

# A method to determine the optimal features for control of a powered lower-limb prostheses

M Todd Farrell  
Biomechatronics Group  
Massachusetts Institute of Technology  
Cambridge, MA 02139  
Email: mtfarrel@mit.edu

Hugh Herr  
Biomechatronics Group  
Massachusetts Institute of Technology  
Cambridge, MA 02139  
Email: hherr@mit.edu

**Abstract**—Lower-limb prostheses are rapidly advancing with greater computing power and sensing modalities. This paper is an attempt to begin exploring the trade-off between extrinsic and intrinsic control modalities. In this case, between electromyographic (extrinsic) and several internal sensors that can be used for intrinsic control. We propose a method that will identify the particular features, taken from two trans-femoral amputee and one trans-tibial amputee, during locomotion on varying terrain, that perfectly discriminate between locomotion modes. From this we are able to identify the source of the discriminability from a large-set of features that does not depend on the type of amputation. Also, we comment on the use of this algorithm in selecting the most discriminatory and least encumbering sensor/feature combination for transitions when the ground underneath the foot is unknown for trans-tibial amputees.

## I. INTRODUCTION

Recently, robotic prostheses for the lower-limbs have been shown to improve the efficiency of level-ground walking [4]. These prostheses incorporate computerized control and can assist users with level-ground walking. The use of embedded computers makes complicated locomotion tasks tractable by allowing more powerful control algorithms to be used during movement. Most robotic prostheses take sensor information from internal sensors (sensors that are located on the prosthesis) to control the behavior of the ankle during a typical gait cycle – this is called intrinsic control. Less frequently, a robotic prosthesis can take information from external sources of information for control algorithms – this is called extrinsic control.

Currently, users can change the mode of their prosthesis manually at the cost of a relatively non-intuitive interface [7]. We feel that these interfaces are too cumbersome for biomimetic terrain adaptation. An interface that requires the user to stop and start when they want to change their mode of locomotion or stare at their hands during movement is never going to be as efficient as human locomotion adaptation. Our solution is to develop a robotic prosthesis that can utilize a group of sensors attached to an instrumented limb to smooth transitions between terrain modes.

Electromyography (EMG) has been used in upper-limb prosthesis control for decades [8][9][10][11]. It is the primary neural control input to the majority of robotic upper-limb

prostheses. It has been shown to be effective when used with pattern recognition algorithms that infer the intention of the user. More recently, the desire to make lower-limb prostheses that can adapt to terrain in a biomimetic way has spurred interest in using neural signals as a control input. Very recently, a pattern recognition method for identifying locomotion modes from EMG has been developed[2]. The results suggest that the thigh muscles of a trans-femoral amputee might be sufficient to obtain reasonably accurate identification of terrain, but they concluded that classification with EMG alone may not be sufficient for robust classification of different locomotion modes. Earlier work by Praeer et. al. [6], show that there is a difference in EMG envelope, which suggests that hip-muscles might be useful in discriminating different locomotion modes. Huang et. al [2], also observed this and developed a system around it capable of discriminating different user-modes. In addition, the author did not select those features of the EMG signal that were the *most* useful. In 2006, Jin et. al. [5] developed an algorithm that identified terrain during level-ground walking. However, features were extracted from one entire gait-cycle, which would make implementation in a real-time system dangerous; the delay introduced by waiting one whole gait-cycle to determine terrain can easily lead to falls. Farrell, et. al. [12] reports that an optimal controller delay for upper-limb prosthesis is between 100ms and 125ms, and there is a linear performance degradation as the system delay is increased. Based on the previous work, it is our opinion that a strategy that uses very fast updates should be used to identify user locomotion modes on varying terrain.

The EMG signal is difficult to use for locomotion mode discrimination; it is time varying and the features of the signal change within the same task over time. In order to quickly discriminate between locomotion modes, the electromyographic recording of each task needs to have a repeatable difference that can be observed by a collection of features. Using a larger window can increase the amount of information available for decision making with a pattern recognition algorithm. However, by using a larger window it is possible that features between two modes might overlap and decrease the accuracy of a pattern recognition algorithm, so instead we used short windows ( 200ms) to extract EMG information. This was observed between toe-off and heel-strike during some trials

in [2].

