

Locomotion Mode Classification Using a Wearable Capacitive Sensing System

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Abstract—Locomotion mode classification is one of the most important aspects for the control of powered lower-limb prostheses. We propose a wearable capacitive sensing system for recognizing locomotion modes as an alternative solution to popular electromyography (EMG)-based systems, aiming to overcome drawbacks of the latter. Eight able-bodied subjects and five transtibial amputees were recruited for automatic classification of six common locomotion modes. The system measured ten channels of capacitance signals from the shank, the thigh, or both. With a phase-dependent linear discriminant analysis classifier and selected time-domain features, the system can achieve a satisfactory classification accuracy of $93.6\% \pm 0.9\%$ and $93.4\% \pm 0.8\%$ for able-bodied subjects and amputee subjects, respectively. The classification accuracy is comparable with that of EMG-based systems. More importantly, we verify that neuro-mechanical delay inherent in capacitive sensing does not affect the timeliness of classification decisions as the system, similar to EMG-based systems, can make multiple judgments during a gait cycle. Experimental results also indicate that capacitance signals from the thigh alone are sufficient for mode classification for both able-bodied and transtibial subjects. Our investigations demonstrate that capacitive sensing is a promising alternative to myoelectric sensing for real-time control of powered lower-limb prostheses.

Index Terms—Capacitive sensing, linear discriminant analysis (LDA), locomotion mode classification, lower-limb prosthesis, gait classification, wearable sensing system.

I. INTRODUCTION

PROSTHESES play an important role in amputees' daily life. Most existing commercial lower-limb prostheses are energetically passive. While they greatly improve the quality of

lower-limb amputees' life, these passive lower-limb prostheses have deficiencies as they are associated with more metabolic power and asymmetrical gait pattern [1]. As a result, powered lower-limb prosthesis is gaining popularity in the research field [1]–[9]. Control of a powered lower-limb prosthesis is a major challenge as the device must “intelligently” recognize people's locomotion patterns and flexibly adjust control modes in a timely manner [10]–[15].

Electromyography (EMG) signals, either conveyed by surface or intra-muscular electrodes, contain rich information from which an actor's movement intention can be detected and recognized. EMG-based pattern classification for upper-limb movements has been investigated for long with remarkable establishment in data segmentation, feature extraction and classification [16]–[20]. EMG has even been applied in the control of prosthetic hands and other upper-limb assisting devices [21]–[23]. Compared with the research on upper-limb prostheses, studies of lower-limb movement classification using EMG are limited [7], [10], [24], possibly due to high demands for safety and stability of lower-limb prostheses. Early investigations on EMG-controlled transtibial prostheses required the amputee to intentionally contract tibialis anterior, medial and lateral gastrocnemius to trigger a transition between control modes of level-ground walking and stair descent [10]. This control scheme is unintuitive and intermittent, falling short of fluent prosthesis control. Later studies systematically applied pattern recognition algorithms to EMG data streams, aided by mechanical signals, to automatically classify locomotion modes [7]–[9]. Though real-time classification is not yet achieved, these studies have generated promising results that are leading us towards viable and practical solutions for intelligent lower-limb prostheses.

Though being widely used, EMG signals have a few limitations for its implementation in prosthesis control. EMG signals are weak signals with microvolt-level intensity. Thus, they are difficult to measure and demand for dedicated signal amplification. Noninvasive surface EMG electrodes are widely used for EMG signal collection since invasive electrodes are not commonly accepted by people. However, surface EMG signals are prone to factors such as muscle fatigue and perspiration [25]. Sweating can also disturb EMG signals. To achieve good signal-to-noise ratio, the powered prosthesis has to be equipped with a well-designed hardware system that is able to amplify, filter and process EMG signals under the constraints of mobility and cost. Another concern is the availability of residual muscles for reliable EMG measurement on amputees. The sites suitable for placing electrodes are limited and they vary

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substantially across amputees. Taken together, the limitations of EMG signal and its measurement hinder its application to prosthesis control.

In the present study, we propose a wearable capacitive sensing system that is low-cost, simple to implement yet capable of performing locomotion mode classification accurately with acceptable delays. The capacitance signals reflect fine changes of leg shapes caused by muscle contractions during locomotive movements. They carry characteristic information about locomotion state such as specific gait phases and gait mode transitions. As indications of movement intention, these signals lag behind neural signals recorded directly from cortex but they closely follow behind EMG signals with delays of tens of milliseconds [26]–[28]. The capacitive sensing has been applied to human movement classification [29], [30] with promising performance. However, this technique has never been applied in locomotion mode classification for amputees. We designed a wearable capacitive sensing system with simple circuits and tested its performance in eight able-bodied subjects and five transtibial amputees. With selected feature sets and a simple phase-dependent linear discriminant analysis classifier (LDA), our system can achieve comparable, if not better, performance in recognizing locomotion modes with current EMG-based systems [7]. Importantly, our system partially overcomes the deficiencies of EMG systems and offers a low-cost alternative for intelligent prosthesis design.

II. MEASUREMENT SYSTEM

We first realized that leg shape changes constantly, driven by stereotypical but well-coordinated muscle contractions during locomotion. Our main goal is to record these shape changes on the shank and the thigh with two separate arrays of capacitors [Fig. 1(a)]. Each set of capacitors are mounted on a customized plastic band (Klarity Medical and Equipment, Guangzhou, China): 17 receiver electrodes made from copper sheets are mounted on the inner surface (seven for the shank and 10 for the thigh) and one transmitter electrode mounted separately above the band. The impedance (Z) between the transmitter and the receiver will vary if the capacitance (C) of the material between them (the soft tissue of human leg in particular) is changed according to $Z = (j\omega C)^{-1}$, where ω is the frequency of the driven signal that remains constant in our system. The capacitance C is determined by a number of factors, such as the area of the electrodes, the distance and the dielectric constant between electrode pairs. When the area and distance are constant or change very little, the capacitance mainly depends on the properties of the material between the electrodes such as its shape and structure [29]. Thus, the leg shape changes can be signified by impedance measurement from capacitor arrays that surround the leg. To register reliable readings from sensors, the sensing band was molded according to individual subject's leg shape. Insulating rubbers were pasted between electrodes to prevent the band from undesired slipping.

We designed the sensing front-end to indirectly measure the capacitance C [Fig. 1(b)]. The transmitter electrode, the impedance C_{body} and the resistor R_c in series make a current

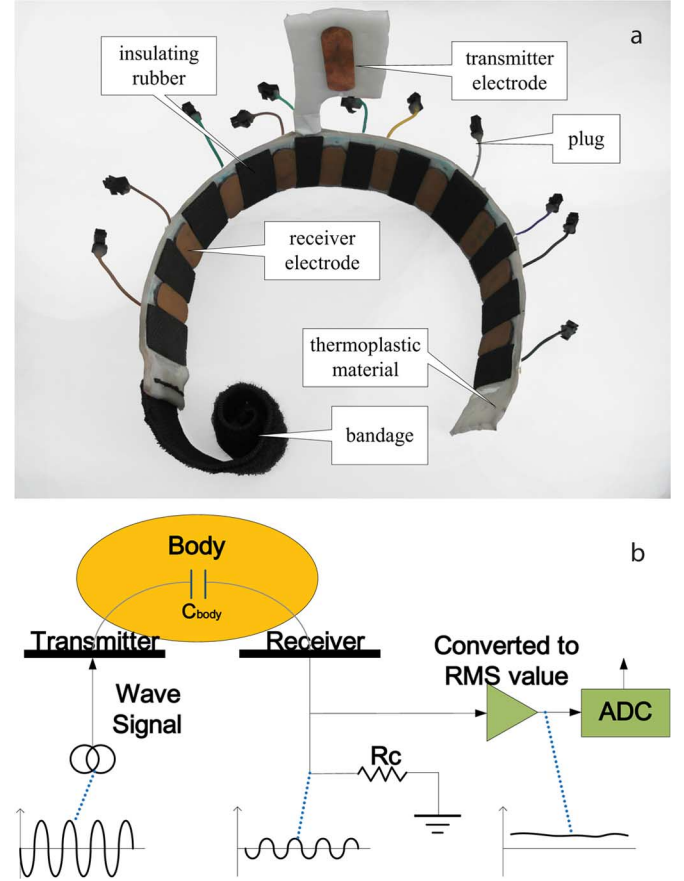


Fig. 1. (a) Sensing front-end used on the thigh. Electrodes are made from 0.3-mm-thick copper sheets and firmly attached to the inner surface of a thermoplastic ring. Area of each copper film is about $5 \times 2.5 \text{ cm}^2$. (b) Illustration of the sensing front-end design. Magnitude of the signal on the receiver electrode is influenced by movement-induced leg shape changes. Signal intensity is quantified by rms values of raw voltage readings.

loop, which is excited by a 100 kHz sinusoid signal from the transmitter. Data measured from the sensing front-end is fed into the processing circuits [Fig. 2(a)], which can process up to ten channels of signals. The oscillation module (MAX038) on the circuit generates the driven signal. To minimize waveform distortion, the signal is amplified by the driver module before applying on the front-end. Root mean square (rms) of raw voltage readings is computed for individual electrodes. It is sampled by a ten-channel 12-bit ADC-integrated Micro-programmed Control Unit (MCU) and then transmitted to a computer. This rms signal is treated as raw signal for pattern recognition. Depending on the subject, the estimated capacitance between electrode pairs is within $1 \sim 30 \text{ nF}$ and the average dielectric constant is about $60 \sim 80$.

