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An Adaptive Pattern Recognition Algorithm for a Powered Lower Limb Prosthesis

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Abstract

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Pattern recognition algorithms have been proposed as a way to control powered lower limb prostheses, specifically for transitioning between the different pre-programmed locomotion modes of the prosthesis (e.g., level ground walking, stair ascent, etc.). However, these algorithms cannot track changes in the statistical characteristics of input signals, and do not generalize well to novel users. Adaptive algorithms that can update their parameters by incorporating new data are a promising solution to these problems. The purpose of this work was to develop and evaluate an adaptive pattern recognition algorithm for controlling powered lower limb prostheses. The algorithm that was developed could track changes in electromyographic (EMG) signals (whose signal quality degrades over time) and could also generalize to novel users. To accomplish these tasks, this algorithm had to: 1) be able to both detect EMG disturbances and ignore the disturbed EMG data to prevent errors, 2) accurately label new patterns of data with the correct label representing the user's intent, and 3) adapt system parameters to create an updated pattern recognition algorithm.

We developed a metric for detecting disturbances in the EMG signals that was based on the probability of observing current EMG signals in comparison to the history of previously observed EMG signals. This metric could reliably detect a wide variety of disturbances, including electrode liftoff, electrode short-circuiting, and electrode shifts caused by donning and doffing the prosthesis. We developed a compensation technique to be used in the circumstance

that EMG signal changes were detected: EMG signals were ignored and only embedded mechanical sensor signals were used to make locomotion mode predictions. This technique prevented many of the errors associated with these disturbances.

A technique for automatically labeling new patterns of data was also developed: mechanical sensor data acquired after the user completes a stride with prosthesis could be accurately classified as one of the locomotion modes of the prosthesis. This technique, termed backwards estimation, accurately provided labels for new patterns of data with performance that was consistent across days and robust to changes in the user's gait patterns.

We evaluated the complete adaptive algorithm (comprised of EMG disturbance detection and labeling via backwards estimation) in a multi-day experiment with transfemoral amputee subjects. Amputee subjects ambulated with a powered lower limb prosthesis as the adaptive algorithm updated the model of EMG data in real-time. The results of this experiment demonstrated that an adaptive algorithm could be used to track EMG signal changes, resulting in low and consistent algorithm error rates over long-term use. A preliminary study on across-user adaptation also demonstrated that the model of mechanical sensor data could be updated, resulting in a system that learned from novel users and improved performance over time.

The research in this dissertation is significant in the field of lower limb prosthetics because it provides a viable method to automatically update pattern recognition algorithms with new training data while the user is ambulating. This allows pattern recognition algorithms to incorporate new EMG information, and allows novel users to ambulate with prosthesis without participating in long experiments to collect training data. The impact of this research is that lower limb pattern recognition algorithms can maintain low error rates over long-term use.

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Dedication

To Mom, Dad, and Louie.

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1 Introduction

1.1 Motivation

Major lower limb amputation (those above the ankle) is a significant impairment to over 650,000 people living in the United States [1]. Prosthetic legs allow lower limb amputees to ambulate despite their disability, but their ambulation is slower, more asymmetric, and more metabolically expensive than that of able-bodied individuals [2], [3]. Moreover, lower limb amputees have a greater propensity to falling and experience great difficulty in navigating uneven terrains, such as ramps or stairs [4]. This is largely because most commercially available prosthetic legs are passive, and their behavior depends on the properties of their mechanical components (e.g. hydraulic valves, pneumatic valves, sliding joints) as well as the coordination of the user's remaining intact muscles. The result is that the function of the prosthesis and the ability of the user are severely limited.

Powered lowered limb prostheses have recently been developed and can produce positive mechanical power at the knee and/or ankle to assist amputees in performing a variety of ambulation tasks [5]–[7]. These devices are generally programmed with multiple different locomotion modes (e.g., level ground walking, stair ascent, ramp descent) that allow the amputee to complete different ambulation tasks beyond level ground walking, (e.g., step-over-step stair climbing, or walking on ramps) [8]. However, one major limitation of these devices is that their current controllers cannot seamlessly transition between the different locomotion modes, and instead require that the user perform unintuitive specific body movements or use a remote key fob to switch modes. The lack of a seamless and automatic method for selecting the desired mode limits the potential of powered prostheses.

