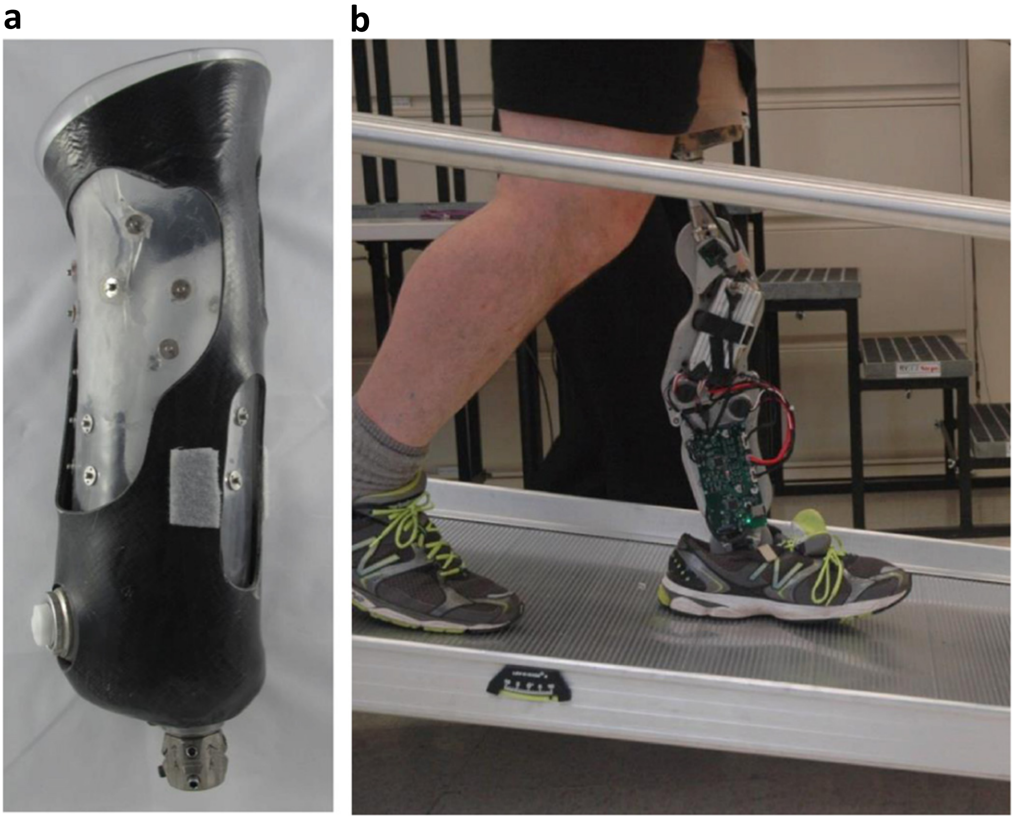

Figure 1. (a) Picture of a custom socket worn by a transfemoral amputee. Dome electrodes were embedded in the socket over the subject's residual muscles to record EMG. A pylon connector attaches the socket to the powered knee and ankle prosthesis. (b) Powered knee and ankle prosthesis used by all subjects.

stationarity of signals (both EMG and mechanical) during gait. The DBN is a pattern classifier capable of incorporating past sensor information together with current sensor information in a probabilistic approach. This classifier is easily implementable in real-time, as a typical Bayesian model is used for classification, and only the probabilities for each locomotion mode need to be saved for the next classification decision. In this study, we also evaluated the contribution of sensor time history, using a DBN, in combination with the EMG and mechanical sensors.

2. Methods

Six subjects with unilateral transfemoral amputations and two subjects with knee disarticulation amputations completed the experiment, which was approved by the Northwestern University Institutional Review Board. Subjects' ages ranged between 21 and 64, heights were between 1.6 m and 1.86 m, and weights were between 52.2 kg and 111.6 kg. All subjects were community ambulators (K3 or K4 level).

2.1. Experimental protocol

A physical therapist identified the following nine muscles on the subjects' residual limbs by palpation: semitendinosus (ST), biceps femoris (BF), tensor fasciae latae (TFL), rectus femoris (RF), vastus lateralis (VL), vastus medialis (VM), sartorius (Sart), adductor magnus (AM), and gracilis (Grac). A suction socket with embedded stainless steel dome electrodes was custom made for each of the subjects. The electrodes were inserted into the custom EMG socket (see figure 1(a)) based on the identified muscle locations. Two subjects instead wore their own socket, and low-profile, self-adhesive, silver-coated carbon electrodes (Arrowhead Medical Resources) were placed underneath their liners over the appropriate muscle locations.

A certified prosthetist aligned and attached the prosthesis to the subjects' sockets. A powered knee and ankle prosthesis (figure 1(b)), designed by the Center for Intelligent Mechatronics at Vanderbilt University [33], was used for this experiment. Subjects had all used this device in previous sessions during which the prosthesis was tuned for the individual subject. Impedance parameters were tuned to each subject for level-ground walking [28], ramp ascent/descent [34], and stair ascent/descent [35] based on previous literature. A physical therapist was present during the experiment to instruct the subject and ensure subject safety.

After a short practice time walking on the prosthesis (~20 min), each subject completed 20 repetitions of a locomotion circuit that included level-ground walking, ramps, and stairs. First, subjects walked across the room and back (~25 feet) over level ground. During this section, subjects normally walked at their self-selected walking speed. During 4 trials, subjects were asked to walk at a faster pace than normal, and during another 4 trials, subjects were asked to walk at a slower pace than normal. During the next part of the circuit, subjects walked over level ground to a 10 degree ramp, ascended the ramp, walked on a level elevated platform, turned around, walked back down the ramp, and transitioned back to walking on level ground. All transitions onto and off of the ramp were manually triggered by an experimenter to occur at heel contact of the prosthesis onto or off of the ramp. For the last part of the circuit, subjects walked over level ground to a 4-step stair case and performed step-over-step stair ascent, leading with their sound side; subjects then transitioned back to level-ground walking on an elevated platform. The experimenter triggered the transitions between stair ascent and level-ground walking at toe off of the prosthesis. Subjects then turned around and descended the stairs step-over-step, leading with the prosthesis on the first step down. Transitions between level-ground walking and stair descent were triggered by the experimenter at heel contact of the prosthesis on the first step on the stairs and then again on the first step of level ground. The data collection protocol typically lasted for an hour and half (including breaks) and allowed for data capture during steady-state locomotion of five locomotion modes (level-ground walking, ramp ascent/descent and stair ascent/descent) and seamless transitions between level-ground walking and the other four locomotion modes (eight types of transition).