Until a reliable form of neural-control is developed, robotic prostheses will likely use data-fusion [13], incorporating sensor information from a variety of sensors, to determine the type of terrain the user is walking over. Without a good feature selection algorithm it would be impossible to develop a robust data-fusion algorithm that can estimate terrain. More specifically, a data-fusion algorithm uses the features of a signal to estimate the state of the robotic-ankle prosthesis continuously. For the data-fusion algorithm to track variables continuously, or discriminate between locomotion modes, the features should have strong discriminatory power. In this work, we take the first step in developing a data-fusion algorithm by first understanding which features of both EMG and other internal sensors are useful in discriminating between locomotion modes.

Outside of EMG there are large range of sensors that can be used, and that are placed directly inside a lower-limb prostheses. Many studies have used accelerometers, gyros, strain gauges, goniometers to infer the state of the ankle in the real world (see [?] and references within).

Our approach is to use wrapper-based feature selection methods [14] to focus on those features and muscles that provide the lowest-error classifiers for two trans-femoral amputees and one trans-tibial amputee. Hargrove, et al. [1] have used similar approaches for upper-limb prostheses. The researchers successfully used uncorrelated linear discriminant analysis (ULDA) to discriminate between movement classes in upper-limb prostheses. Their results suggest that using several different classifiers that train between several pairs different tasks might be more practical than building one classifier for all classes. The individual classifiers could be combined in an intelligent way to produce a classification based on the weighting among those individual classifiers. Later work [2], showed it is possible to extract large amounts of neuromuscular information from electromyography from windows at important points of the gait cycle. However, in previous work no one has picked out the particular features of the lower limbs that are mostly responsible for classification accuracy. Our work builds off these two previous works and develops a novel feature selection method that can be used with above-knee and below-knee amputees and directly attribute classification accuracy with specific features. Specific results concerning both groups are discussed. There are way to improve this method and specific ways this method can be improved will be discussed.

## II. METHODS

### A. Participants and Measurements

This study was conducted with approvals from Institutional Review Board (IRB) approval and informed consent of all subjects. The trans-tibial subject contained data collected with the approval from the Committee on Humans as Experimental Subjects (COUHES). The ages of our subjects were 55 and 50 for the trans-femoral amputees and 46 for the trans-tibial amputee.

The muscles used for the trans-tibial and trans-femoral amputees are listed in Table I. The two trans-femoral subjects, TF01 and TF04, were 42 and 16 years post-amputation, respectively. The level of amputation was unavailable at the time of submission.

We used active surface electrodes to record signals from the subjects. For the trans-tibial subject the electrodes were manufactured by Motion Labs Systems(MA-411-002, Motion Lab System, Inc.) which consisted of two contacts only. For the trans-femoral and trans-tibial subjects, electrodes (MA-411-002, Motion Lab System, Inc.) consisted of two contacts only, and were mounted in an experimental socket liner. They were similar to conventional electrodes, but were designed to be stable while inside a patient mounted socket.

The gait-events were recorded using force-sensitive resistor-based foot switches that were place under the ball of the foot and the heel in all cases. For the trans-tibial amputee, six-axis Inertial Measurement Unit (IMU) data were simulated using optical motion capture data. 10mm reflective markers were placed on the shank, lateral knee, and lateral ankle. The plane formed by these three markers were used to estimate the roll, pitch, and yaw of the plane in space, and in addition to gyroscoping measures, the location of each marker's three dimensional position in lab-frame coordinates. The motion capture system we used for the trans-tibial amputee, was a Vicon 8i system with 12 cameras. The capture rate was 120 hz with sub-millimeter accuracy of the center of each reflective marker.

### B. Experimental Protocol

1) *Trans-femoral Protocol*: We studied four different locomotion modes that are listed in TableII. Level ground was tested on a flat walk-way in a laboratory setting. The ramps were 5 degree ramps going up and down. During the obstacle condition we asked the participant to step over an obstacle with dimensions (10 cm x 10 cm x 50 cm). Each trial only recorded a specific activity and not the transitions between particular terrains.

2) *Trans-tibial Protocol*: We studied two different terrains; positive 15 degree to negative 15 degree ramps and negative 15 degree to positive 15 degree ramps. The subject was asked to start walking after a short count and recorded ended one they finished a climb on each of the long 15 degree ramps.