Studies have investigated using pattern recognition algorithms as a method for transitioning lower limb prostheses between locomotion modes. These algorithms predict the user's desired mode by decoding different types of data (e.g., kinetic/kinematic, electromyography [EMG], environmental), and then modify the behavior of the prosthesis accordingly [9]–[12]. They have been shown to successfully transition the prosthesis into the desired mode in both offline and online studies.

However, obstacles remain in implementing these algorithms within a control system that is clinically viable for long-term use. First, the pattern recognition algorithms that have been implemented are static and do not accommodate changes in the user's patterns over time. For example, neural data acquired from EMGs have been shown to add important information that significantly reduces algorithm error rates, but their signal quality degrades over time [10], [13], [14]. Disturbances in the EMG signals (e.g., electrode shifts, loss of skin-electrode contact, or variations in electrode/skin impedance), in combination with a static pattern recognition algorithm, eliminate the benefits associated with using EMGs, and cause the algorithm's performance to deteriorate over time [15]–[17].

Second, pattern recognition algorithms for lower limb prostheses require large amounts of data. These data are used train the algorithm to learn user-specific patterns and recognize how a particular user completes the different mode transitions. Though these subject-specific data are needed for the algorithm to perform at a high level, the protocol to collect them is long and burdensome to complete for amputee patients. Some studies have addressed this limitation by training the algorithm with data collected from multiple other users (i.e., a user-independent system) [18]. However, these user-independent systems have increased error rates, suggesting that subject-specific data is required for optimal performance.

Both of these limitations highlight a critical need for pattern recognition algorithms: the ability to incorporate new data as the user is ambulating. An algorithm that automatically adapts its parameters as it encounters new data would provide solutions to both of the aforementioned problems. An adaptive algorithm could learn from signals that change over time such as EMG. Such an algorithm could also adapt a user-independent system with data that is specific to a novel user, and eventually reach a level of performance associated with user-dependent systems. Therefore, the objective of this work was to develop and evaluate an adaptive pattern recognition algorithm for a powered lower limb prosthesis.

Specifically in this dissertation, an adaptive pattern recognition algorithm was evaluated with transfemoral amputees ambulating with a powered knee-ankle prosthesis. The algorithm investigated in this work adapted its parameters as the subjects were ambulating in real time. I present results showing that the algorithm can learn to track changes in EMG signals for individual subjects. I also present preliminary results demonstrating an adaptive user-independent system that learns subject-specific data over time and improves performance.

1.2 Background

1.2.1 Powered Lower Limb Prostheses and Control of Locomotion Modes

Powered prosthetic legs have recently become commercially available, and several research prototypes are currently being investigated [5], [8], [19]. These devices have motors that actuate the joints of the prosthesis, and can produce positive mechanical power. These devices typically use closed-loop control through onboard mechanical sensors and a microprocessor. The controller uses state-based control wherein the controller receives kinematic and force information from the sensors embedded in the prosthesis, detects the gait phase, and adjusts the impedance of the knee joint to match able-bodied gait data [20]. In addition, multiple different impedance trajectories (i.e., locomotion modes) can be programmed to allow the amputee to complete different ambulation tasks beyond level ground walking, such as step-over-step stair climbing, walking on inclined surfaces, or completing sit-to-stand activities [6], [9], [21].