Two footswitches are mounted on subjects' shoes to register foot contact events [Fig. 2(b) and (c)]. A detection circuit is integrated on the measuring system accordingly. A trigger signal is generated and sent to the main circuit whenever the footswitch contacts or leaves the ground. The main circuit samples the capacitance data and the footswitch data at a frequency of 1 kHz and passes them to the computer via Universal Asynchronous Receiver Transmitter (UART).

III. METHODS

A. Subjects and Experiment Protocol

Eight able-bodied subjects and five transtibial amputee subjects participated in the study and provided written and informed consent. Able-bodied subjects' age mean $\pm$ std was 24.3 ± 3.6 years, height was 1.76 ± 0.07 m, and weight was 76.1 ± 5.8 kg. The amputee subjects' age was 36.4 ± 13.0 years, height was 1.74 ± 0.04 m, and weight was 71.6 ± 15.1 kg. They wore their own prostheses during the experiment. Average ratio between the length of the residual shank (the distance between patella to the amputated site) to that of the sound shank (measured from patella to malleolus lateralis) was 0.43 ± 0.08 .

For able-bodied subjects, two capacitive sensing bands were worn on the thigh and the shank, respectively [Fig. 2(c)]. Half of the subjects wore the band on the left leg and the other half on the right. For the shank, we placed the band above the most prominent part of the calf to prevent the band from slipping. The other band was placed above the knee at the lower portion of the thigh. Transmitter electrodes were placed on bony areas or positions where muscle changes are minimal. The position of the sensing band was adjusted for each subject when first mounted to guarantee good sensor reading and comfort. Subjects then familiarized themselves for the tasks to be performed. During these familiarization trials, we manually selected five channels on each band that exhibited greatest signal changes. Only these channels were recorded for later analyses. In practice, the electrodes on the lateral and posterior sides of the thigh and the lateral side of the shank were often chosen. The transtibial amputees only wore the thigh sensing band on the amputated leg and all ten channels were measured and analyzed.

Six locomotion modes were examined in our experiment: standing, sitting, stair ascent, stair descent, obstacle clearance, and normal level-ground walking. We selected these locomotion modes for two considerations. First, these locomotion modes occur most frequently in daily life. Second, they demand for different control modes for powered lower-limb prostheses. Lateral turns (turning left or right on the level ground) were omitted as they share similar control schemes with level-ground walking. Each mode was performed in trials. For standing, subjects were asked to stand still for 10 s in a trial. For sitting, all the able-bodied subjects and four of the five amputee subjects were required to sit on a 42-cm-high chair while the remaining amputee subject on a 65-cm-high chair in his favor for 10 s. For stair ascent and descent, subjects walked up and down a four-stair staircase. Each stair was 75 cm in width, 40 cm in depth, and 15 cm in height. All the able-bodied subjects and two of the amputee subjects could climb stairs with a normal alternating pattern. The other three amputee subjects walked down one stair at a time for stair descent. For obstacle clearance, subjects were required to step over eight obstacles that were separated 70 cm apart on a straight and level path. Obstacles were 40 cm wide, 18 cm deep, and 25 cm high for able-bodied subjects, and they were adjusted to 40 cm wide, 25 cm deep, and 18 cm high for amputee subjects for safety. For able-bodied subjects, the nontested leg was required to step over obstacles first, followed by the tested leg. All amputee subjects stepped over obstacles with the amputated

leg first according to their preferences. For walking, all the subjects walked 13 steps in a straight line at their preferred speed. We organized the experiment trials into blocks, within which different movement modes were performed consecutively in a random but predefined order. Each mode was tested in trials; the numbers of trials within a block were 5, 5, 6, 5, 15, and 15 for standing, sitting, walking, obstacle clearance, stair ascent, and descent, respectively. The trial numbers were chosen in order to keep the number of steps approximately the same across movement modes. The experiment consisted of seven blocks with a rest time of 3 ~ 5 min in between. For amputee subjects, the rest time can be extended to up to 10 min by their request.

B. Classification

1) *Phase-Dependent Classification*: Similar to EMG signals, capacitance signals are quasi-cyclic (Fig. 3). In other words, capacitance signals within a gait cycle are phase-dependent and signal patterns are similar at the same phase. The signals from amputees exhibit different characteristics due to altered gait patterns but they are similarly quasi-cyclic (not shown). Given phase dependency of the signals, we performed classification within specific phases of a gait cycle that were delimited by two salient events, foot contact (FC) and off (FO) of the ground [7]. FO was determined at the first moment when both footswitches were off, while FC was determined at the first moment when one of the footswitches was on. Anchored on these two events, four phases were defined as prior to FC (Pre-FC), after FC (Post-FC), prior to FO (Pre-FO), and after FO (Post-FO). Analyses on sitting and standing did not require phase detection as no foot contact events could be utilized. To make continuous classification decisions, sliding windows were used on the data stream in each phase (see below).

2) *Feature Set and Classifier*: Though capacitance-based sensing has been proposed for long, there are few systematic investigations of suitable feature sets for classifying motion modes [29]. Time-domain features emerged as suitable candidates after initial examination of the capacitive signals. We evaluated an array of time-domain features that included mean, rms, standard deviation, maximum, minimum, interquartile range and mean absolute deviation of original signals as well as those of first-derivatives (including their absolute values) of original signals. A forward selection method was employed to select the feature set. Individual features were used for classification and then the ones that outperformed others were shortlisted. They were then grouped in pairs and tested again. The outstanding pair was again shortlisted and added with a third feature. These steps were repeated until a newly added feature could not further improve classification accuracy across subjects. The failure of further improvement was detected if 1) average improvement in cross-validation accuracy (see below) across subjects was less than 0.05%, or 2) classification accuracy decreased more than 0.5% for one or more subjects. In addition, we evaluated the performance of three classifiers including LDA (linear discriminant analysis), QDA (quadratic discriminant analysis), and LR (logistic regression). Their optimal feature sets were selected separately.

3) *Performance Evaluation*: To reliably evaluate the classification performance, we used leave-one-out-cross-validation

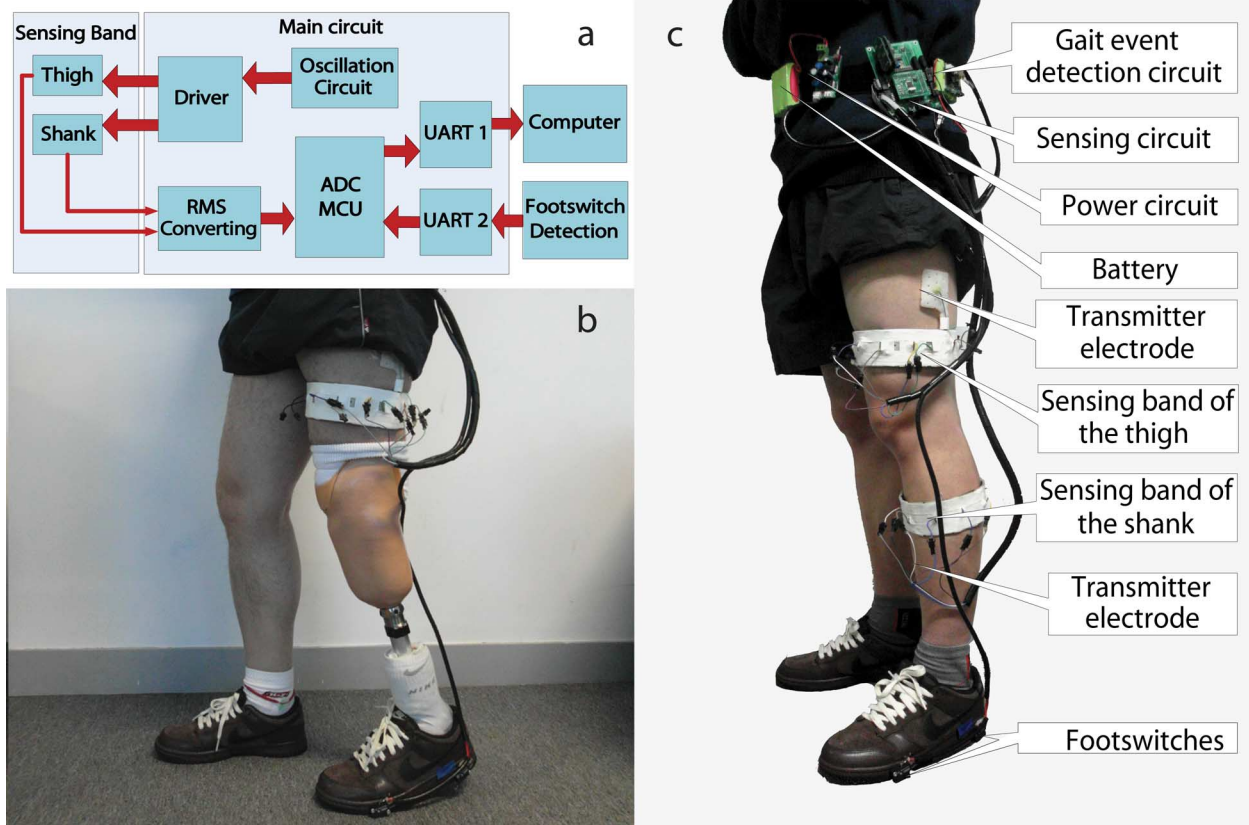


Fig. 2. (a) Architecture of the measurement system. Oscillation circuit generates sinusoid waveforms that are amplified by a driver and subsequently fed to the sensing-end. Signals from the sensing end and the footswitch are received by the MCU which performs AD conversion. MCU then transmits the data to the computer. (b) Capacitive sensing system worn on a transtibial amputee subject. (c) Capacitive sensing system worn on an able-bodied subject.

