Locomotion Mode Identification for Lower Limbs using Neuromuscular and Joint Kinematic Signals

Taimoor Afzal, *Student member, IEEE,* Gannon White, Andrew B. Wright and Kamran Iqbal

***Abstract*— Recent development in lower limb prosthetics has seen an emergence of powered prosthesis that have the capability to operate in different locomotion modes. However, these devices cannot transition seamlessly between modes such as level walking, stair ascent and descent and up slope and down slope walking. They require some form of user input that defines the human intent. The purpose of this study was to develop a locomotion mode detection system and evaluate its performance for different sensor configurations and to study the effect of locomotion mode detection with and without electromyography (EMG) signals while using kinematic data from hip joint of non-dominant/impaired limb and an accelerometer. Data was collected from four able bodied subjects that completed two circuits that contained standing, level-walking, ramp ascent and descent and stair ascent and descent. By using only the kinematic data from the hip joint and accelerometer data the system was able to identify the transitions, stance and swing phases with similar performance as compared to using only EMG and accelerometer data. However, significant improvement in classification error was observed when EMG, kinematic and accelerometer data were used together to identify the locomotion modes. The higher recognition rates when using the kinematic data along with EMG shows that the joint kinematics could be beneficial in intent recognition systems of locomotion modes.**

I. INTRODUCTION

Recently there have been many advances in the field of lower limb prosthetic devices. Powered prosthetic devices have been developed to aid amputees to walk on different terrains. To utilize a powered prosthesis for walking on different terrains, seamless transition in joint trajectories, command signals (or modes) is required. Current users have to either press a button to switch between modes or perform non-intuitive muscle contractions to signal the prosthesis to change modes [1]. For seamless transition neural information from the user is required. This information is present in the form of electromyography (EMG) signals.

Various intent recognition techniques are being developed to address mode transition. An intent recognition system that uses mechanical sensors on the prosthetic device to switch between level walking, sitting and standing has been developed in [2]. In an extension to [2] walking on five and ten degrees slopes was further added in [3]. A strategy using EMG signals to switch between two walking modes: level ground walking and stair descent was developed in [1]. For level walking to stair descent, the amputee flexed the gastrocnemius muscles and to switch from stair-descent to level ground walking the amputee flexed the tibialis anterior muscle. A real-time implementation for locomotion mode detection using EMG signals and mechanical sensors (6-DOF load cell) from the prosthetic knee was presented in [4]. Similar work has been done in [5] where the signals from the mechanical sensors (six-axis inertial measurement unit, axial load sensor, motor potentiometers and encoders) attached to the prosthetic were used to classify locomotion modes based on time history information. They implemented the technique using dynamic Bayesian networks that are useful for integrating time series information over time. In a subsequent paper, data from the mechanical sensors attached to the prosthetic limb was used using Linear Discriminant Analysis (LDA) to classify five walking modes and transitions between them [6]. A neuromuscular fusion approach similar to [4] was implemented in [11] where a combination of 9 EMG signals and 13 mechanical sensors were used to classify transitions and steady state for 5 locomotion modes based on time history information. Earlier work for achieving transition from one mode to another was done by [8]. They implemented an 'echo control' approach in which the sound side of the amputee was instrumented and knee angle profile was measured. For achieving various gaits the amputated side had to mimic the behavior of the sound side to achieve various gaits.

Apart from EMG signals, the joint kinematics can also be utilized as a form of user intent as they are a measurement of the joint movement which is a result of the activation of different muscles. For transfemoral amputees, the hip joint, and for transtibial amputees, both the knee and hip joint kinematics can be used to classify locomotion modes. Recent studies have used sensory information from the amputated side to characterize locomotion modes and either the EMG or mechanical sensors on the prosthetic limb or a combination of both have been utilized. The authors have not come across a study that utilizes kinematic information from the hip joint to characterize the locomotion modes.