2.2. Signal processing

Signals from thirteen mechanical sensors were recorded at 500 Hz and used for gait classification in an offline analysis. The sensors were divided into three groups: kinematic sensors, kinetic sensors, and inertial sensors. The kinematic sensors determined the positions and the velocities of the knee and ankle. The kinetic sensors comprised an axial load cell (through the shank) and torque delivered to the knee and ankle. The load cell signal was smoothed by low pass filtering at 20 Hz. The inertial sensors included a six-axis IMU located on the shank with three accelerometers and three gyroscopes. EMG signals were recorded at 1000 Hz from electrode locations over the nine residual muscles listed above. A custom-built EMG system was used to record the signals and included a hardware bandpass filter between 20 and 450 Hz. An analysis was performed across these four sensor sets (kinematic, kinetic, inertial and EMG) to determine the contribution of each set alone and in combination with each other sensor set.

Data were segmented into analysis windows of 300 ms before eight different gait events. These events included 0, 25, 50, and 75% of stance and swing phase, where 0% of stance was initial heel contact and 0% of swing was the end of toe off. Features extracted from each analysis window included the mean, maximum, minimum, and standard deviation for mechanical sensor signals [28], and mean absolute value, waveform length, zero crossing, slope sign changes, and the first two autoregressive coefficients of a sixth order autoregressive model for EMG signals [10, 36].

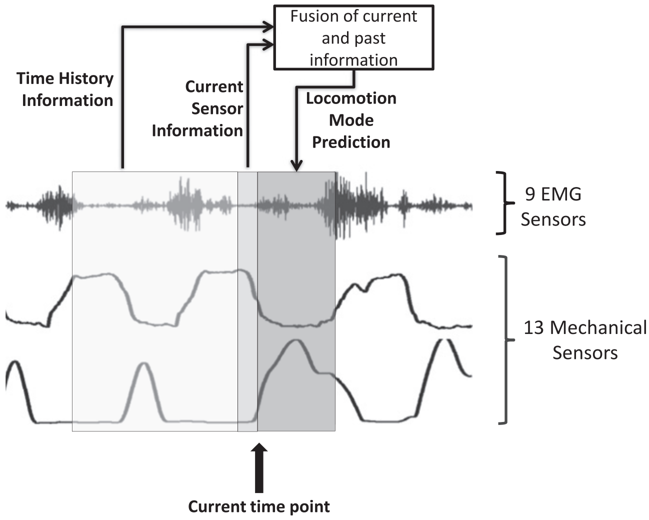

Figure 2. Use of sensor information by the dynamic Bayesian network. Information from current sensor information is fused with past information throughout the gait cycle through Bayes' law to obtain a locomotion mode prediction. Time history and current information is used both from the 9 surface EMG sensors embedded in the socket on the residual limb and the 13 mechanical sensors on the leg prosthesis.

2.3. Off-line classification analysis

2.3.1. Control strategy 1: time history-based classification using a DBN. A DBN [37] algorithm takes into account the time history of signals over the entire stride (see figure 2). Previous work [32] details the algorithm. Briefly, Bayes' law was used to combine past information, in the form of a *prior*, with current likelihood information. A different likelihood model was trained for each gait event (total of 8). The likelihood model at each gait event produced a set of probabilities for each locomotion mode and these were multiplied by the probabilities for each locomotion mode based on past information (the priors). This produced a set of posterior probabilities—the mode with the highest posterior probability was used as the locomotion mode prediction. The posterior probabilities were then multiplied by a transitional probability matrix—a matrix describing the probabilities that a transition from any given locomotion mode to another occurred during training—to form the prior probabilities for the next gait event.

2.3.2. Control approach 2: classification using linear discriminant analysis (LDA); no time history. For this method, only two likelihood models (LDAs) were trained—one at heel contact and one at toe off. Since transitions only occurred at these points, models without time history are only necessary at these two gait events as the prosthesis is only allowed to switch locomotion modes at these two events.

2.3.3. Control approach 3: time history–based classification using majority vote across multiple LDA decisions (LDA + MV). Multiple studies have implemented time history information in the form of a majority vote strategy