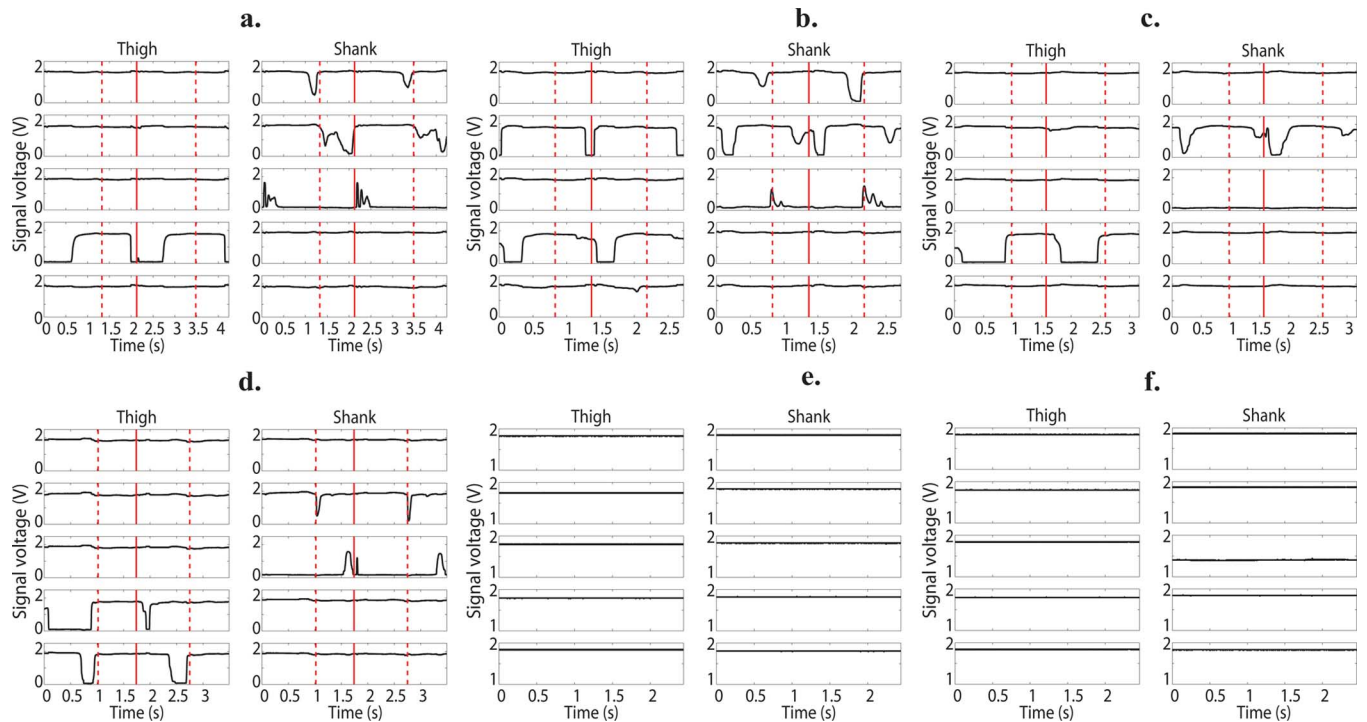


Fig. 3. Raw rms signals recorded from ten capacitive sensor channels during obstacle clearance, walking, stair ascent, stair descent, sitting and standing from an able-bodied subject. Five signal channels are from the thigh and the other five from the shank. For stair ascent, obstacle clearance, stair descent and walking, the signals of a full gait cycle are shown. The gait cycle begins at a foot contact with the ground and ends at the next foot contact. For sitting and standing, the signals shown are randomly selected during a trial with a length of 2.5 s. The solid red line denotes foot contact (FC) and the dash red line denotes foot off (FO). (a) Obstacle clearance. (b) Walking. (c) Stair ascent. (d) Stair descent. (e) Sitting. (f) Standing.

(LOOCV) for calculating classification error. Among seven experiment blocks, we randomly selected six blocks as the training dataset and the remaining block as the test dataset to evaluate the accuracy of classification. This procedure was repeated seven times and the overall performance was calculated.

The overall classification error (CE) is calculated by

$$CE = \frac{N_{\text{mis}}}{N_{\text{total}}} \times 100\% \quad (1)$$

where N_{mis} is the number of mislabeled test events and N_{total} is total number of test events.

Precision and recall are defined as

$$\text{Precision}(k) = \frac{tp_k}{tp_k + fp_k} \quad (2)$$

and

$$\text{Recall}(k) = \frac{tp_k}{tp_k + fn_k} \quad (3)$$

where tp_k , fp_k , and fn_k are the numbers of true positives, false negatives, and false positives for mode k , respectively.

As certain modes tend to be more frequently mislabeled as some other modes, we constructed the confusion matrix to quantify the error distribution

$$C = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{16} \\ c_{21} & c_{22} & \cdots & c_{26} \\ \cdots & \cdots & \cdots & \cdots \\ c_{61} & c_{62} & \cdots & c_{66} \end{pmatrix} \quad (4)$$

where each element is defined as

$$c_{ij} = \frac{n_{ij}}{\bar{n}_{i\bullet}} \times 100\% \quad (5)$$

n_{ij} is the number of events in mode i that are mistakenly labeled as mode j and $\bar{n}_{i\bullet}$ is the total number of events in mode i . Thus, higher off-diagonal numbers indicate higher misclassification rates.

C. Parameters in Classification

The continuous data stream is segmented in order to make multiple classification decisions within a gait cycle. For our phase-dependent classification, the parameters that affect data segmentation include the size of data segment (window size), the size of phase window (phase size), the increment of data window (window increment), and the combination of selected signal channels (measurement location).

1) *Window Size*: The continuous capacitance data stream is windowed into segments within which features can be derived. On one hand, larger windows usually lead to better classification accuracy as more relevant information can be extracted. On the other hand, large windows will cause delay in recognizing a mode transition and thus compromise real-time prosthesis control. We therefore need to determine the optimal window size by trading off between accuracy and response time. We systematically varied window size between 70 to 190 ms and investigated its impact on performance.

2) *Phase Size*: Four phases (Pre-FC, Post-FC, Pre-FO, and Post-FO) are defined to segment the data stream before performing classification. This phase-dependent classification has

been successfully applied in EMG-based locomotion classification [7]. Phase size determines the total amount of data in the continuous stream that can be used for classification. However, it is also bounded by the interval size between foot contact events (FC and FO) because overlap of phases should be avoided. Among our examined tasks, normal walking had the smallest inter-events interval of 439 and 499 ms for able-bodied subjects and amputee subjects, respectively. We thus defined the maximum phase size as 220 ms (half of the minimal interval). Under this constraint, phase size was varied to evaluate its impacts on classification performance.

3) *Window Increment*: The data window can be slid within a phase to make multiple classification judgments. This window increment determines the delay between decisions and, in conjunction with window size, the number of classification decisions. We investigated the effect of window increment by varying it from 10 to 50 ms.

4) *Measurement Location*: For able-bodied subjects, signals from both the shank and the thigh can be measured. But for transtibial amputees, we can only collected signals from the thigh. To investigate how much useful information can be extracted from different locations on the leg, we compared classification performance that were based on signals from only the shank, from only the thigh and from both. We also compared amputee subjects (with thigh sensors only) with able-bodied subjects with different sensor combinations.

D. Other Confounding Factors

1) *Sweating*: Sweat between the electrodes and the skin can influence the capacitance reading and it is inevitable after prolonged activity. For some sensors, e.g., EMG, it can influence recognition performance significantly [25]. Sweating is hardly noticed for the first half of experiments, while it can be observed during the last half of experiments. Therefore, the influence of sweating on our sensing system can be evaluated by comparing classification performance based on signals from the first three blocks and performance based on signals from the last three blocks.