Since surface EMG signals precede the movement [4] they are useful in predicting task transitions. The goal of this study is to use the information from the hip joint of the impaired limb, EMG signals from the thigh muscles, and a mechanical sensor (3-axis accelerometer) to classify six locomotion modes (standing, level walking, stair ascent, stair descent, ramp ascent, ramp descent) and transitions between them. Joint kinematic information can be useful since it is a result of EMG muscle activity. Locomotion mode detection has been done and the performance has been evaluated for using the sensory information from one limb.

I. METHODS

A. Experimental Protocol

Four able bodied subjects completed an experiment approved by Institutional review board at the University of Arkansas at Little Rock. The participants gave written consent to take part in the study and were free to withdraw at any time during the data collection. The non-dominant limb of the participants was assumed to be the impaired side. For transfemoral amputees, the sensory information available is the residual thigh muscles and hip joint angle therefore the thigh muscles of the able-bodied subjects were used to acquire EMG signals. Five muscles were located on the non-dominant limb of the participants namely: Sartorius (SART), Rectus Femoris (RF), Bicep Femoris longhead (BFL), Bicep Femoris shorthead (BFS) and Semitendinosus (ST). A two-axis electrical goniometer was attached to the hip joint that measured the hip angle in the sagittal plane and the coronal plane. Three-axis accelerometer was attached to the shin of the impaired side.

The subjects completed 10 trials each for two circuits. In the first circuit the subjects stood for 5 sec, then walked four steps, climbed four step stairs, walked four steps and stopped. Then they turned around, again stood for 5 sec, walked four steps, went down the four step stairs and walked four steps.

In the second circuit the subjects walked one step, climbed ramp and walked one step and turned around. Then they walked one step on level ground, walked down ramp and walked one step and stopped.

B. Signal Processing, Feature Extraction and Pattern Classification

The entire sensor signals were sampled at 1500 Hz. Three kinematic sensors (three axis accelerometer, two axis goniometer for the hip joint) and five EMG sensor were used for classification. Foot switches were used to detect the heel contact (HC) and toe-off (TO) points. A 250 ms analysis window was used with window increment of 30 ms. Five windows prior to TO and 5 windows prior to HC were used for classification. Thus a total length of 370 ms duration was used for classification. In each analysis window, features are extracted from all channels. Data windowing scheme is shown in figure 1.

For the EMG signals, six time-domain features were computed for classification. They were mean absolute value (MAV), minimum, maximum, variance, slope length and number of zero-crossings. For the remaining sensors, five time domain features used for classification were MAV, minimum, maximum, variance and slope length. The features were concatenated to make one feature vector with fifty-five components. Only time domain features were used in this study. According to [7] time-domain features have similar performance compared to time-domain autoregressive features (TDAR).

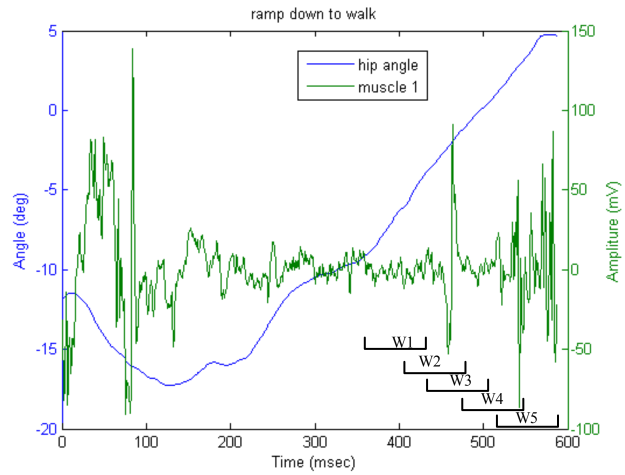

Figure 1: Data windowing scheme for transition from ramp descent to walking. Five windows at the end of the stance phase are shown. Sample EMG signal of BFS is shown in green. Hip angle is shown in blue.

LDA was used for classification of locomotion modes. LDA has been reported to have comparable performance with other complex classifiers [9] and is computationally efficient for real-time prosthesis control [10].