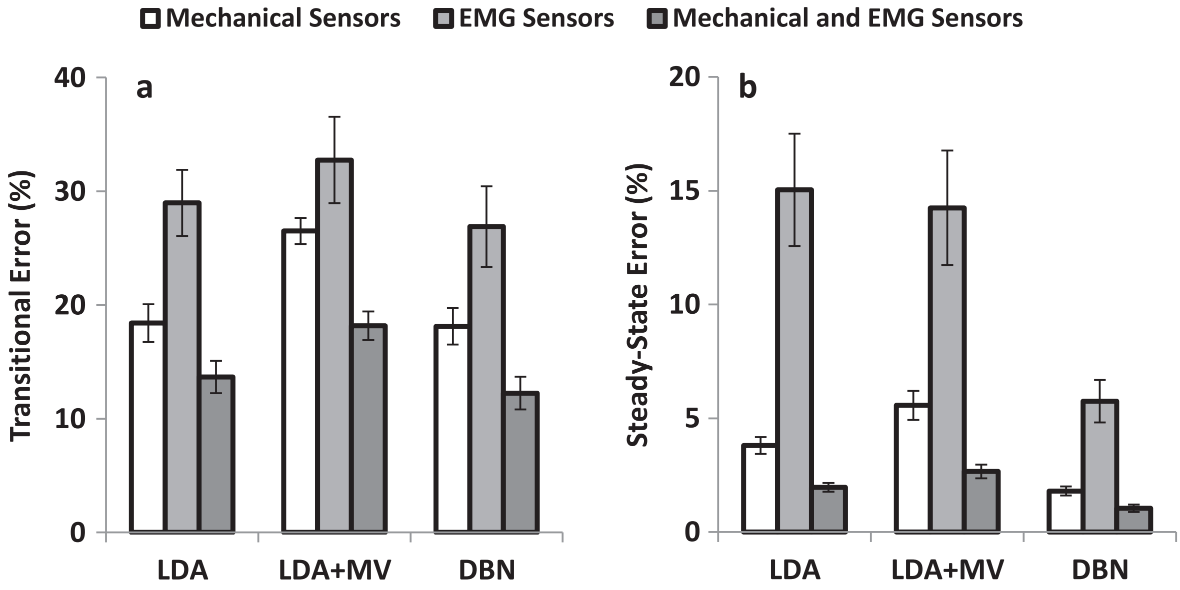

Figure 3. Effect of classification strategy and sensor set on (a) transitional and (b) steady-state error. Classification strategies tested were a dynamic Bayesian network (DBN), a linear discriminant analysis (LDA), and an LDA with a majority vote strategy (LDA + MV). Data are averages of eight subjects and error bars represent +/−1 SEM. Note different *y*-axis scales in (a) and (b).

which uses previous decisions to obtain more consistent class output [28, 31]. A transition is triggered once a majority of previous windows agree on a new locomotion mode. This method was implemented by extracting five 300 ms windows before each heel contact and toe off event with increments of 20 ms between them. A five-count majority vote was performed across the five windows and the class with the most votes was used to select the locomotion mode. This implementation was consistent with majority vote implementation in previous studies [28, 31].

2.4. Evaluation of intent recognition

The number of intent recognition errors was evaluated using 20-fold cross validation with the 20 circuit trials (19 trials in the training set and 1 trial in the test set, repeated 20 times such that each trial was the test set once). Performance was reported in terms of misclassification rates only at heel contact and toe off as these are critical points for transitions. Errors were split into two categories: transitional error—the percentage of misclassified transition steps, and steady-state error —the percentage of misclassified steps that did not occur at a transition. Means and 1 standard error of the mean (+/−1 SEM) were reported.

A comparison was made between the three classification strategies (DBN, LDA, and LDA+MV) using mechanical sensors only, EMG sensors only, and a combination of EMG and mechanical sensors. A two way ANOVA was performed for both transitional and steady-state error with error as the response, sensor type and classification strategy as fixed factors, and subject as a random factor. For steady-state error, variances between groups were not homogeneous based on a Levene’s Test, thus all data were log transformed to fit the homogeneity assumption for ANOVA [38]. Post-hoc tests were conducted on statistically significant variables of interest.

Only the DBN classifier was used for additional analyses. In order to determine how many channels were necessary and which of the nine EMG channels were useful, forward sequential selection was performed across the nine EMG channels. This analysis was performed by calculating the overall intent recognition error averaged across subjects after adding each EMG channel to the mechanical sensor set. The EMG sensor that reduced error the most was selected and a new set of errors were calculated for adding each of the remaining EMG sensors. This forward selection continued until all EMG channels had been added. A one-way ANOVA was performed to determine how many sensors were needed to make a statistically significant improvement for both transitional and steady-state error.

Additional scenarios were tested to determine the importance of EMG for intent recognition classification. Specifically, intent recognition rates were tested on ramp trials separately from stair trials to determine if improvements were more pronounced for certain types of locomotion modes. Additionally, performance was compared between using mechanical sensors, EMG sensors, and mechanical sensors with EMG sensors when labeling the ramp class as level-ground walking. This type of classification strategy may reduce intent recognition errors, but requires either an additional slope estimator that has been presented previously [34] or that the amputee walk on ramps using the level-ground walking controller.

Finally, the analysis window for EMG and mechanical sensors was tested to determine if changes could increase performance. Analysis windows between 50 ms and 450 ms were tested for both EMG and mechanical sensors (in combination and separately).

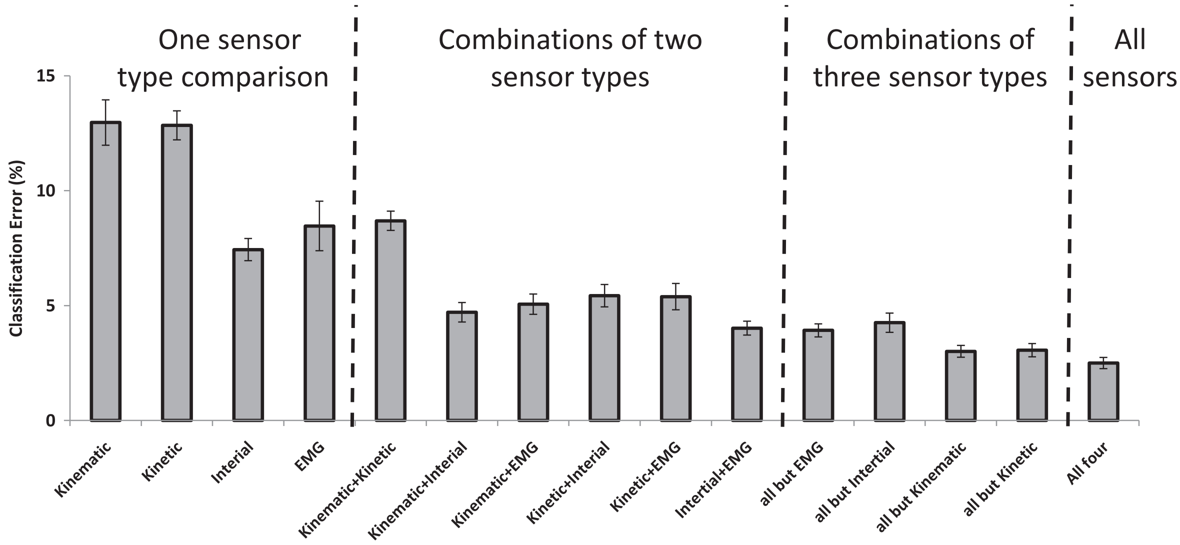

Figure 4. Effect of sensor set and number of sensor sets on intent recognition error rates. Four sets of sensors—kinematic, kinetic, inertial, and EMG—were compared separately and in all possible combinations with each other. The inertial and EMG sensors sets performed significantly better than the kinematic and kinetic sets. Data are averages of eight subjects and error bars represent +/−1 SEM.