### C. Data Analysis

The data analysis of the clinical EMG data took place in three parts; the data from EMG was first filtered, then features were extracted to obtain features that characterized the EMG signal from each of the 10 channels of recorded clinical data, and the final step classified these data into each separate task-type. A wrapper method, Sequential-Forward-Search, was used to find the subset of features that maximized the leave-one-out-cross-validation (LOOCV) performance on the training.

Notation Legend	
ID	IMU position
D	displacement
Y	yaw
P	pitch
R	roll
Trans-femoral	
ID	Muscle
VM	vastus medialis
GN	left gastrocnemius
RF	rectus femoris
MG	medial gastrocnemius
VL	vastus lateralis
RBF	right bicep femoris
BF	bicep femoris
RRF	right rectus femoris
ST	semitendinosus
GM	gluteus maximus
Trans-tibial	
ID	Muscle
VM	vastus medialis
GN	left gastrocnemius
RF	left rectus femoris
MG	medial gastrocnemius
VL	vastus lateralis
LBF	left bicep femoris
RBF	right bicep femoris
RRF	right rectus femoris
ST	semitendinosus
GM	gluteus maximus
TA	tibialis anterior

TABLE I  
THE INTRINSIC AND EXTRINSIC SENSING WAS DONE WITH ACCELEROMETERS AND ELECTROMYOGRAPHY, RESPECTIVELY.

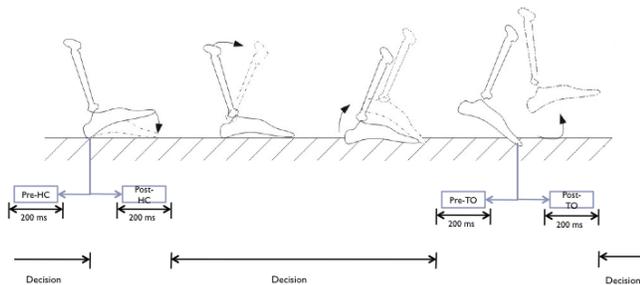


Fig. 1. The layout of the sliding windows in the setting described in [2]. Decisions are made at the beginning and end of stance with the time between devoted to identification of the terrain underneath the foot.

1) *Phase-dependent Bayes Classifier*: The phase-dependent classifier was introduced in [2] to account for the non-stationary behavior of EMG over time and increase the responsiveness of the system. The windows are placed near important points in the signal. The majority of muscular information is likely to be present in the extrinsic and intrinsic signals primarily during stance and near the beginning of swing.

Classifiers that use longer time windows are subject to continual changes in the EMG signal. The phase-dependent classifier relies on the quasi-cyclic nature of the EMG signal at these key points in the gait cycle. At these points the signal has low-variation in the second order moment of the signal, is

quasi-stationary, and repeatable at the same time in the gait cycle. This benefits any classifier that uses the statistics of the signal to perform pattern recognition.

The *naive bayes classifier* is a simple probabilistic classifier that makes strong assumptions about the independence of the features – essentially, it is an independent feature model. Mathematically, given a terrain of type,  $T$ , and a feature vector  $\mathbf{X} = (X_1, \dots, X_n)$  we have likelihood of the data as,

$$P(\mathbf{X}|T) = \prod_{i=1}^n P(X_i|T).$$

This assumption is highly unrealistic since the majority of features are related in complicated ways. The success of the method is largely due to the nature of optimality in terms of the *zero-one loss* which does not require a high-fidelity model of the probability distribution. The optimal classifier is obtained as long as the actual and estimated probability distributions agree on the most likely class.

For the trans-femoral amputees, the training data obtained from each trial is used to train the classifier. Each window has it's own unique classifier that is trained from data taken during a 200ms window at heel-contact and toe-off. The window size was chosen so that the EMG signal in that region was quasi-stationary. The mechanical sensors, for simplicity, were also sampled in the same 200ms window. However, their signals have less variance than EMG does, so this window-length should be sufficient for the purpose of classification. For trans-tibial amputees, the window was much smaller  $\approx 100$  for just the transition. This was largely due to the nature of a transition between terrain. In particular, for our participant they transitions very quickly between terrains. A slower transition speed could produce better results with a EMG-based features.