2) *Leg Dominance*: Gait characteristics are usually different for the dominant and the nondominant side of the body. This asymmetry is subtle for the healthy but we want to investigate whether it affects our classification performance. The possible influence of leg dominance is also meaningful for amputees as their affected side can be different. Hence, for healthy controls half of them wore the system on the left (nondominant) leg and the other half on the right (dominant) leg. Classification performance was compared between these two groups. The amputees always wore the system on their affected leg.

IV. RESULTS

A. Feature Set and Classifier

Three candidate classifiers (LDA, LR, and QDA) were examined for feature selection separately. The optimal feature set for the LDA classifier included mean, maximum, minimum and rms of windowed signals, whereas it included maximum, minimum, rms, and standard deviation for the LR classifier and mean and minimum for the QDA classifier. The classification

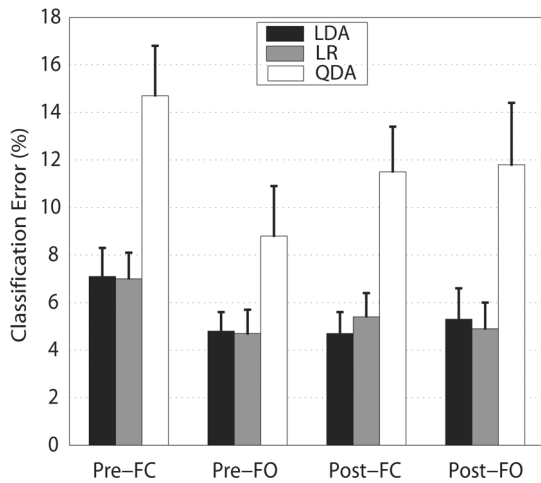


Fig. 4. Classification error for LDA, LR, and QDA in four gait phases. Data shown are averages $\pm$ SEM across eight able-bodied subjects. These classification errors were generated with optimal combinations of feature set, phase size, analysis window size, and window increment (see below).

performance of three classifiers with their optimal feature sets and optimal combination of parameters (phase size, window size, and window increment; see their selection process below) were compared side by side (Fig. 4). A one-way repeated measures ANOVA was performed to compare the classification error from three classifiers for each phase separately. It revealed that average classification errors for LDA and LR were similar ($5.46\% \pm 0.82\%$ and $5.51\% \pm 0.88\%$, respectively). Their error rates did not differ significantly for all four phases ($p = 0.899, 0.567, 0.195$, and 0.699 for Pre-FC, Pre-FO, Post-FC, and Post-FO, respectively). QDA offered worse performance as it produced significantly more errors ($11.73\% \pm 1.85\%$) than LDA and LR for all the four phases ($p < 0.05$).

Because LDA offered slightly better prediction accuracy and fast execution, we selected it for subsequent analyses.

B. Phase Size, Analysis Window Size, Window Increment, and Measurement Location

We first tested whether a real-time classification without foot contact events could achieve acceptable classification performance. The classification was conducted with a 150-ms analysis window and a LDA classifier. Classification errors with 10-ms and 50-ms window increment were 28.94% and 28.89%, respectively. These results were apparently unacceptable for practical use. We subsequently halved the data stream into stance phase (from FC to FO) and swing phase (from FO to FC), and performed the same sliding-window classification within each phase separately. Classification errors for swing phase were 17.03% and 17.22% for 10-ms and 50-ms window increment, respectively. For stance phase they were 24.53% and 24.78%, respectively. Again, this pseudo real-time classification could not achieve satisfactory classification performance, suggesting that phase-dependent classification is necessary.

We then used four phase windows as defined in Section III. Overall, classification error increased when phase size increased from 150 to 220 ms whereas window increment did not make significant difference [Fig. 5(a)]. Classification error was significantly higher with larger phase sizes ($p < 0.005$, one-way

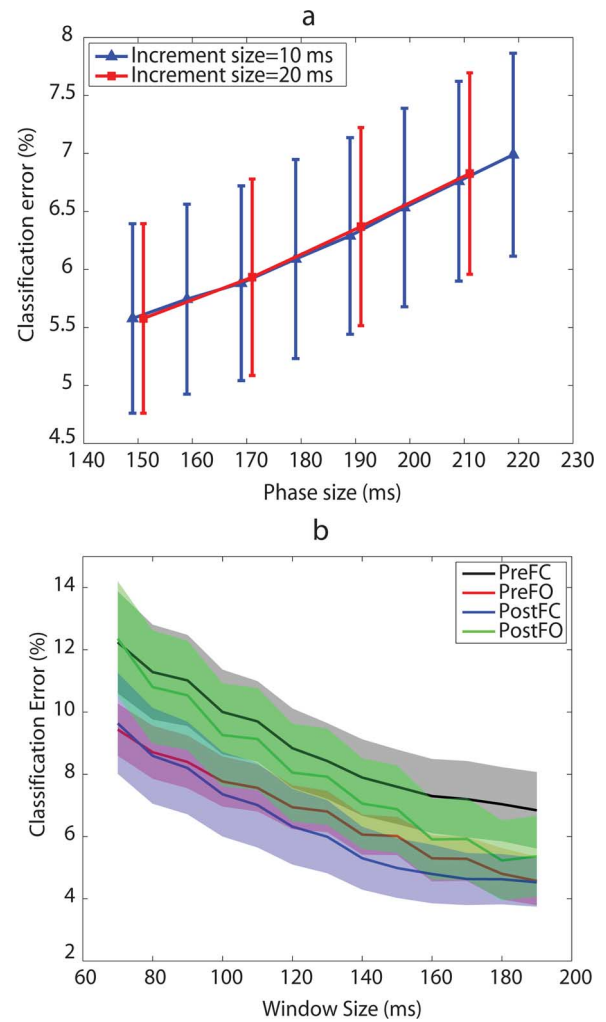


Fig. 5. (a) Average classification errors over eight able-bodied subjects using 10-ms and 20-ms window increments with phase size ranging from 150 to 220 ms. Results are obtained by using a LDA classifier and an analysis window size of 150 ms. Note that less data is shown for 20-ms window increment than for 10-ms window increment since the analysis window shifts less often with a larger window increment. (b) Average classification errors as a function of window size. Four phases (Pre-FC, Post-FC, Pre-FO, and Post-FO) are plotted separately. Data are from eight able-bodied subjects with a LDA classifier, a phase size of 190 ms and a window increment of 20 ms. Error bars and color shades denote SEMs across subjects.

repeated measures ANOVA). All pair-wise comparisons were significant, indicating that every increase in phase size led to increase in error. However, this error increase was merely 1.25% when phase size varied from 150 to 210 ms with a fixed window increment of 20 ms. The influence of window increment onto classification performance was also minimal. For example, classification error increased 0.89% when the increment changed from 10 to 50 ms with a fixed phase size of 190 ms. Trading off between accuracy and timeliness of classification decisions, we set phase size at 190 ms and window increment at 20 ms for subsequent analyses.

Window size greatly affected classification performance [Fig. 5(b)]. Smaller window meant that less data was used for classification and this in turn led to large errors. The error dropped dramatically with increasing window size but it leveled off around 150 ms. This trend was similar for different gait

phases. We thus took the average across phases and performed a one-way repeated measures ANOVA on window size. The main effect was significant ($p < 0.001$). Pair-wise comparisons between successive sizes yielded significant effect until 150 ms onwards. Thus, we selected 150 ms as our optimal window size as a trade-off between accuracy and response time.

We compared the classification performance with signals from the thigh, the shank, and from both [Fig. 6(a)]. For all the four phases, classification using signals from both the shank and the thigh achieved the best performance while using signals from the shank alone performed the worst. The differences were statistically significant for all the four phases as shown by one-way repeated-measure ANOVA. Post-hoc pair-wise comparisons confirmed that the best classification performance was indeed with signals from both the shank and the thigh and the difference between using shank alone and using thigh alone was not significantly in all the four phases ($p = 0.069, 0.112, 0.124$, and 0.231 for Pre-FC, Post-FC, Pre-FO, and Post-FO, respectively). Surprisingly, classification performance of amputee subjects using signals from the thigh only was on par with that of the able-bodied subjects. In fact, the performances were even slightly better than the average performance of able-bodied subjects in phase Pre-FC and Post-FO. It should be noted that ten channels of signals were measured from the thigh for amputee subjects, while only five channels of signals were measured for able-bodied subjects from the thigh. Thus, it appears that it is the number of signal channels that determines the classification performance for capacitive sensing. We therefore selected all the eight able-bodied subjects with ten channels of capacitance data from the thigh [Fig. 6(b)]. Using all ten channels of signals on the thigh yielded significantly lower classification error as compared to using only five channels ($p = 0.011$). In addition, we did not find significant difference between using ten thigh channels and using five shank and five thigh channels ($p = 0.077$). These results confirmed our conjecture that it was the number, instead of locations, of data channels that determined the classification accuracy. The performance was similar with ten channels of data no matter whether they were taken from one location (the thigh) or from two locations (the thigh and the shank). Taken together, our results imply that satisfactory classification can be achieved with signals from the thigh alone for the able-bodied participants as well as transtibial amputees.