Table 1. Confusion matrix for DBN using EMG and mechanical sensors for transitional steps.

		Estimated locomotion modes				
		Level walking	Ramp ascent	Ramp descent	Stair ascent	Stair descent
True locomotion modes	Level walking	80.1	4.3	15.6	0.0	0.0
	Ramp ascent	2.7	96.6	0.7	0.0	0.0
	Ramp descent	8.7	0.0	91.3	0.0	0.0
	Stair ascent	2.6	0.0	0.0	97.4	0.0
	Stair descent	1.3	0.0	0.0	0.0	98.7

Table 2. Confusion matrix for DBN using EMG and mechanical sensors for steady-state steps.

		Estimated locomotion modes				
		Level walking	Ramp ascent	Ramp descent	Stair ascent	Stair descent
True locomotion modes	Level walking	98.9	0.4	0.4	0.2	0.1
	Ramp ascent	1.1	98.9	0.0	0.0	0.0
	Ramp descent	1.0	0.0	99.0	0.0	0.0
	Stair ascent	0.0	0.2	0.0	99.8	0.0
	Stair descent	0.2	0.0	0.0	0.0	99.8

3. Results

3.1. Effect of EMG and classification strategy

Mechanical sensors alone performed significantly better ($p < 0.05$) than EMG sensors alone for both transitional and steady state error (figure 3). A combination of EMG and mechanical sensors significantly reduced ($p < 0.05$) transitional and steady-state errors compared to using either EMG or mechanical sensors only across all classification strategies. The DBN strategy performed significantly better ($p < 0.05$) than the LDA and LDA + MV strategies for steady-state error. Both the DBN and LDA performed significantly better ($p < 0.05$) than the LDA + MV strategy for transitional errors. The best overall condition for both transitional and steady-state errors was the DBN strategy using both mechanical and EMG sensors. A representative confusion matrix detailing errors between all five locomotion modes is presented in table 1 for transitional steps and table 2 for steady-state steps.

3.2. Effect of sensor set on intent recognition performance

Sensors sets were divided into four groups (kinematic, kinetic, inertial, and EMG) and performance was compared with

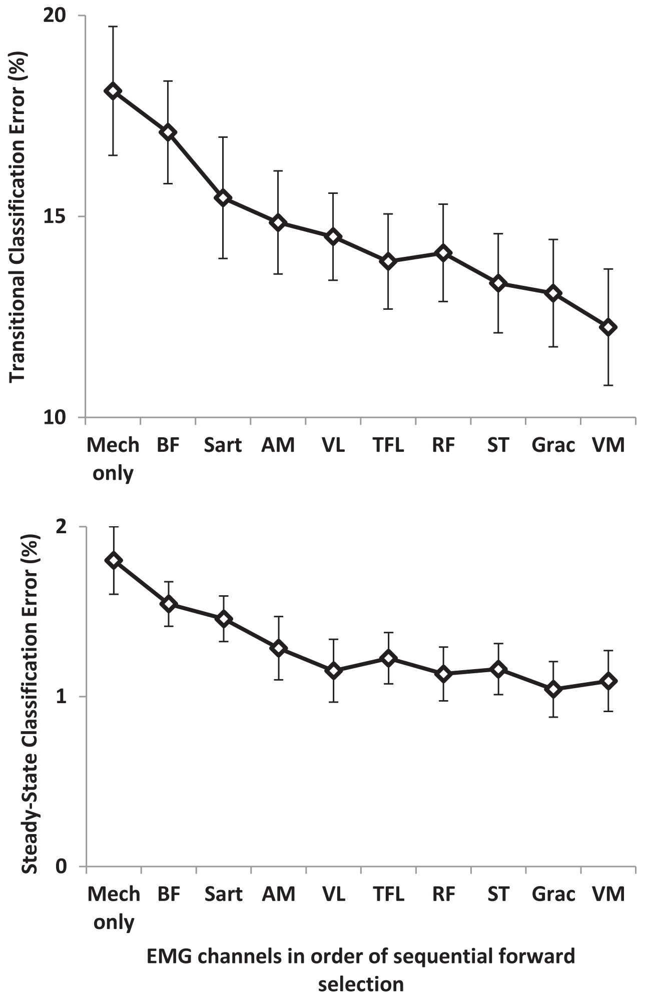

Figure 5. Effect of sequential addition of EMG channels on classification error. EMG channels were selected based on a sequential forward search where performance for each channel was measured by the overall misclassification rate averaged across all subjects. Forward selection is displayed from left to right on the graph with the selection of EMG sites (most to least valuable) being as follows: biceps femoris (BF), sartorius (Sart), adductor magnus (AM), vastus lateralis (VL), tensor fasciae latae (TFL), rectus femoris (RF), semitendinosus (ST), gracilis (Grac), and vastus medialis (VM). Mechanical sensors served as the baseline condition, and EMG sensors were added to the mechanical sensor set during selection. The top graph shows transitional error while the bottom graph shows steady-state error. Data are averages of eight subjects and error bars represent +/−1 SEM.

sensor sets individually and in combination with each other (figure 4). Individually, EMG and inertial sensors performed with significantly fewer errors ($p<0.05$) than kinematic and kinetic sensors. This trend held in combination with any given starting sensor set, adding EMG or inertial sensors was always most beneficial and removing EMG or inertial sensors always increased errors the most. Notably, errors always decreased by adding a new set of sensors; the lowest error rates were obtained when using all four sensor sets.