2) *Binary Comparison Between Terrains with Trans-femoral Amptuees*: In this study there were several different types of terrain that a classifier has to discriminate between. A classifier is normally trained to identify each type of terrain in a window. However, we would like to investigate the value of binary comparisons between different terrains, in addition to, a more general classifier in identifying important features. This will result in more classifiers for each window and is done to evaluate the possibility of there being a few very powerful features available for terrain identification beyond those that are found in a more general classifier.

3) *Pre-Foot Hold/Post-Foot Hold and Heel-Contact Toe-Off Windows for a Trans-tibial Amputee*: Analysis windows, as mentioned above, are usually taken around points where the most muscular information is likely to be available. The standard configuration, Fig. 1, uses the toe-off and heel-contact points to extract musculo-skeletal information for terrain identification. We believe it is better to determine the ground before an instrumented leg comes into contact with the terrain.

Transitions between terrain, in the standard window setup, would cause the ankle to fail. An example of this is given in Fig. 2.

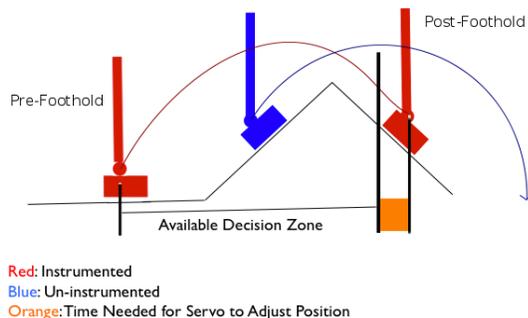


Fig. 2. If the instrumented leg (red) does not encounter the up-slope ramp with a high-peak and has to adapt to a down-slope current IMU based algorithms and the standard window method will fail.

In this work the analysis window is taken when the instrumented leg lifts off the ground and ends right before the heel hits the ground, assuming there is enough time to servo into the correct position, on the final terrain. In this way, the instrumented leg knows nothing about what the un-instrumented leg experiences on the first part of the terrain, in the figure this is up-ramp, so that it does not effect the classifier for the opposite side, in this case down-slope.

4) *Feature Extraction:* Feature extraction resulted in eight separate features for each sensor as depicted in Fig. 3. The features were chosen so that they would pay attention to common measurable in the EMG signal: power, power-spectrum, stationarity. Similar to [2], we use time-domain (TD) and autoregressive (AR) features in addition to the mean, maximum, and minimum. This is done because TDAR and the mean, max, and min features never require a signal-transformation to compute and are fast on a variety of system configurations.

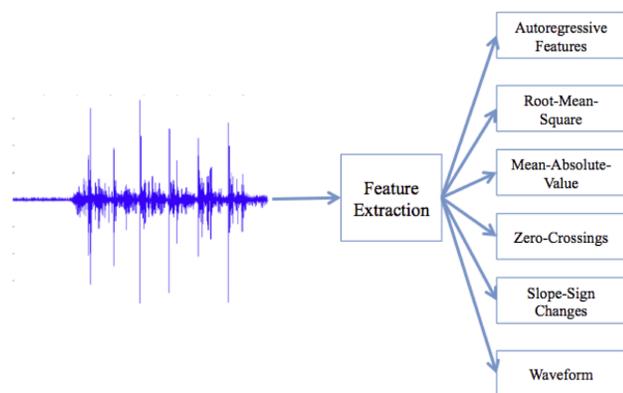


Fig. 3. The layout of the feature extraction algorithm applied to an individual signal. The features are extracted to represent the signal as a combination of power spectrum, autoregressive, and other statistical properties of the signal.

#### D. Hierarchy of Sensors

As the number of sensors that are attached to the body to control external powered prostheses increases, the users get

more and more encumbered. To avoid this an attempt to select those sensors that are least invasive. For example, the use of EMG electrodes is far more encumbering than just using an IMU that is implanted inside a robotic ankle. It also serves as a "tie-breaker" between different sensing modalities. When two sensors can both accurately discriminate between two terrain conditions it makes sense to pick the one that is least invasive.

### III. RESULTS AND DISCUSSION

Data were collected from three different subjects. Two of these subjects were trans-femoral amputees and one of these was a trans-tibial amputee. The first results presented below are a study on the different features for steady-state motions, excluding transitions, of differing terrains. The second study included only transitions between a peak and valley at a 15 degree grade. Figure 2 shows the 15 degree peak and the opposite was the 15 degree valley.