C. Classifier Performance Evaluation

The performance of the classifier was evaluated using 4-fold cross validation for the 10 circuit trials collected from 4 participants. In this procedure, 75% of the data was randomly selected for training and 25% data was selected for testing. This procedure was repeated 10 times. The classification error (CE) is defined as:

$$CE = \frac{\textit{Number of misclassified testing data}}{\textit{Total number of applied testing data}} \text{ X } 100 \qquad (1)$$

II. RESULTS

A. Effect of Sensor Configurations on Classification Error

The effect of different sensor configurations was investigated for transitions, stance phase and swing phase. Five sensor configurations were used and their effect was evaluated on transitions, stance phase, swing phase, transitions involving stairs and transitions involving ramps. The sensors configurations used were: (1) EMG only, (2) EMG and Accelerometer, (3) EMG, accelerometer and hip goniometer, (4) EMG, accelerometer, hip goniometer and knee goniometer, and (5) accelerometer and hip goniometer.

The different configurations of the sensors were tested for the transition phase, stance phase and swing phase. The transitions were required to be identified at the end of the stance phase of the impaired side. The transition phase consisted of the transitions from level walking to standing, ramp ascent, ramp descent, stair ascent, stair descent and to level walking from standing, ramp ascent, ramp descent, stair ascent and stair descent. Thus the transition phase was classifying 10 transitions. The stance phase consisted of 6 phases i.e. level walking, standing, ramp ascent, ramp descent, stair ascent and stair descent. The swing phase consisted of 5 modes namely level waking, ramp ascent, ramp descent, stair ascent and stair descent.

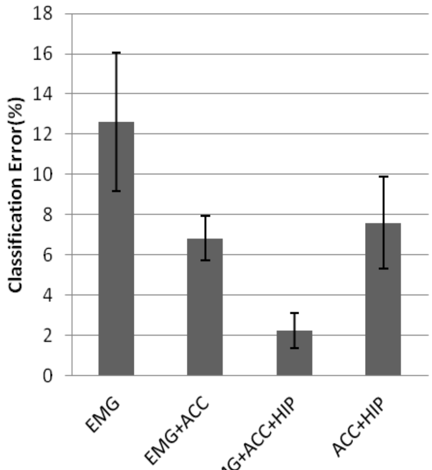

Figure 2: Classification error during transitions averaged over 4 able bodied subjects for different sensor configurations.

Statistical analysis was performed using 1-Way ANOVA. To further look for which configuration had the most significant effect on classification error, Tukey's HSD *post-hoc* analysis was performed. The lowest classification error was produced when all sensors on one limb were used i.e. EMG, accelerometer and hip goniometer. This was statistically significant *($p < 0.01$)*. The classification error during transitions when using EMG as the only source was 12.61%. It was significantly reduced *($p<0.01$)* when EMG was combined with either the hip joint angle or the accelerometer. There was no significant difference *($p>0.05$)* when EMG and accelerometer or hip joint angle and accelerometer were used. Both were significantly better than using only EMG for classification. But combining the three sources significantly reduced the classification error. This result indicates that sensory information from the sound limb can be useful in identifying the transitions when used with the EMG signals (see figure 2).

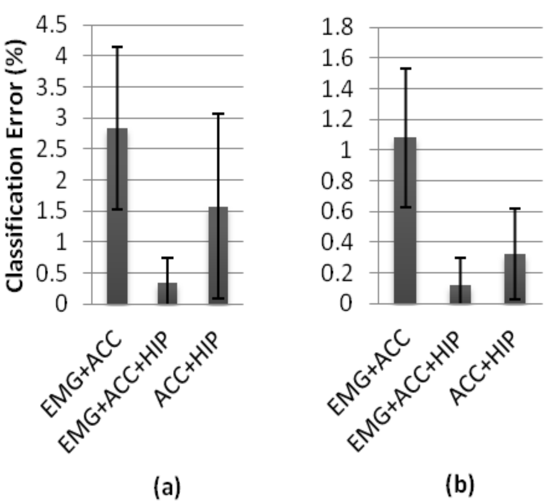

Figure 3. Classification error for different sensor configurations for (a) swing phase (b) stance phase, averaged over 4 subjects.