One challenge in the control of devices is determining how to transition the prosthesis between the different locomotion modes. The most basic strategies include requiring the user to a press a button on a key fob or perform an exaggerated motion with the residual limb. While useful, these strategies are cumbersome and unintuitive, and do not seamlessly and naturally transition the prosthesis between locomotion modes. Another investigated strategy is “echo control,” wherein the prosthesis mimics the motion of the sound limb [22]. However, this strategy has several disadvantages. It requires that the sound limb be instrumented with sensors, that the user lead with the sound limb, and that the performed activities are symmetric. In addition, with echo control the user must be a unilateral amputee. Overall, while the proposed strategies can transition the prosthesis between modes, they are neither seamless nor transparent to user, which limits the potential of powered leg prosthesis. Ideally, transitions between modes should be completed automatically, reliably, and without user intervention.

1.2.2 Pattern Recognition Algorithms for Lower Limb Prosthetics

One potential strategy for achieving seamless transitions that are transparent to the user is the use of pattern recognition algorithms. These algorithms infer the user’s intent from signals acquired before the user’s stride with the prosthesis, and the prosthesis is then transitioned automatically into the predicted mode [9], [23]. A variety of sensor sets have been used to accomplish this, including signals acquired from the user (e.g., EMG) [23], the prosthesis (e.g., kinetic/kinematic information acquired from embedded or instrumented mechanical sensors) [9], [24], and/or the environment (e.g., vision) [11], [12]. Moreover, different classification methods have been used, including linear discriminant analysis (LDA) [10], artificial neural networks (ANNs) [23], support vector machines (SVMs) [10], Gaussian mixture models (GMMs) [9], and dynamic Bayesian networks (DBNs) [24]. Studies evaluating these different algorithms first began with instrumented passive devices, but have since started to include powered legs in both offline and online analyses [13], [14], [24], [25], demonstrating their potential for the control of lower limb prostheses.

1.2.2.1 Benefits of Adding EMG Signals for Locomotion Mode Prediction

One specific set of sensor information that has received attention recently for use in lower limb pattern recognition is EMG acquired from the user. EMG signals precede the onset of movement, with reported electromechanical delays of 30 – 100ms [26]. This is contrasted with other sets of sensors (e.g. mechanical sensors) that respond to the movements of the user and the prosthesis. EMGs have been used clinically in upper limb applications for decades, with users performing steady muscle contraction to actuate the prosthesis [27]. However, until recently, their use has been absent from lower limb applications. This is because most leg prostheses are passive, and have not required information from EMG. With the introduction of powered devices, studies have started investigating whether the neural information acquired from EMG signals could potentially be used to predict the desired locomotion mode of the user.

Research investigating the use of EMG signals with pattern recognition in lower limb applications has focused on “phased-based” classification. This strategy classifies windows of data right before specific transition points corresponding to gait events (e.g., heel contact, toe-off) [10], [18]. Lower limb EMG patterns, which change throughout the gait cycle, are assumed to be stationary and appropriate for pattern recognition in these windows. Huang et al. demonstrated that surface EMG could be used to reliably identify the different locomotion modes in a 2007 study involving amputees using a passive device [23]. Huang et al. expanded this work in 2011 study wherein EMG information was fused with mechanical sensor information acquired from an instrumented passive prosthesis [10]. This study demonstrated that the information provided by EMG and embedded mechanical sensors is complementary, and results in a significant reduction of prediction error rates. Since then, other studies have also demonstrated the benefit of using DBNs to incorporate the time history into the classification and utilize the patterns of EMG activations over the gait cycle [24]. This research has culminated in online studies involving lower limb amputees ambulating with powered prostheses while EMG information, mechanical sensor information, and time history information were used to predict and transition the prosthesis into the desired mode of the user [14], [25]. These studies again showed that EMG information and time history information is useful in locomotion mode prediction, and demonstrated the feasibility of an online EMG-based pattern recognition system for a powered lower limb device.