#### A. Trans-Femoral Results

1) *Selected Features:* The trans-femoral experiment was run to determine the importance of particular features that discriminate among four different walking conditions: level ground, downramp with a passive prosthesis, obstacle, upramp with a passive prosthesis. See Table II for acronyms.

Terrain Legend	
Number	Terrain
LG	Level Ground
DP	Downramp Passive
OB	Obstacle
UP	Upramp Passive

TABLE II  
LEGEND FOR THE FOUR DIFFERENT TERRAINS TRAVERSED BY ABOVE-KNEE AMPUTEES.

The results suggest that our algorithm reduces the number of needed features to guarantee 100% accuracy with EMG while discriminating between different classes except in one case<sup>1</sup>. In the "DP,UP" condition there was still reduction, but was not quite as profound as the other conditions. The difference between ramps, at a 5 degree grade, did not show significant enough difference to be distinguishable with a major reduction in the number of features. However, the results show that for many of the binary discrimination tasks very few different features were needed between different transitions, Table III.

The most frequent features to appear in the above tables are the ones corresponding to the mean-absolute-value of the bicep femoris, the mean-absolute-value of the vastus medialis, and the root-mean-square of the rectus femoris. Note that others did appear, but the most significant ones, in terms of their apparent frequency, were the ones we just listed.

<sup>1</sup>The total number of features used for trans-femoral amputees was 209 independent features.

TF01 Results		
Transition	TF01 Backward Heel Results	TF01 Forward Heel Results
LG,DP	RMS of GM	MAV of the RF
LG,OB	MAV of the BF	MAV of the RF
LG,UP	MAV of the BF	MAV of the RF
DP,OB	MAV of the VM	MAV of the RF
DP,UP	NDF	NDF
OB,UP	MAV of the VM	MAV of the RF

TABLE III

THESE RESULTS ARE REPORTED FOR TWO WINDOWS TAKEN FROM THE FIRST TRANS-FEMORAL AMPUTEES. IN MOST CASES A SIGNIFICANT REDUCTION OF THE NUMBER OF NEEDED FEATURES IS OBSERVED. IN THE DOWNRAMP/UPRAMP CONDITION, IN BOTH CASES, THERE WAS NOT A SIGNIFICANT REDUCTION.

TF04 Results		
Transition	TF04 Backward Heel Results	TF04 Forward Heel Results
LG,DP	MAV of BF	MAV of the RF
LG,OB	208	MAV of BF
LG,UP	MAV of BF	MAV of the RF
DP,OB	MAV of BF	MAV of BF
DP,UP	NDF	NDF
OB,UP	MAV of VM	MAV of BF

TABLE IV

THESE ARE THE RESULTS OBTAINED BY RUNNING THIS ALGORITHM ON THE SECOND TRANS-TIBIAL AMPUTEE.

### B. Trans-Tibial Results

A trans-tibial amputee walked and performed transitions between a peak and valley similar to the set up described earlier. It is worth noting that the period of transition was approximately 100 ms, so EMG features should not be useful during this period – previous work has shown[10] that 200 ms is needed for the EMG signal to be quasi-stationary. Despite this we used our algorithm with both sets of features. The reason being that if we want to build a real-time EMG system, without intrinsic sensing, transitions will have to be handled by EMG. Our argument, and is verified below, that IMUs are superior to EMG for these types of transitions. Results, Table V, suggest that intrinsic sensing will reliably predict the terrain before foot-flat, or post-foothold, with 100% accuracy.

The results in Table V suggest two things: 1) that the window is too short for EMG to be a useable signal and 2) that IMU sensors might be a better choice than EMG for

Window Size	Best Feature Set	Accuracy
30	mean of IMU height at knee	100
40	mean of IMU height at knee	100
50	mean of IMU height at knee	100
80	mean of IMU height at knee	100
82	mean of IMU height at knee	100
85	mean of IMU height at knee	100

TABLE V

DIFFERENT WINDOW SIZES WERE USED TO ASSESS THE STABILITY OF DIFFERENT FEATURES IN DISCRIMINATING BETWEEN THE PEAK AND VALLEY CONDITIONS. THE SAME FEATURE WAS FOUND TO BE USEFUL FOR ALL FEASIBLE WINDOW LENGTHS.

transitions with peaks that take place in short time windows, see Fig. 4. In particular, since the knee-marker was so useful in discriminating these two conditions there could be something about the position of the knee prior to landing on the opposite side of a peak or valley that is unique. This could be that the knee contributes quite a bit to determine the end slope during terrain transitions.