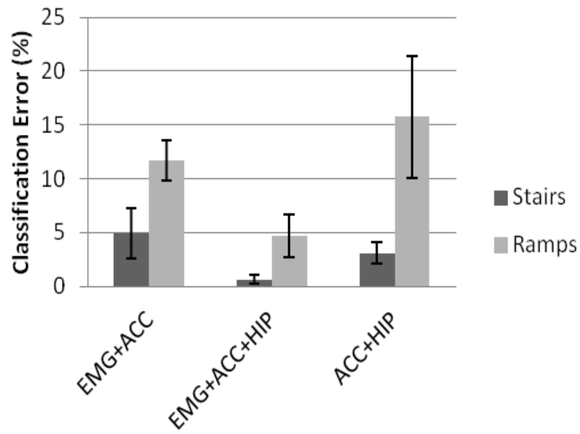

Figure 4: Classification error for stairs and ramps in transition phase for sensors from different sensor configurations averaged over 4 subjects.

For the swing and stance phases using the hip joint angle and accelerometer without EMG significantly improved *($p<0.05$)* the classification error compared to using only EMG and accelerometer. Combining the three produced statistically significant results *($p<0.02$)* compared to all other sensor configurations for both swing and stance phases. This result showed that addition of hip angular information along with EMG signals can be useful for identifying the stance and swing phases (see figure 3).

B. *Effect of Sensor Configuration on Transitions Involving Ramps and Stairs*

The classification performance of three sensor configurations was further compared for transitions involving ramps and stairs. The results indicate that transitions to and from stairs were more accurately identified as compared to transitions to and from ramps. For the transitions involving stairs the addition of hip joint angle significantly improved *($p<0.01$)* the classification error compared to using only accelerometer and EMG data. There was no significant effect *($p>0.05$)* on classification error for stair transitions if EMG was used or not used. However, for the transitions involving ramps removing the EMG information significantly increased the error *($p<0.01$)*. The most significant result in case of ramp transitions was when all the sensors on the impaired limb were used (see figure 4).

Comparing our results with a previous study [11] for the transitions involving stairs and ramps, the classification errors are similar for both the ramps and stairs when EMG signal is being used with the accelerometer i.e. 12% error for Ramps and 5% error for stairs (figure 4). The past study has reported 13% error for transitions involving ramps and 2% error for stairs [11]. However in our study, when the hip angle is included along with the EMG and accelerometer information the transition error for the ramps significantly decreases to 5% and the error for stairs decreases to 1%. This is significant reduction showing that additional information from the hip joint is useful in discriminating between locomotion modes.

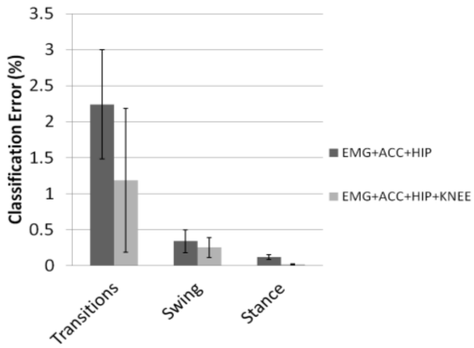

Figure 5: Classification accuracies for transitions, swing and stance phases with using information from one limb (dark grey bars) and using information from both limbs (light grey bars). No significant change was observed. Note: EMG, accelerometer and hip joint angles were measured from the non-dominant limb while the knee angle was measured from the dominant limb.

III. DISCUSSION

This preliminary study found that using the sensory information from the biological joints was useful in classification of locomotion modes. Using the joint angle of the hip joint of the non-dominant limb along with the EMG signals and accelerometer information significantly reduced *(p<0.01)* the transitions classification error. Swing phase classification error has been higher than the stance phase with EMG and mechanical information from the prosthesis in some previous studies like [4]. Our results indicate that using the joint kinematic information along with the EMG and the accelerometer significantly decreased the classification error of the swing phase. In this study we considered looking for classification at the critical points i.e. at HC and TO therefore, only windows prior to HC and TO were considered.