3.3. Lower limb EMG channel selection

Forward sequential selection across the nine EMG channels was performed, with the mechanical sensors only as a baseline (figure 5). The order of selection from most to least error reduction was: biceps femoris (BF), sartorius (Sart), adductor magnus (AM), vastus lateralis (VL), tensor fasciae latae (TFL), rectus femoris (RF), semitendinosus (ST), gracilis (Grac) and vastus medialis (VM). Transitional error was significantly reduced after adding three EMG channels (BF, Sart and AM) compared to using mechanical sensors only. Transitional error continued to decrease as each of the nine EMG channels was added (figure 5(a)). Steady-state error was significantly reduced after adding only two EMG channels (BF and Sart) compared to mechanical sensors only and was lowest at eight channels, but little improvement in steady-state error was noticeable after four channels were added (figure 5(b)).

3.4. Comparison of ramps and stairs with EMG information

Stair trials were more accurately identified by the DBN classifier ($p<0.05$) than ramp trials (figure 6) for both transition and steady-state steps, regardless of the underlying sensor set. The trend across sensor sets was that a combination of mechanical and EMG sensors had the lowest error compared to the other sensor sets; this trend was the same for both stairs and ramps. Additionally, mechanical sensors alone had lower error rate than EMG sensors alone for both transitions and steady-state locomotion.

3.5. Labeling ramps as the level-ground walking class for improved performance

By retraining the ramp steps as level-ground walking patterns—and hence reducing the number of locomotion modes to select—error rates could be reduced for both transitional and steady-state error ($p<0.05$) (figure 7). With only three classes (both ramp descent and ramp ascent), classification rates were similar to the stair classification rate in figure 6 for any given sensor set. By labeling only the ramp ascent patterns into the level walking class, the transitional error rate was not affected, but the steady-state error rate was significantly reduced ($p<0.05$) to a rate between that of the five class and three class conditions. The trend across sensor sets was similar; the combination of EMG and mechanical sensors outperformed the either sensor type alone, and mechanical sensors alone outperformed EMG sensors alone.

3.6. Effect of EMG and mechanical sensor analysis window on classification error rates

Classification error rates on the transition steps were generally lower with analysis window sizes between 200–300 ms for both mechanical and EMG sensors (figure 8). For steady-state errors larger window sizes for both EMG and mechanical sensors tended to result in lower errors.

3.7. Representative data plots

Mechanical and EMG sensor data varied based on locomotion mode and phase of gait. Representative data depicting all the

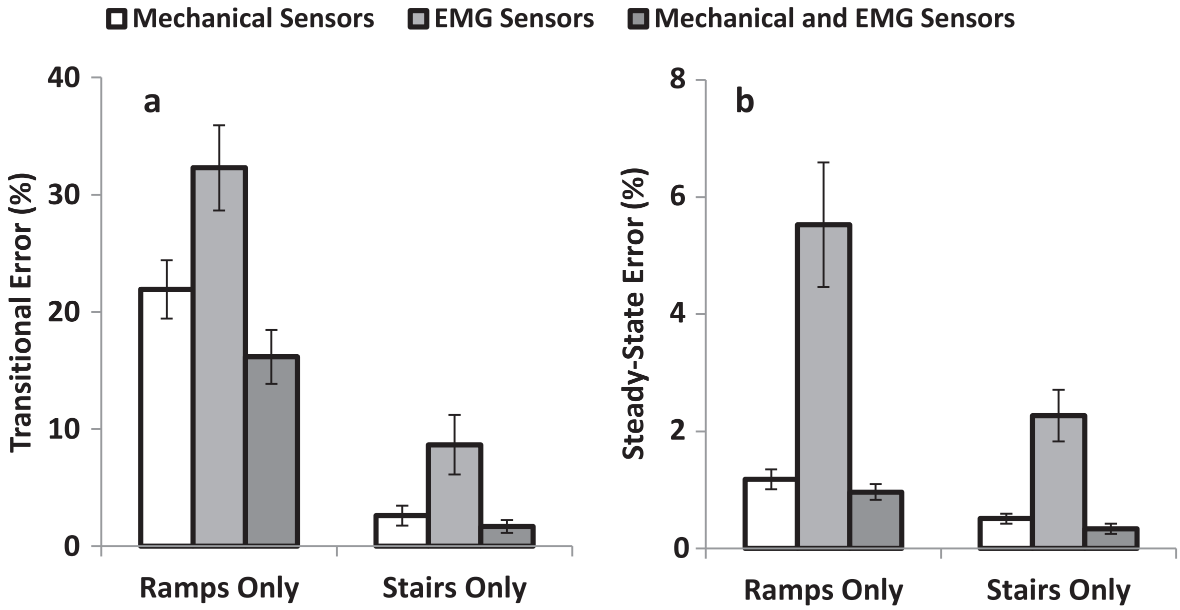

Figure 6. Comparison of intent recognition classification for ramps and stairs. Mechanical sensors or EMG sensors alone, or a combination of the two sensor types were compared during both ramp and stair trials for both (a) transitional and (b) steady-state errors. Stairs had significantly lower error rates than ramps for both transitions and steady-state steps. Data are averages of eight subjects and error bars represent +/−1 SEM.