1.2.2.2 Disadvantages of Pattern Recognition Algorithms

Though pattern recognition is useful in controlling powered leg prostheses, it has limitations that prevent its implementation within a clinically viable control system. First, the proposed lower limb pattern recognition algorithms in the literature are static; they do not change their parameters during prosthesis use and therefore do not accommodate changes in the user's patterns over time. This limitation is particularly pronounced in systems where EMG is used. Despite being useful in short-term experimental sessions performed on a single day, the signal quality of EMG decreases over time. Disturbances in the EMG signals can be caused by electrode shifts relative to the muscles of interest that occur during donning and doffing, loss of skin-electrode contact, fatigue, or variations in electrode/skin impedance, and regularly occur during long-term prosthesis use [15], [16]. A static pattern recognition algorithm cannot track these changes, eliminating the benefits associated with using EMGs, and causing the algorithm's performance to deteriorate over time. This is particularly significant in lower limb applications, where a misclassification could cause a stumble or fall. Studies have investigated collecting additional data from multiple plausible electrode site locations to build a robust model of EMG data [15]. This strategy, while useful, would require additional time to acquire this data, limiting its clinical viability.

Second, properly training pattern recognition algorithms for lower limb prostheses requires a large amount of data. These data are used create a model of how a particular user completes the different mode transitions, which the algorithm then uses to make locomotion mode predictions during ambulation [28]. Acquiring these data requires that the user complete a protocol where he or she uses the prosthesis to complete the different mode transitions. The protocol to collect these subject-specific data requires a large amount of time, is difficult for most amputees to complete, and has so far been completed in a laboratory setting with the help of research engineers and clinicians. This limitation has led to studies investigating the use of a pattern recognition algorithm trained with data collected from multiple other users, which would make collecting subject-specific data unnecessary [18]. However, findings from these studies have shown that these user-independent systems (i.e., those that are trained with data from multiple users but without the novel user's unique data) have increased error rates, suggesting that subject-specific data is needed to properly train the algorithm.

1.2.2.3 The Case for Adaptation

To address these limitations, pattern recognition algorithms must reincorporate new data that represents the changed signal inputs and adapt its parameters to include the novel data as part of its model for the user's ambulation. Ideally, this process would happen as the user is ambulating with the prosthesis. Adaptation would allow the algorithm to learn from changing signal inputs, such as those acquired from EMG. In addition, adaptation could be useful in across user applications. A novel user could use an adaptive algorithm to gather their subject-specific data during ambulation outside a research environment, transforming a user-independent algorithm into user-dependent system, and decreasing error rates over time. Such an adaptive algorithm was developed in this dissertation.

1.2.3 Adaptive Pattern Recognition in Myoelectric Prosthetic Devices

1.2.3.1 EMG Disturbance Detection

Multiple adaptive pattern recognition algorithms have been proposed for upper limb prosthetic devices, specifically those that use myoelectric control systems. One main focus of these algorithms is mitigating the effects of EMG signal disturbances. Some studies have investigated periodically retraining the algorithm with a new set of labeled data [29], or acquiring data from multiple plausible electrode locations to create a robust training dataset [15]. While these re-training approaches have been shown to maintain high levels of performance, they require time to acquire new data, are not automatic, and cannot immediately prevent potentially dangerous misclassifications in lower limb applications. An adaptive algorithm should be able to ignore signals that have been corrupted with disturbances, and instead rely on alternative data sources to make locomotion mode predictions. Previous studies in upper limb applications have implemented techniques that allow the algorithm to ignore specific channels of EMG that contain disturbances [30], [31]. While useful, this technique has the drawback of removing too many EMG channels, resulting in a loss of information that hurts classification performance. For our application, the leg prosthesis could ignore affected channels of EMG and instead rely on embedded mechanical sensors. Such an approach was developed in this dissertation work.

1.2.3.2 Supervision of Adaptation

Another main focus of adaptive algorithms for prosthetic devices is providing a class label to new patterns that are added to the training dataset. This is because most of these algorithms feature supervised learning, meaning that every pattern in the training dataset must be paired with a label representing the intent of the user. For upper limb systems, class labels can be provided by an experimenter or a computer, and can even be completed outside a laboratory setting using pre-programmed prosthesis movements that guide the user to retrain the prosthesis [29]. Training lower limb systems, on the other hand, has been confined to laboratory settings, wherein an experimenter with a key fob controls the prosthesis as the user is ambulating and then labels the data after it is collected [28]. Collecting new data to update the algorithm with this method is again time-consuming and not automatic. Ideally, an adaptive algorithm that is adding new data during real-time use for a leg prosthesis should be able to automatically and accurately label new data as the user is ambulating without any outside assistance.