C. Other Confounding Factors

We performed separate analyses with data from the first three blocks and the last three blocks to evaluate possible effects of sweat. Average errors over eight able-bodied subjects were $10.17\% \pm 1.50\%$ and $8.34\% \pm 1.58\%$ for these two periods, respectively. Thus, the accuracy was not significantly different between these two periods ($p = 0.362$, Wilcoxon signed-rank test), suggesting that sweat induced by long-time use does not significantly impact recognition performance.

We also compared classification performances with measurements from the dominant leg and with those from the nondominant. The average classification errors were $5.34\% \pm 2.90\%$ and $7.40\% \pm 1.56\%$ for the left wearers and the right wearers, respectively. The difference was not statistically significant ($p =$

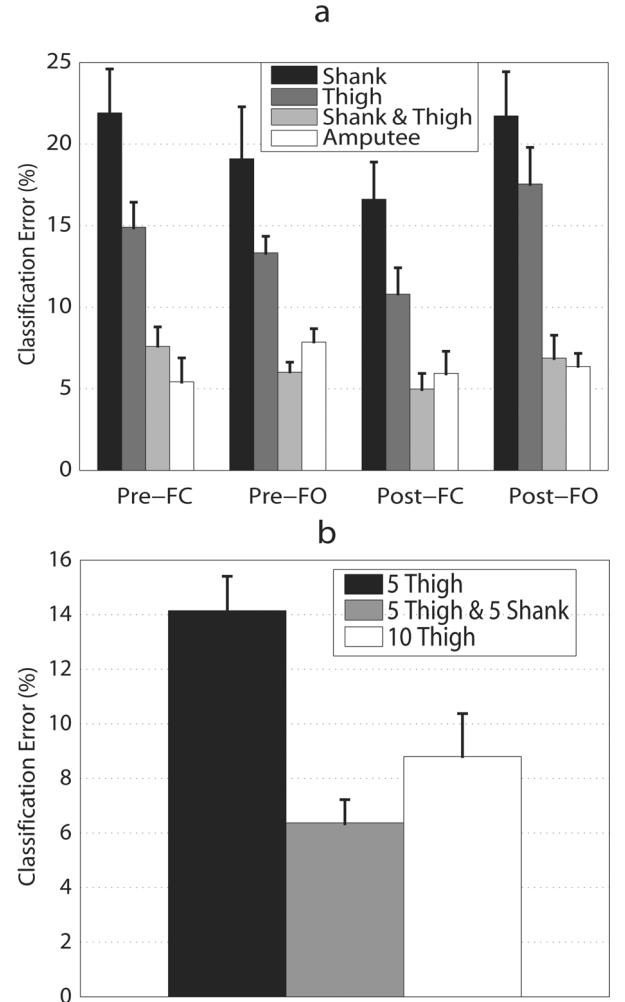


Fig. 6. (a) Classification errors of different combinations of signal channels. Data are from eight able-bodied subjects. Results are obtained by using a LDA classifier with 150-ms window size, 20-ms window increment, and 190-ms phase size. (b) Classification errors with different combinations of signal channels from eight able-bodied subjects who also participated in a control experiment where ten channels of data were taken from the thigh. The classification errors from this control experiment and from the original experiment are shown.

0.248, Mann-Whitney test). Thus, the leg dominance does not affect the classification performance of the system.

D. Overall Classification Accuracy

With optimal parameters determined above (phase size 190 ms, window size 150 ms, and window increment 20 ms), we estimated overall classification accuracies, precisions and recalls for all subjects. For eight able-bodied subjects, average precisions for obstacle clearance, walking, stair ascent, stair descent, sitting, and standing were 0.923 ± 0.005 , 0.930 ± 0.004 , 0.945 ± 0.005 , 0.950 ± 0.005 , 0.970 ± 0.009 , and 0.971 ± 0.004 , respectively. Corresponding average recalls were 0.908 ± 0.005 , 0.917 ± 0.005 , 0.938 ± 0.004 , 0.939 ± 0.003 , 0.964 ± 0.006 , and 0.951 ± 0.004 (Table I). Overall classification accuracies were $92.4\% \pm 1.2\%$, $95.0\% \pm 1.0\%$, $94.0\% \pm 0.6\%$, $93.1\% \pm 1.4\%$ for Pre-FC, Post-FC, Pre-FO, and Post-FO, respectively. We also constructed confusion matrixes to assess whether some modes tended to be mislabeled as some other specific modes

TABLE I
PRECISION AND RECALL (MEAN $\pm$ SEM) FOR EIGHT ABLE-BODIED SUBJECTS

		Locomotion mode					
	Phase	Obstacle Clearance	Walking	Stair Ascent	Stair Descent	Sitting	Standing
Precision	Pre-FC	0.956 $\pm$ 0.004	0.900 $\pm$ 0.008	0.931 $\pm$ 0.010	0.933 $\pm$ 0.009	0.929 $\pm$ 0.007	0.977 $\pm$ 0.004
	Post-FC	0.916 $\pm$ 0.007	0.955 $\pm$ 0.006	0.981 $\pm$ 0.004	0.952 $\pm$ 0.005	0.981 $\pm$ 0.008	0.974 $\pm$ 0.003
	Pre-FO	0.901 $\pm$ 0.008	0.914 $\pm$ 0.006	0.957 $\pm$ 0.003	0.978 $\pm$ 0.003	0.984 $\pm$ 0.003	0.947 $\pm$ 0.007
	Post-FO	0.918 $\pm$ 0.011	0.948 $\pm$ 0.007	0.912 $\pm$ 0.009	0.935 $\pm$ 0.007	0.960 $\pm$ 0.006	0.984 $\pm$ 0.005
Recall	Pre-FC	0.890 $\pm$ 0.017	0.900 $\pm$ 0.021	0.953 $\pm$ 0.013	0.912 $\pm$ 0.013	0.954 $\pm$ 0.023	0.935 $\pm$ 0.021
	Post-FC	0.920 $\pm$ 0.018	0.946 $\pm$ 0.018	0.981 $\pm$ 0.007	0.919 $\pm$ 0.021	0.973 $\pm$ 0.019	0.962 $\pm$ 0.012
	Pre-FO	0.915 $\pm$ 0.017	0.895 $\pm$ 0.018	0.920 $\pm$ 0.020	0.994 $\pm$ 0.003	0.965 $\pm$ 0.014	0.950 $\pm$ 0.017
	Post-FO	0.909 $\pm$ 0.032	0.929 $\pm$ 0.030	0.897 $\pm$ 0.021	0.931 $\pm$ 0.019	0.966 $\pm$ 0.019	0.956 $\pm$ 0.015

TABLE II
CONFUSION MATRIX (MEAN $\pm$ SEM) FOR EIGHT ABLE-BODIED SUBJECTS (%)