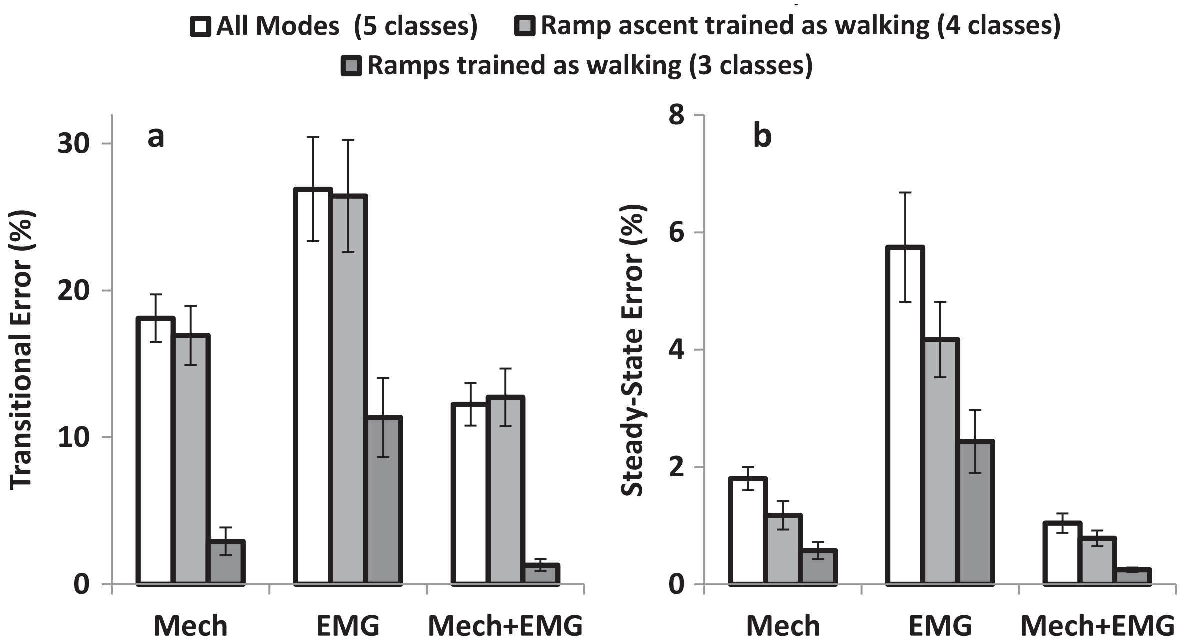

Figure 7 Effect of including ramps in the level-ground walking class on intent recognition performance using the DBN classifier. By labeling the ramps to be in the level-ground walking class (decreasing the number of the classes in the classifier from 5 to 3), both transitional (a) and steady-state (b) errors were reduced. This was true across all three sensor sets (mechanical sensors or EMG sensors alone or a combination of the two). Data are averages of eight subjects and error bars represent +/−1 SEM.

sensors for two strides are shown in figure 9 for each locomotion mode.

4. Discussion

The results of this study indicate that EMG information from the residual limb of a person with a transfemoral amputation can moderately improve mode selection accuracy for an intent recognition system when combined with data from mechanical sensors on a powered prosthesis. Significant error reductions were observed for both transitional steps and during steady state locomotion when EMG information was included. This reduction in error was similar regardless of classifier architecture (figure 3), as transitional error was reduced by 30% and steady state error by 48% across

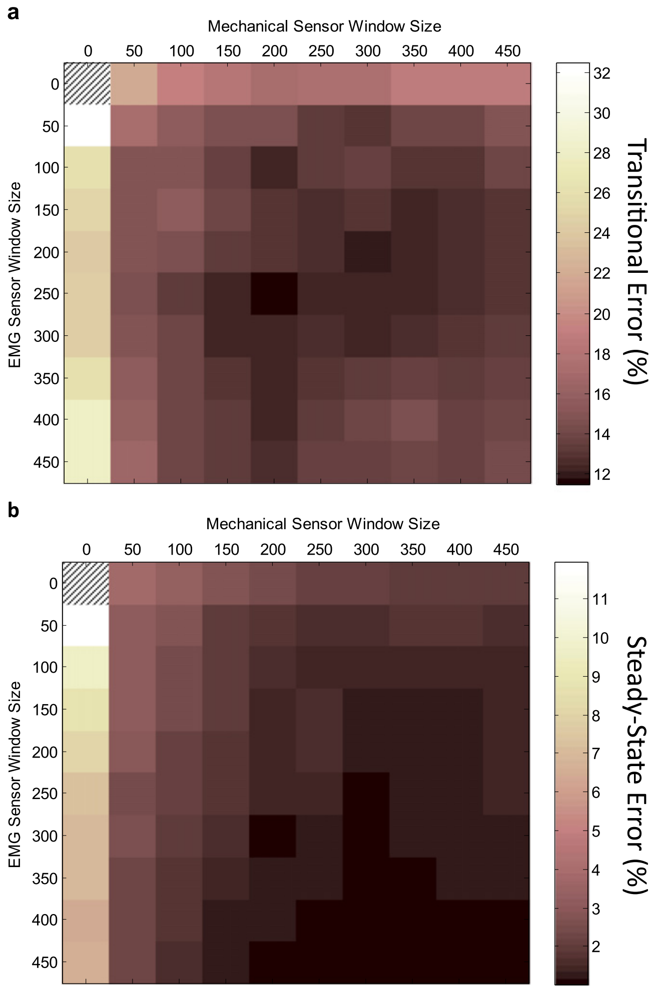

Figure 8. Effect of EMG and mechanical sensor analysis window on classification. Figure 8(a) color codes the transitional error and figure 8(b) the steady-state error. For both diagrams, the *y*-axis is the EMG sensor window size (varied between 0 and 450 ms) and the *x*-axis is the mechanical sensor window size (varied between 0 and 450 ms). The 0ms condition equates to not using the signal, thus the first column is EMG only and the first row is mechanical sensor only.

conditions. Including time history information using a DBN with EMG and mechanical sensor information maximally reduced both transitional and steady state errors compared to LDA or LDA with majority vote strategies. Our goal now is to test this control system configuration in real-time.