The results show that the kinematic information from the biological joints significantly improves the classification accuracies for transitions, swing phases and stance phases. Therefore, this information can also be used in a system that has a primary classifier based on EMG data. In such a system a secondary classifier could be based on the joint kinematics to identify the modes for greater accuracy or a combination of the two modes can be used to improve the classification accuracy. The transitions involving ramps and stairs can be identified separately using EMG signals for stairs and kinematic signals for ramps.

As mentioned in previous studies, this study also concludes that a multi-sensor data fusion system comprising of EMG signals from the limbs and the kinematic information can be an effective method in classifying locomotion modes.

Some preliminary investigation was also done by including the information from the dominant/unimpaired limb for classification. A 2-axis electrical goniometer was attached to the knee joint on the dominant limb to gather the angular information in the sagittal and coronal plane. The results indicate that there was no statistically significant improvement *(p>0.05)* in classification error for transitions, stance and swing phases if the information from the dominant limb was included along with the information from the non-dominant limb for classification (see figure 5). However, more information like the EMG signals from both legs can be included to observe its affect on classification error.

In this study subjects with both intact limbs were used for data collection. One study has reported similar classification with EMG signals collected from the residual thigh muscles of amputee subjects and able bodied subjects [4]. In another study the hip joint kinematics has been reported to be similar for above knee amputees and able bodied subjects [12]. Therefore, it may be assumed that similar classification accuracy may be expected when the system is tested with amputees in future and the performance of the system is evaluated in real-time.

REFERENCES

[1] S. Au, M. Berniker and H. Herr, "Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits," *Neural Networks,* vol. 21, no. 4, pp. 654-666, 2008.

[2] H. A. Varol, F. Sup and M. Goldfarb, "Multiclass real-time intent recognition of a powered lower limb prosthesis," *IEEE Transactions Biomedical Engineering,* vol. 57, no. 3, pp. 542-551, 2010.

[3] F. Sup, H. A. Varol and M. Goldfarb, "Upslope walking with a powered knee and ankle prosthesis: Initial results with an amputee subject," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 19, no. 1, pp. 71-78, 2011.

[4] H. Huang, F. Zhang, L. J. Hargrove, D. Zhi, D. R. Rogers and K. B. Englehart, "Continuous Locomotion-Mode Identification for Prosthetic Legs Based on Neuromuscular–Mechanical Fusion," *IEEE Transactions on Biomedical Engineering,* pp. 2867-2875, 2011.

[5] A. J. Young, A. M. Simon, N. P. Fey and L. J. Hargrove, "Intent Recognition in a Powered Lower Limb Prosthesis Using Time History Information," *Annals of biomedical engineering ,* pp. 1-11, 2013.

[6] A. J. Young, A. M. Simon and L. J. Hargrove, "A Training Method for Locomotion Mode Prediction Using Powered Prosthesis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* 2013.

[7] H. Huang, T. A. Kuiken and R. D. Lipschutz, "A strategy for identifying locomotion modes using surface electromyography," *IEEE Transactions on Biomedical Engineering,* vol. 56, no. 1, pp. 65-73, 2009.

[8] D. L. Grimes, "An active multi-mode above knee prosthesis controller," Doctoral dissertation, MIT, 1979.

[9] Englehart, Kevin, Bernard Hudgins, Philip A. Parker, and Maryhelen Stevenson. "Classification of the myoelectric signal using time-frequency based representations." *Medical engineering & physics* 21, no. 6 (1999): 431-438.

[10] Englehart, Kevin, and Bernard Hudgins. "A robust, real-time control scheme for multifunction myoelectric control." *IEEE Transactions on Biomedical Engineering,* 50, no. 7 (2003): 848-854.

[11] A. J. Young, A. M. Simon, and L. J. Hargrove. "An intent recognition strategy for transfemoral amputee ambulation across different locomotion modes." In *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pp. 1587-1590. IEEE, 2013.

[12] A. D. Segal, M. S. Orendurff, G. K. Klute, M. L. McDowell, J. A. Pecoraro, J. Shofer, and J. M. Czerniecki. "Kinematic and kinetic comparisons of transfemoral amputee gait using C-Leg and Mauch SNS prosthetic knees." In *Journal of Rehabilitation Research & Development,* vol. 43, no. 7, pp. 857-869, 2006.