		Estimated Mode					
Phase	Targeted Mode	Obstacle Clearance	Walking	Stair Ascent	Stair Descent	Sitting	Standing
Pre-FC	Obstacle Clearance	89.0 $\pm$ 1.7	4.5 $\pm$ 1.4	4.5 $\pm$ 1.8	1.7 $\pm$ 0.5	0.3 $\pm$ 0.2	0.0 $\pm$ 0.0
	Walking	2.3 $\pm$ 0.8	90.0 $\pm$ 2.1	2.0 $\pm$ 1.4	5.3 $\pm$ 2.2	0.2 $\pm$ 0.1	0.2 $\pm$ 0.2
	Stair Ascent	0.9 $\pm$ 0.4	1.0 $\pm$ 0.5	95.3 $\pm$ 1.3	0.7 $\pm$ 0.5	2.0 $\pm$ 1.4	0.0 $\pm$ 0.0
	Stair Descent	0.9 $\pm$ 0.5	5.0 $\pm$ 1.2	0.7 $\pm$ 0.3	91.2 $\pm$ 1.3	1.9 $\pm$ 1.3	0.4 $\pm$ 0.2
	Sitting	0.0 $\pm$ 0.0	0.3 $\pm$ 0.2	1.7 $\pm$ 1.7	1.5 $\pm$ 1.5	95.4 $\pm$ 2.3	1.1 $\pm$ 1.1
	Standing	0.0 $\pm$ 0.0	0.1 $\pm$ 0.1	0.2 $\pm$ 0.2	3.4 $\pm$ 2.2	2.8 $\pm$ 1.6	93.5 $\pm$ 2.1
Post-FC	Obstacle Clearance	92.0 $\pm$ 1.8	2.8 $\pm$ 1.8	1.2 $\pm$ 0.6	2.7 $\pm$ 1.2	0.1 $\pm$ 0.1	1.2 $\pm$ 1.0
	Walking	3.4 $\pm$ 1.6	94.6 $\pm$ 1.8	0.4 $\pm$ 0.4	1.4 $\pm$ 1.1	0.2 $\pm$ 0.2	0.1 $\pm$ 0.1
	Stair Ascent	1.0 $\pm$ 0.8	0.1 $\pm$ 0.1	98.1 $\pm$ 0.7	0.3 $\pm$ 0.2	0.5 $\pm$ 0.2	0.0 $\pm$ 0.0
	Stair Descent	4.7 $\pm$ 1.3	1.6 $\pm$ 1.1	0.0 $\pm$ 0.0	91.9 $\pm$ 2.1	0.1 $\pm$ 0.1	1.7 $\pm$ 1.0
	Sitting	0.0 $\pm$ 0.0	0.1 $\pm$ 0.1	0.9 $\pm$ 0.9	1.6 $\pm$ 1.6	97.3 $\pm$ 1.9	0.0 $\pm$ 0.0
	Standing	0.2 $\pm$ 0.2	1.2 $\pm$ 0.9	0.0 $\pm$ 0.0	1.1 $\pm$ 1.1	1.4 $\pm$ 0.8	96.2 $\pm$ 1.2
Pre-FO	Obstacle Clearance	91.5 $\pm$ 1.7	4.0 $\pm$ 0.9	2.9 $\pm$ 1.3	0.9 $\pm$ 0.8	0.0 $\pm$ 0.0	0.7 $\pm$ 0.4
	Walking	6.9 $\pm$ 1.8	89.5 $\pm$ 1.8	1.7 $\pm$ 0.7	0.6 $\pm$ 0.2	0.0 $\pm$ 0.0	1.3 $\pm$ 1.2
	Stair Ascent	5.0 $\pm$ 2.4	2.1 $\pm$ 1.0	92.0 $\pm$ 2.0	0.3 $\pm$ 0.2	0.2 $\pm$ 0.2	0.5 $\pm$ 0.3
	Stair Descent	0.2 $\pm$ 0.1	0.2 $\pm$ 0.1	0.1 $\pm$ 0.1	99.4 $\pm$ 0.3	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0
	Sitting	0.0 $\pm$ 0.0	1.1 $\pm$ 1.1	0.0 $\pm$ 0.0	0.8 $\pm$ 0.8	96.5 $\pm$ 1.4	1.6 $\pm$ 1.1
	Standing	2.1 $\pm$ 1.0	1.1 $\pm$ 0.8	0.3 $\pm$ 0.2	0.0 $\pm$ 0.0	1.5 $\pm$ 1.0	95.0 $\pm$ 1.7
Post-FO	Obstacle Clearance	90.9 $\pm$ 3.2	3.2 $\pm$ 1.6	4.4 $\pm$ 1.7	1.3 $\pm$ 0.4	0.2 $\pm$ 0.1	0.0 $\pm$ 0.0
	Walking	2.1 $\pm$ 1.4	92.9 $\pm$ 3.0	1.5 $\pm$ 0.8	3.1 $\pm$ 2.6	0.0 $\pm$ 0.0	0.4 $\pm$ 0.4
	Stair Ascent	6.4 $\pm$ 1.9	1.4 $\pm$ 0.9	89.7 $\pm$ 2.1	2.4 $\pm$ 1.1	0.0 $\pm$ 0.0	0.1 $\pm$ 0.0
	Stair Descent	2.2 $\pm$ 1.1	1.3 $\pm$ 0.5	2.1 $\pm$ 0.9	93.1 $\pm$ 1.9	0.7 $\pm$ 0.3	0.5 $\pm$ 0.5
	Sitting	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	1.8 $\pm$ 1.8	0.9 $\pm$ 0.9	96.6 $\pm$ 1.9	0.7 $\pm$ 0.7
	Standing	0.5 $\pm$ 0.4	0.1 $\pm$ 0.1	0.5 $\pm$ 0.4	1.6 $\pm$ 1.0	1.7 $\pm$ 0.8	95.6 $\pm$ 1.5

(Table II). The confusion matrix appeared remarkably similar across phases. Sitting was most accurately recognized with an average accuracy of 96.5% over four phases; obstacle clearance and walking were the two modes with the lowest classification accuracies of 90.8% and 91.7%, respectively. For Pre-FC, walking and stair descent tended to be confused with each other: walking was mislabeled as stair descent 5.3% of the time and stair descent mislabeled as walking 5.0% of the time. For Post-FC, stair descent was mislabeled as obstacle clearance with an error of 4.7%. For Pre-FO, walking was mislabeled as obstacle clearance 6.9% of the time. For Post-FO, obstacle clearance and stair ascent were often confused with each other.

For five amputee subjects, average precisions were 0.928 ± 0.002 , 0.943 ± 0.007 , 0.902 ± 0.009 , 0.908 ± 0.010 , 0.995 ± 0.001 , and 0.967 ± 0.009 for obstacle clearance, walking, stair ascent, stair descent, sitting, and standing, respectively. Corresponding average recalls were 0.869 ± 0.013 , 0.941 ± 0.007 , 0.928 ± 0.007 , 0.906 ± 0.005 , 0.980 ± 0.009 , and 0.992 ± 0.001 (Table III). Overall classification accuracies were similar to those obtained from able-bodied subjects and they were $94.4 \pm 1.5\%$, $94.0 \pm 1.4\%$, $92.1 \pm 0.8\%$, and $93.3 \pm 0.8\%$ for Pre-FC, Post-FC, Pre-FO, and Post-FO, respectively (Table IV). However, phase-dependence of the

confusion matrix was slightly different for the amputees. Standing and sitting were the two modes with the highest recognition accuracies of 99.2% and 98.0%. Obstacle clearance was the most-likely mislabeled modes with average accuracy of 86.9%. For Pre-FC, obstacle clearance was easy to be mislabeled as stair ascent (4.8%) and stair descent (4.9%). For Post-FC, obstacle clearance, walking, and stair descent were easy to be mislabeled as each other. For Pre-FO and Post-FO, obstacle clearance, stair ascent, and stair descent were easy to be confused with each other.

V. DISCUSSION

We validated the use of a wearable capacitive sensing system for locomotion mode classification in the healthy and in the amputee. After exploring an array of signal features and classifiers, we provided evidence that capacitive sensing systems can achieve excellent classification performance, on par with EMG-based systems, with appropriately selected feature sets and system parameters. Our system also delivered excellent performance with signals measured from the residue limb of transtibial amputees, further demonstrating its robustness and the validity. We propose capacitive sensing as a promising

TABLE III
PRECISION AND RECALL (MEAN $\pm$ SEM) FOR FIVE AMPUTEE SUBJECTS

		Locomotion mode					
	Phase	Obstacle Clearance	Walking	Stair Ascent	Stair Descent	Sitting	Standing
Precision	Pre-FC	0.971 $\pm$ 0.005	0.928 $\pm$ 0.011	0.872 $\pm$ 0.016	0.921 $\pm$ 0.013	0.999 $\pm$ 0.000	0.978 $\pm$ 0.010
	Post-FC	0.916 $\pm$ 0.010	0.886 $\pm$ 0.017	0.971 $\pm$ 0.007	0.923 $\pm$ 0.013	0.994 $\pm$ 0.001	0.985 $\pm$ 0.005
	Pre-FO	0.878 $\pm$ 0.010	0.993 $\pm$ 0.001	0.871 $\pm$ 0.015	0.884 $\pm$ 0.021	0.996 $\pm$ 0.001	0.948 $\pm$ 0.011
	Post-FO	0.947 $\pm$ 0.004	0.967 $\pm$ 0.008	0.893 $\pm$ 0.016	0.903 $\pm$ 0.017	0.991 $\pm$ 0.002	0.958 $\pm$ 0.010
Recall	Pre-FC	0.885 $\pm$ 0.040	0.914 $\pm$ 0.030	0.951 $\pm$ 0.036	0.943 $\pm$ 0.020	0.983 $\pm$ 0.017	0.999 $\pm$ 0.001
	Post-FC	0.885 $\pm$ 0.033	0.910 $\pm$ 0.028	0.972 $\pm$ 0.010	0.910 $\pm$ 0.018	0.976 $\pm$ 0.024	0.989 $\pm$ 0.008
	Pre-FO	0.832 $\pm$ 0.046	0.957 $\pm$ 0.022	0.907 $\pm$ 0.022	0.871 $\pm$ 0.026	0.979 $\pm$ 0.021	0.983 $\pm$ 0.010
	Post-FO	0.873 $\pm$ 0.034	0.982 $\pm$ 0.011	0.883 $\pm$ 0.013	0.899 $\pm$ 0.038	0.983 $\pm$ 0.017	0.998 $\pm$ 0.002

TABLE IV
CONFUSION MATRIX (MEAN $\pm$ SEM) FOR FIVE AMPUTEE SUBJECTS (%)