To determine the contribution of EMG for intent recognition, a large number of EMG channels (9) were studied. Only three EMG sensors—those placed over the biceps femoris, sartorius, and adductor magnus—were necessary to obtain significantly reduced transitional and steady state errors (figure 5). With the addition of up to nine EMG channels, transitional error continued to decrease, but steady-state error was fairly constant with only a slight decrease. Thus, it is likely that a reduced set of EMG channels could provide most of the necessary information. This is advantageous as fewer channels are easier to implement, less costly, and more robust in that fewer signal contacts must be maintained. It should be noted that while this study shows that only a few EMG channels are highly useful for intent recognition, if the classification problem were expanded to include additional transitions, more locomotion modes, and/or earlier identification of transitions then additional EMG channels may be beneficial.

The analysis of sensor set influence on intent recognition performance revealed that no single sensor set alone yielded low classification errors (all > 5%). Kinematic sensors are necessary for implementing impedance-based control [27], and kinetic sensors are necessary for state-based control of stance and swing [28]. Thus, these sensors are likely to be included on a powered prosthesis regardless of their importance for intent recognition. EMG and inertial (IMU) sensors are optional and not necessarily critical to the operation of the prosthesis. However, both inertial and EMG sensors were more valuable than kinematic or kinetic sensors for intent recognition purposes. Including EMG or inertial sensors alone reduced error by 39% (figure 4), but combining both sensor sets reduced errors by a total of 63%. These data indicate that including an IMU on the shank enhanced intent recognition. EMG sensors were equally valuable and a promising new tool for the control of powered leg prostheses.

The fusion of EMG sensor data with data from mechanical sensors helped to reduce transitional and steady state errors across a variety of conditions including ramps only, stairs only, and configurations in which ramps were labeled as level walking. These results indicate that even with changing classifier configuration (figure 3), locomotion modes (figure 6) and training strategy (figure 7), EMG sensor data provided important information in combination with the mechanical sensor data. As indicated by these results, the combination of EMG and mechanical sensors is beneficial and robust over a wide variety of situations.

The classification error achieved in this study using EMG sensors only was similar to that achieved in closely related studies on amputees using passive devices. In Huang's 2009 study [21], using nine residual limb EMG channels (similar locations to the ones in this study) and an LDA classifier, an average of 13.9% steady-state error was achieved (averaged between pre-heel contact and pre-toe off conditions similar to those used in this study) in two transfemoral amputees using a passive prosthesis for six locomotion modes and standing. In our study, using nine residual limb EMG channels and an LDA classifier, an average of 15.0% steady-state error was achieved across eight transfemoral amputees using a powered prosthesis for five locomotion modes. Thus, similar error rates were achieved when only using EMG for both a powered and a passive prosthesis. Notably, using a DBN reduced the steady-state error when using only EMG from 15.0% to 5.7%, demonstrating the advantage of time history strategy when applied to EMG signals.

In Huang's 2011 study [31], which tested five transfemoral amputees on a passive device, a combination of EMG and mechanical sensors reduced errors compared to either set alone, similar to the findings of our study. A notable difference was that while the EMG only performance reported in Huang 2011 was similar to that of Huang 2009 and our study, the mechanical sensor only performance reported in