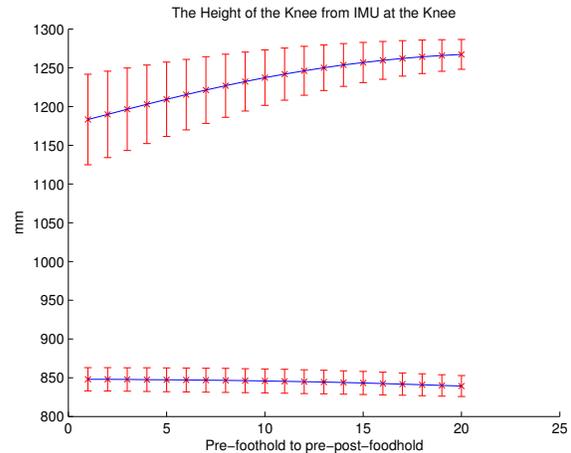


Fig. 4. This figures shows the average height (blue line) and one standard deviation error bars (red) of the knee IMU. There is no overlap of the values within one standard deviation. This suggests that the feature obtained by this algorithm is very good at discriminating between 30 degree peaks and 30 degree valleys for this subject.

The above result<sup>2</sup> with a trans-tibial amputee was verified by obtaining the same exact results for an able-bodied matched subject. This suggests that we are biologically selecting the correct feature. However, several different features can accurately discriminate between these two rather extreme conditions. We seek to choose the least invasive sensor in this case.

Table VI, shows that several different markers can discriminate with 100% accuracy between these two terrains.

1) *Discussion:* The method above was able to work well at finding those features that contribute heavily to the discriminability of both above and below knee amputees. In each case, above and below knee, we used different windows to extract information from the sensors recording gait information. It would be interesting to using similar windows for both above and below knee amputations. Then we could compare the features produced by this algorithm to see how closely they are related.

Peaks and valleys in this case is in important step forward, but also a very simplistic case. The trans-tibial subject experienced pain while walking due to custom liner with electrodes which shortened the inter-step length. An improved liner has been developed and will be used instead of the current type. Due to the limitation imposed by the current liner a limited range of terrains could be studied. Expanding the range of

<sup>2</sup>The total number of features used for trans-tibial amputees was 225.

Feature	Accuracy (%)
root-mean-square of shank height	99.99
mean-absolute-value of shank height	100
maximum window value of shank height	100
minimum window value of shank height	100
mean window value of shank height	100
root-mean-square of knee height	100
mean-absolute-value of knee height	100
maximum window value of knee height	100
minimum window value of knee height	100
mean window value of knee height	100

TABLE VI

SEVERAL DIFFERENT SIMULATED IMU LOCATIONS ON THE LOWER LIMB CAN DISTINGUISH BETWEEN THESE TWO TERRAINS WITH 100% ACCURACY. SOME ARE EASIER TO USE ON A PHYSICAL ROBOT THAN OTHERS. IN PARTICULAR, THOSE LOCATED MORE DISTALLY WILL BE CONTAINED IN THE ROBOT ANKLE, RATHER THAN INCONVENIENTLY, ON THE BODY OF THE AMPUTEE.

terrains needs to be pursued and these factors will be addressed in the follow-up study and subsequent paper.

It is interesting that this method had trouble with trans-femoral amputees on ramps. Perhaps the degree of the incline and decline were not different enough and this could have confounded the discrimination between the two conditions. More work will have to be done to understand the circumstances that effect this algorithm on ramps.

Another area to pursue is building a weight scheme or voting scheme to combine individual classifiers to come to a conclusion about the terrain. In particular, creating a sliding window technique for trans-tibial amputees that builds on the transition work reported here and the foot-contact and heel-contact work for trans-femoral amputees applied to trans-tibial amputees.