		Estimated Mode					
Phase	Targeted Mode	Obstacle Clearance	Walking	Stair Ascent	Stair Descent	Sitting	Standing
Pre-FC	Obstacle Clearance	88.5 $\pm$ 4.0	1.7 $\pm$ 1.1	4.8 $\pm$ 2.2	4.9 $\pm$ 1.9	0.0 $\pm$ 0.0	0.2 $\pm$ 0.2
	Walking	1.5 $\pm$ 0.7	91.4 $\pm$ 3.0	3.6 $\pm$ 1.8	1.7 $\pm$ 1.2	0.0 $\pm$ 0.0	1.8 $\pm$ 1.8
	Stair Ascent	0.2 $\pm$ 0.1	2.8 $\pm$ 2.2	95.1 $\pm$ 3.6	0.4 $\pm$ 0.2	0.0 $\pm$ 0.0	1.5 $\pm$ 1.5
	Stair Descent	1.9 $\pm$ 0.7	2.0 $\pm$ 1.2	1.7 $\pm$ 1.4	94.3 $\pm$ 2.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0
	Sitting	0.0 $\pm$ 0.0	1.4 $\pm$ 1.4	0.0 $\pm$ 0.0	0.3 $\pm$ 0.3	98.3 $\pm$ 1.7	0.0 $\pm$ 0.0
	Standing	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.1 $\pm$ 0.1	99.9 $\pm$ 0.1
Post-FC	Obstacle Clearance	88.5 $\pm$ 3.3	6.2 $\pm$ 2.0	1.5 $\pm$ 1.1	3.5 $\pm$ 1.7	0.0 $\pm$ 0.0	0.3 $\pm$ 0.2
	Walking	5.2 $\pm$ 2.0	91.0 $\pm$ 2.8	0.5 $\pm$ 0.2	1.9 $\pm$ 1.1	0.2 $\pm$ 0.2	1.2 $\pm$ 1.2
	Stair Ascent	1.3 $\pm$ 0.5	0.9 $\pm$ 0.7	97.2 $\pm$ 1.0	0.1 $\pm$ 0.1	0.2 $\pm$ 0.2	0.2 $\pm$ 0.1
	Stair Descent	5.3 $\pm$ 1.1	3.0 $\pm$ 1.1	0.2 $\pm$ 0.1	91.0 $\pm$ 1.8	0.1 $\pm$ 0.1	0.3 $\pm$ 0.2
	Sitting	0.0 $\pm$ 0.0	1.2 $\pm$ 1.2	0.0 $\pm$ 0.0	1.2 $\pm$ 1.2	97.6 $\pm$ 2.4	0.0 $\pm$ 0.0
	Standing	0.0 $\pm$ 0.0	0.4 $\pm$ 0.4	0.0 $\pm$ 0.0	0.4 $\pm$ 0.4	0.2 $\pm$ 0.2	98.9 $\pm$ 0.8
Pre-FO	Obstacle Clearance	83.2 $\pm$ 4.6	0.1 $\pm$ 0.1	6.5 $\pm$ 2.7	8.6 $\pm$ 4.1	0.0 $\pm$ 0.0	1.6 $\pm$ 0.9
	Walking	0.0 $\pm$ 0.0	95.7 $\pm$ 2.2	2.3 $\pm$ 0.7	0.2 $\pm$ 0.1	0.0 $\pm$ 0.0	1.9 $\pm$ 1.6
	Stair Ascent	4.8 $\pm$ 1.9	0.3 $\pm$ 0.2	90.7 $\pm$ 2.2	1.8 $\pm$ 1.1	0.0 $\pm$ 0.0	2.4 $\pm$ 2.1
	Stair Descent	8.9 $\pm$ 2.3	0.2 $\pm$ 0.2	2.3 $\pm$ 0.9	87.1 $\pm$ 2.6	0.2 $\pm$ 0.2	1.3 $\pm$ 1.2
	Sitting	1.5 $\pm$ 1.5	0.0 $\pm$ 0.0	0.3 $\pm$ 0.3	0.3 $\pm$ 0.3	97.9 $\pm$ 2.1	0.0 $\pm$ 0.0
	Standing	1.1 $\pm$ 1.1	0.0 $\pm$ 0.0	0.4 $\pm$ 0.4	0.0 $\pm$ 0.0	0.2 $\pm$ 0.2	98.3 $\pm$ 1.0
Post-FO	Obstacle Clearance	87.3 $\pm$ 3.4	0.7 $\pm$ 0.6	6.4 $\pm$ 3.2	5.3 $\pm$ 2.3	0.0 $\pm$ 0.0	0.2 $\pm$ 0.2
	Walking	0.3 $\pm$ 0.3	98.2 $\pm$ 1.1	0.6 $\pm$ 0.4	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.9 $\pm$ 0.8
	Stair Ascent	3.4 $\pm$ 1.0	2.7 $\pm$ 1.4	88.3 $\pm$ 1.3	4.5 $\pm$ 2.2	0.8 $\pm$ 0.6	0.3 $\pm$ 0.1
	Stair Descent	2.8 $\pm$ 1.3	0.6 $\pm$ 0.3	2.1 $\pm$ 0.9	89.9 $\pm$ 3.8	0.2 $\pm$ 0.2	4.5 $\pm$ 3.4
	Sitting	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	1.7 $\pm$ 1.7	0.0 $\pm$ 0.0	98.3 $\pm$ 1.7	0.0 $\pm$ 0.0
	Standing	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.2 $\pm$ 0.2	99.8 $\pm$ 0.2

alternative to myoelectric sensing for real-time mode classification in powered intelligent prostheses.

Capacitance-based sensing system is a promising alternative for the following reasons. First, the system can offer excellent accuracy and fast response as benchmarked to EMG-based systems. The average accuracy is 93.6% and 93.4% for the healthy controls and the amputees, respectively. A combination of a phase-dependent classification scheme and a 150 ms sliding-window on the data stream can yield multiple classification decisions within a gait cycle. This result is encouraging since a crucial concern for using capacitive sensing as an alternative to EMG is that the capacitance signal, reflecting miniature limb deformations, is temporally lagged behind muscular activation. Our results suggest that the small time lag do not affect the overall classification performance.

Second, the performance of the system is scalable with the number of signal channels. For healthy controls the system performed substantially better with ten capacitive channels than with five channels [Fig. 6(a) and (b)]. An interesting finding is that this performance boost was independent of the locations of the extra five channels, being on the shank or on the thigh. Furthermore, the performance was equally well for the amputees and the healthy controls when both groups had all ten chan-

nels on the thigh. These results suggest that measurements on a single location of the limb can provide sufficient information for locomotion mode classification in the healthy and amputees. We postulate that the performance can be further improved if more capacitive channels are mounted. Note this easy scalability of the system is another advantage over EMG systems, which are constrained by limited electrode sites on the residue limb that are available for collecting quality myoelectric signals.

Third, signal preprocessing in our capacitance-based system is minimalistic. The raw voltage signal is digitized and numerically converted to rms values without any amplifying or filtering, both of which are mandatory for EMG systems. This means that preprocessing module for the system can be simplified. Combined with simple capacitance sensors, the overall cost of the capacitive system is considerably lower than that of EMG-based systems.

The present investigation constitutes our initial effort for building intelligent prosthesis control with capacitive sensing. Based on our experimental results we make the following recommendations. First, phase-dependent approach is necessary to achieve acceptable classification performance. Classification accuracy was substantially degraded when we applied a real-time sliding-window scheme to our dataset without consid-

ering foot contact events. Similar findings have been reported in studies based on EMG signals [7]. Under the scheme with foot contact-determined phases, the classification accuracy was acceptable with a range of phase sizes and window increment sizes [Fig. 5(a)] as long as a sufficiently large window size was used. Second, for acceptable performance the window size for signals should be no less than 150 ms. Larger window of data led to better performance in general, but its improvement quickly saturated [Fig. 5(b)]. A window size of 150 ms is optimal in balancing accuracy and timely response. Third, a limited set of time-domain features and a simple LDA classifier suffice for our classification purpose. Unlike EMG signals spanning a large frequency band, capacitance-based signals, rms voltage signals in particular, are slow-varying signals that can be characterized sufficiently well with time-domain features. We postulate that this is one of the major reasons that our seemingly simple feature set and a plain LDA classifier can achieve excellent performance.

The error rate in classification depended on gait phases and this dependence was slightly different between the amputees and the healthy controls. For healthy controls, obstacle clearance was prone to being mislabeled as walking and stair ascent during Pre-FC, while walking and stair descent were often confused with each other. These patterns of classification error were similar observed in the Post-FO phase, suggesting that leg shape changes similarly in these locomotion modes during free swing. Correspondingly, these two phases had the highest overall classification error rate among four phases. In contrast, for amputees the average classification error was similar across four phases. We observed obstacle clearance, stair ascent and stair descent were easy to be confused with each other during two phases before and after foot off (Pre-FO and Post-FO). This was probably caused by the missing of toe joint and ankle joint: they lifted the prosthetic foot without pushing off the ground as the healthy controls did at the beginning of swing, which made it similar for the three locomotion modes. We also found that obstacle clearance, walking and stair descent were often mislabeled as each other in phase Post-FC. This tendency was possibly related to the particular way amputees used the affected leg: they preferred to place the affected (and tested) leg to the lower stair and used it as a pivot for swinging the untested leg. Similarly, they stepped over the obstacles with the affected leg first to provide the support. The passive loading on the tested leg during the support phases supposedly induced similar leg shape changes.