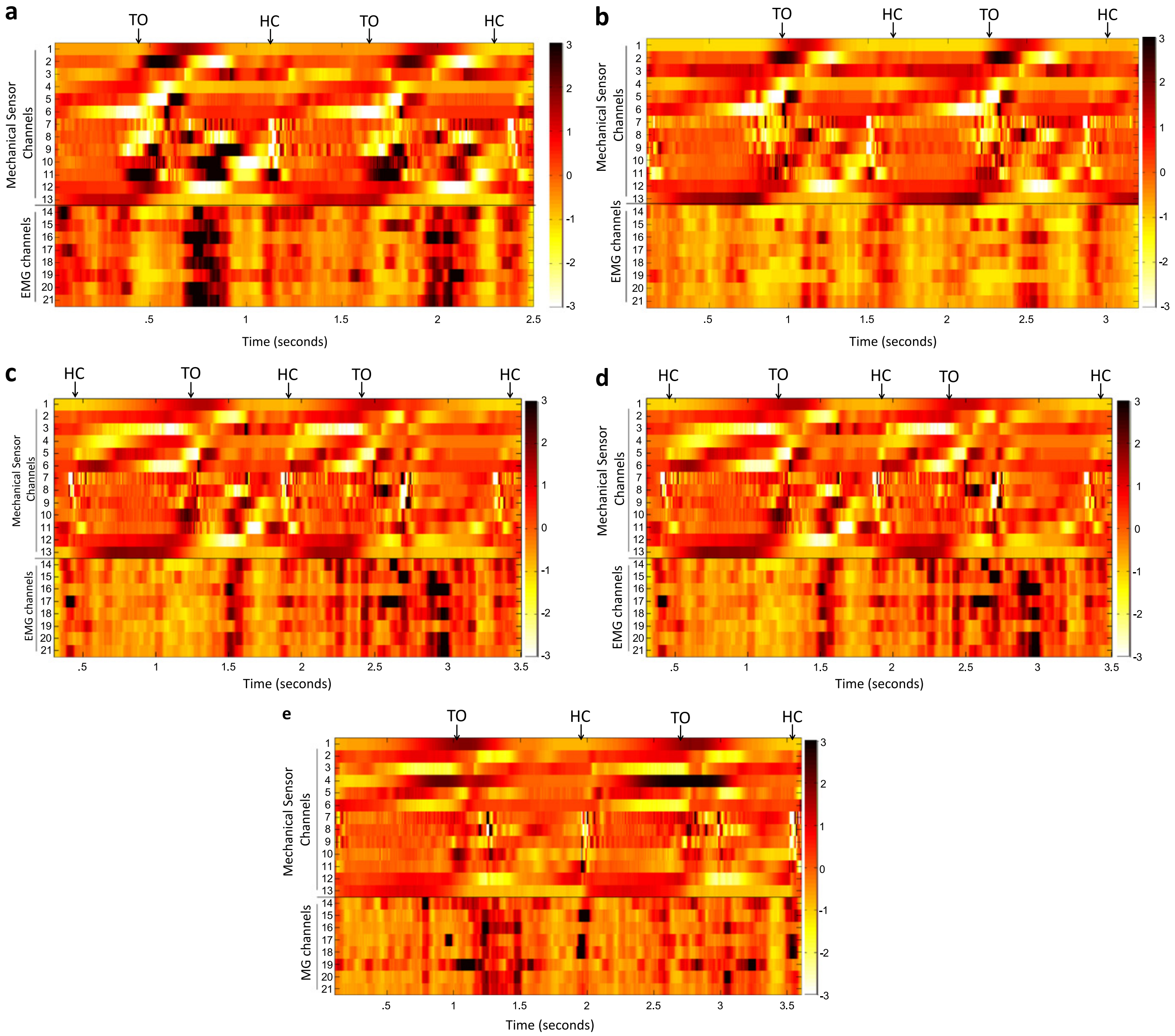

Figure 9. Data plots for EMG and Mechanical Sensors. These heatmaps show the sensor data over two strides of the gait cycle for each task: (a) walking, (b) ramp ascent, (c) ramp descent, (d) stair ascent, and (e) stair descent. The phase of gait is delineated by labeling the toe off (TO) and heel contact (HC) points within each stride. All data were from one representative subject, and all sensor data are shown based on the number of standard deviations from the mean for that channel. The channels are as follows: (1)—knee position, (2)—knee velocity, (3)—knee torque, (4)—ankle position, (5)—ankle velocity, (6)—ankle current, (7)–(9) accelerometers, (10)–(12) gyroscopes, (13)—load, (14)–(21) EMG.

Huang 2011 was worse than the EMG only performance (mechanical sensors in that study had ~13-14% steady state error in late stance and >40% in swing using a LDA classifier). In contrast, in our study the mechanical sensors only had much lower error than EMG only (see figures 3, 6, and 7); in our study, with 5 locomotion modes and using LDA (same as Huang 2011) we obtained an overall steady-state error of 3.8% using mechanical sensors. This difference is likely because the mechanical sensor set used in this study was much more comprehensive—including angular position and velocity sensors, an IMU, motor current sensors, and a load cell—than that used in Huang's study (2011), which comprised only a 6-DOF load cell. Similar to Huang's 2011 study, Miller's 2012 study [39] showed that the inclusion of inertial sensors did not add any additional information to the EMG sensors, again concluding that EMG was the superior information set. Based on the breakdown of classification error by sensor type (figure 4), the inclusion of additional mechanical sensor sources greatly reduced errors. A single set, such as those used in Huang 2011 or Miller 2012, did not perform better than EMG, but a combination of multiple types (kinematic, load, torque and inertial) had superior performance to EMG. To effectively determine the value of EMG sensor data for lower limb intent recognition, it is more useful to compare performance with EMG to that of a large, diverse set of mechanical sensors, which are much more easily implemented on a powered device than are EMG sensors. This study demonstrates that EMG enhances intent recognition for a powered device that is instrumented with a diverse array of mechanical sensors, but is the less valuable set.

The results of this study indicate that ramp steps are much more difficult to classify than stair steps for both transitional and steady state locomotion regardless of the underlying sensor set used. One potential solution to minimize ramp errors is to train the ramp patterns in the level-ground walking class. This strategy heavily reduces intent recognition errors (see figure 7) across all sensor sets but has the clear disadvantage of forcing the amputee to use the level-ground walking controller on a ramp. In these experiments, some amputees preferred to have the consistency provided by an intent recognition system with ramps labeled as walking, but others much preferred having specific ramp modes as an option. The authors thus only suggest labeling the ramps to level walking strategy as one option for reducing intent recognition errors. Alternatively, ramps could be labeled as level-ground walking and a slope estimator could be used, such as the one presently previously by Sup [34] that uses a single triaxial accelerometer attached to the foot of the prosthesis. This device could be used to estimate ramp grade, while the intent recognition system estimates whether the user intends to climb or descend stairs.

One of the potential limitations of the pattern recognition approach presented is the ability of the classifier to perform robustly when variations in the signal occur due to different factors such as gait speed. For this reason, multiple level walking speeds were included during the training set. Average ambulation rates were similar across subjects and tasks as the cadence for level walking was 1.28 steps/s (S.D.: 0.13), 1.26 steps/s (S.D.: 0.11) for ramp ascent, 1.30 steps/s (S.D.: 0.19) for ramp descent, 0.93 steps/s (S.D.: 0.11), and 1.26 steps/s (S.D. 0.23) for stair descent. Stair ascent notably took longer to perform and more variability was observed across subjects for stair descent. Another potential limitation of the pattern recognition approach is its ability to generalize to novel slopes and stair inclinations. While it is likely that the very different biomechanical characteristics of stairs may be classified correctly on different stair grades, the same may not be true for different slopes. Smaller slopes than the one tested (10°) may look similar to level-walking while steeper slopes could even begin to look like stairs. Future tests will be needed to be made to test variations to different grades and inclinations of stairs and ramps.

While EMG may enhance a lower limb intent recognition system, EMG interfaces have considerable disadvantages that have been well documented in studies of upper limb myoelectric control. Environmental factors such as user fatigue, sweating, and electrode shift can change surface EMG patterns and degrade classification performance over time. Electrode channels may also fail or become noisy due to loss of skin contact. Retraining of the intent recognition system may be necessary if EMG signals change on a day to day basis due to these factors. In addition, in order to use EMG signals, a fully embedded EMG system including socket-mounted electrodes and an acquisition system is necessary.

While these hurdles are significant, myoelectric control is standard for powered upper limb devices. If EMG data provides superior control, clinicians and patients may also accept an EMG interface for lower limb prostheses. Future work will focus on adaptive intent recognition systems which may be able to effectively use EMG over time by accommodating changes in signal characteristics due to the various environmental and physiological factors. Another practical solution may be to train the system over multiple days to accommodate variation in EMG signals and enable a more robust system. Such strategies may enable EMG to be implemented as a practical control signal for lower limb devices. As electronics become smaller, embedding EMG acquisition systems within the prosthesis is a realizable goal.

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