#### IV. CONCLUSION

We have shown in this work that using a Naive Bayes classifier with sequential forward search can locate and elucidate the primary factors contributing to the discrimination between several types of terrain for above and below knee amputees. For trans-femoral amputees we identified the most important factors that contribute to terrain identification from EMG. For trans-tibial amputees we showed that with data take before foot-flat in a difficult situation 100% classification accuracies can be achieved, there are several sensors that can accomplish this, and that intrinsic ones are best.

More work needs to be done to acquire additional data to verify the utility of the knee in discriminating between peaks and valleys. Ways in which these ideas can be used in physical hardware will be pursued in later work. Also, a large dataset with more sensors will be collected and this same method will be applied to trans-tibial amputees to understand factors that contribute to effective terrain adaptation. Finally, our results suggest that the use of intrinsic control in some cases trumps the use of EMG for the identification of terrain.

#### ACKNOWLEDGMENT

The authors would like to thank Dr. Levi Hargrove and Dr. Todd Kuiken of the Chicago Rehabilitation Institute for their assistance with the preparation of this paper. Thanks also to Matthew Williams whose edits and assistance during the study were important in the completion of this work.

#### REFERENCES

- [1] Hargrove, L.J. and Scheme, E.J. and Englehart, K.B. and Hudgins, B.S., *Multiple Binary Classifications via Linear Discriminant Analysis for Improved Controllability of a Powered Prosthesis*, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2010.
- [2] He Huang and Kuiken, T.A. and Lipschutz, R.D., *A Strategy for Identifying Locomotion Modes Using Surface Electromyography*, IEEE Transactions on Biomedical Engineering, 2009.
- [3] R. Psonak, *Transfemoral prosthetics*, in Orthotics and Prosthetics in Rehabilitation, M. M. Lusardi and C. C. Nielsen, Eds. Boston, MA: Butterworth-Heinemann Publications, 2000.
- [4] Au S. K. and Berniker, M., and Herr, H. *Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits*, Neural Networks vol. 21, pp.654?666, 2008.
- [5] D. Jin, J.Yang, R. Zhang, R.Wang, and J. Zhang, *Terrain identification for prosthetic knees based on electromyographic signal features*, Tsinghua Sci. Technol., vol. 11, pp. 7479, 2006.
- [6] L. Peeraer, B. Aeyels, and G. Van Der Perre, *Development of EMGbased mode and intent recognition algorithms for a computer-controlled above-knee prosthesis*, J. Biomed. Eng., vol. 12, pp. 178182, 1990.
- [7] R. Psonak, *Transfemoral prosthetics*, in Orthotics and Prosthetics in Rehabilitation, M. M. Lusardi and C. C. Nielsen, Eds. Boston, MA: Butterworth-Heinemann Publications, 2000.
- [8] T. W. Williams III, *Practical methods for controlling powered upperextremity prostheses*, Assist. Technol., vol. 2, pp. 318, 1990.
- [9] P. A. Parker and R. N. Scott, *Myoelectric control of prostheses*, Crit. Rev. Biomed. Eng., vol. 13, pp. 283310, 1986.
- [10] B. Hudgins, P. Parker, and R. N. Scott, *A new strategy for multifunction myoelectric control*, IEEE Trans. Biomed. Eng., vol. 40, no. 1, pp. 8294, Jan. 1993.
- [11] K. Englehart and B. Hudgins, *A robust, real-time control scheme for multifunction myoelectric control*, IEEE Trans. Biomed. Eng., vol. 50, no. 7, pp. 848854, Jul. 2003.
- [12] T.R. Farrell and R.F. Weir, *"The optimal controller delay for Myoelectric Prostheses,"* IEEE Trans. Neural Systems and Rehab. Eng., vol. 15, no. 1, pp. 111-118
- [13] D. L. Hall and J. Llinas, *Introduction to Multisensor Data Fusion*, Proc. of IEEE , Vol. 85, No. 1, pp. 6 23, Jan 1997.
- [14] I. Guyon and A. Elisseeff, *"An Introduction to Variable and Feature Selection."* Journal of Machine Learning Research 3 (2003) 1157-1182 Submitted 11
- [15] E. F. Delagi and A. Perotto, *Anatomic Guide for the Electromyographer The Limbs*, 2d ed. Springfield, IL: Thomas, 1980.