Our capacitive sensing system, though being promising, has its limitations and needs further improvements. It is not sufficient to be used independently for an intelligent prosthesis control system and should be used in combination with other sensors (similar to EMG sensing). In its current hardware format, it is difficult to mount on the thigh for transfemoral amputees who probably need to integrate the sensing band into the prosthetic socket. Its effectiveness in the socket needs further experimental validation. For example, long-term use of the hard sensing band in the socket might induce pressure ulcers which might contaminate the signal. One potential solution is to replace the current sensing front-end with fiber sensing materials that are more flexible and accurate [29]. Soft fiber material means that it can be worn at multiple locations, including within socket and on the

unaffected leg if necessary to provide more meaningful motion information for control and classification.

We are currently using two foot switches on the shoe for providing trigger signals to segment gait phases. They can be replaced with strain gauge mounted at the ankle joint of the prosthesis to provide phase detection as well as information about contact force for better recognition. We believe this will not only simplify the system but also make it more robust against terrain changes. We can also quantify capacitive signals by using measures other than rms of voltage signals. This might open the opportunities for finding better feature sets.

Powered prosthetic legs usually have various sensors on-board, including gyroscope, goniometer, and force sensor arrays under the foot and within socket, as well as EMG electrodes [2], [8], [10], [13]. We believe capacitive sensing can be an important addition to this arsenal given its similar performance as those of EMG-based systems.

VI. CONCLUSION

In the present study, we propose a capacitive sensing system as a locomotion mode classification tool for lower-limb prosthesis control. Our system is simple in design and implementation, yet it offers excellent classification accuracy and timely response similar to those offered by EMG-based systems. The capacitive sensing essentially measures shape changes of the leg during activities; our experiments evidence that this information, even collected from the residue limb of transtibial amputees, is sufficient for locomotion mode classification without much time lags. As a viable and inexpensive alternative to EMG-based systems, capacitive sensing can be further improved by continuing endeavors on hardware design, integration with other sensors and more thorough experiments.

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REFERENCES

- [1] S. Au, J. Weber, and H. Herr, "Powered ankle-foot prosthesis Improves walking metabolic economy," *IEEE Trans. Robotics*, vol. 25, no. 1, pp. 51–66, Feb. 2009.
- [2] F. Sup, H. Varol, J. Mitchell, T. Withrow, and M. Goldfarb, "Preliminary evaluations of a self-contained anthropomorphic transfemoral prosthesis," *IEEE/ASME Trans. Mechatronics*, vol. 14, no. 6, pp. 667–676, Dec. 2009.
- [3] J. Hitt, T. Sugar, M. Holgate, R. Bellmann, and K. Hollander, "Robotic transtibial prosthesis with biomechanical energy regeneration," *Indust. Robot.*, vol. 36, no. 5, pp. 441–447, 2009.
- [4] R. Versluis, A. Desomer, G. Lenaerts, M. Van Damme, P. Bey, G. Van der Perre, L. Peeraer, and D. Lefeber, "A pneumatically powered below-knee prosthesis: Design specifications and first experiments with an amputee," in *Proc. 2nd IEEE/RAS-EMBS Int. Conf. Biomed. Robot. Biomechatron.*, Oct. 2008, pp. 372–377.
- [5] R. Bellman, M. Holgate, and T. Sugar, "SPARKy 3: Design of an active robotic ankle prosthesis with two actuated degrees of freedom using regenerative kinetics," in *Proc. 2nd IEEE/RAS-EMBS Int. Conf. Biomed. Robot. Biomechatron.*, Oct. 2008, pp. 511–516.
- [6] B. Bergelin, J. Mattos, J. Wells, Jr, and P. Voglewede, "Concept through preliminary bench testing of a powered lower limb prosthetic device," *J. Mech. Robot.*, vol. 2, no. 4, pp. 41005–41013, Nov. 2010.

- [7] H. Huang, T. A. Kuiken, and R. D. Lipschutz, "A strategy for identifying locomotion modes using surface electromyography," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 1, pp. 65–72, Jan. 2009.
- [8] H. Huang, F. Zhang, L. Hargrove, Z. Dou, D. Rogers, and K. Englehart, "Continuous locomotion mode identification for prosthetic legs based on neuromuscular-mechanical fusion," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 10, pp. 2867–2875, Oct. 2011.
- [9] H. Huang, F. Zhang, Y. Sun, and H. He, "Design of a robust EMG sensing interface for pattern classification," *J. Neural Eng.*, vol. 7, no. 5, p. 056005, Oct. 2010.
- [10] S. Au, M. Berniker, and H. Herr, "Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits," *Neural Netw.*, vol. 21, no. 4, pp. 654–666, May 2008.
- [11] E. C. Martinez-Villalpando and H. Herr, "Agonist-antagonist active knee prosthesis: A preliminary study in level-ground walking," *J. Rehabil. Res. Develop.*, vol. 46, pp. 361–373, 2009.
- [12] H. A. Varol, F. Sup, and M. Goldfarb, "Powered sit-to-stand and assistive stand-to-sit framework for a powered transfemoral prosthesis," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, Jun. 2009, pp. 645–651.
- [13] H. A. Varol, F. Sup, and M. Goldfarb, "Multiclass real-time intent recognition of a powered lower limb prosthesis," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 3, pp. 542–551, Mar. 2010.
- [14] F. Sup, H. A. Varol, and M. Goldfarb, "Upslope walking with a powered knee and ankle prosthesis: Initial results with an amputee subject," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 1, pp. 71–78, Feb. 2011.
- [15] K. Yuan, J. Zhu, Q. Wang, and L. Wang, "Finite-state control of powered below-knee prosthesis with ankle and toe," in *Proc. 18th IFAC World Congress*, Aug. 2011, pp. 2865–2870.
- [16] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, Jan. 1993.
- [17] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.
- [18] J. U. Chu, I. Moon, and M. S. Mun, "A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 11, pp. 2232–2239, Nov. 2006.
- [19] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, Aug. 2008.
- [20] G. Li, A. E. Schultz, and T. A. Kuiken, "Quantifying pattern recognition-based myoelectric control of multifunctional transradial prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 185–192, Apr. 2010.
- [21] O. Fukuda, T. Tsuji, M. Kaneko, and A. Otsuka, "A human-assisting manipulator teleoperated by EMG signals and arm motions," *IEEE Trans. Robot. Autom.*, vol. 19, no. 2, pp. 210–222, Apr. 2003.
- [22] C. Cipriani, F. Zaccane, S. Micera, and M. C. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: Analysis of user-prosthesis interaction," *IEEE Trans. Robotics*, vol. 24, no. 1, pp. 170–184, Feb. 2008.
- [23] C. Castellini and P. van der Smagt, "Surface EMG in advanced hand prosthetics," *Biol. Cybern.*, vol. 100, no. 1, pp. 35–47, Jan. 2009.
- [24] L. Peeraer, B. Aeyels, and G. Van Der Perre, "Development of EMG based mode and intent recognition algorithms for a computer-controlled above-knee prosthesis," *J. Biomed. Eng.*, vol. 12, pp. 178–182, May 1990.
- [25] J. W. Sensinger, B. A. Lock, and T. A. Kuiken, "Adaptive pattern recognition of myoelectric signals: Exploration of conceptual framework and practical algorithms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 3, pp. 270–278, Jun. 2009.
- [26] P. Cavanagh and P. Komi, "Electromechanical delay in human skeletal muscle under concentric and eccentric contractions," *Eur. J. Appl. Physiol. Occupat. Physiol.*, vol. 42, no. 3, pp. 159–163, 1979.
- [27] L. Li and B. Baum, "Electromechanical delay estimated by using electromyography during cycling at different pedaling frequencies," *J. Electromyogr. Kinesiol.*, vol. 14, no. 6, pp. 647–652, Dec. 2004.
- [28] R. Norman and P. Komi, "Electromechanical delay in skeletal muscle under normal movement conditions," *Acta Physiol. Scand.*, vol. 106, no. 3, pp. 241–248, Jul. 1979.
- [29] J. Cheng, O. Amft, and P. Lukowicz, "Active capacitive sensing: Exploring a new wearable sensing modality for activity recognition," in *Pervasive Computing*. New York: Springer, Jan. 2010, Lecture Notes Computer Sci., pp. 319–336.

- [30] J. Rekimoto, "Gesturewrist and gesturepad: Unobtrusive wearable interaction devices," in *Proc. 5th Int. Symp. Wearable Comput.*, Oct. 2001, pp. 21–27.



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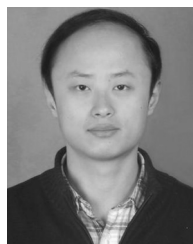
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