Automatic labeling of new data patterns has been previously explored in myoelectric upper limb applications. In these studies, the true intent of the user was unknown, and the algorithm had to provide a best guess for the true label for the new data pattern. Both Fukuda et al. and Sensinger et al. used entropy as a metric for monitoring the confidence of a classification decision and added new data points to the training dataset if their entropy met certain criteria [17], [32]. These studies then used the output of the algorithm as a label for the new data. The primary weakness of this method is that an algorithm presented with changed EMG signals will likely make incorrect classifications, meaning that new patterns will be labeled with the wrong class label. This is problematic because mislabeled data that are added to the training set can cause a drastic deterioration in the classification performance.

One potential strategy for accurately labeling new data is to wait until after the user completes a stride with their prosthesis, determine if the predicted movement was what the user actually intended, and then label the movement with the correct class label. This is possible because, in contrast to upper limb applications, human walking is cyclic and has distinct kinematic, kinetic, and EMG patterns [33]–[35]. These characteristics of gait are also consistent within different locomotion modes [36], [37]. Using pattern recognition techniques, these unique patterns can be automatically detected and categorized. Such techniques have already been used to distinguish between able-bodied gait and geriatric or abnormal gait [38]–[40]. For our application, we would segment the gait into strides, extract features from the stride, and then classify it as one of the locomotion modes of the prosthesis. We term this process backwards estimation, and its use in adaptive lower limb pattern recognition is demonstrated in this dissertation.

1.3 Specific Aims

Review of previous lower limb prosthetic control literature has revealed several limitations and potential for improved pattern recognition control. This work is innovative in the field of lower limb prosthesis control because 1) no known studies have demonstrated online adaptive intent-recognition with a powered knee-ankle prosthesis, 2) it will expand the use of EMG to control lower limb prostheses so that neural information can be incorporated over long-term use, and 3) it will allow for the development of user-independent pattern recognition algorithms that learn from subject-specific data and continually improves performance over time.

The following specific aims were investigated in this dissertation work. The overall objective of this dissertation was to develop and evaluate an online adaptive intent recognition algorithm for a powered lower limb prosthesis. My central hypothesis is that an adaptive algorithm will have lower error rates than a non-adaptive algorithm. The rationale behind this hypothesis is that previously proposed intent recognition studies did not use adaptive algorithms that could track changes in input signals and therefore are prone to make more errors when these changes occur.

Specific Aim 1: Develop a technique for detecting and compensating for changes in the quality of input signals, specifically those obtained from EMG

In addition to relearning the new model of EMG data, the adaptive algorithm needed a mechanism for detecting disturbances in EMG signals and preventing the errors associated with those disturbances. To do this, we looked at the likelihood of observing a novel pattern given the training dataset, and determined that it contained a disturbance if the likelihood was below a certain threshold. In this case, only the information acquired from embedded mechanical sensors were used to make a mode prediction. The working hypothesis is that a system using this technique will make fewer errors when presented with EMG data that contains disturbances. This aim is addressed in Chapter 2.

Specific Aim 2: Develop a technique for automatically supervising novel patterns used for adaptation with a label representing the user's intent

Our adaptive algorithm featured supervised learning, meaning that every pattern used to train the system had to be paired with label that matched the user's intent. To accomplish this, we waited until after the user completed a stride with the prosthesis, classified it as one of the locomotion modes of the prosthesis, and applied the label to the novel pattern (i.e., backwards estimation). The working hypothesis is that backward estimation will outperform other labeling strategies. This aim is addressed in Chapter 3.

Specific Aim 3: Evaluate the online adaptive system online with amputee subjects using a powered transfemoral prosthesis

I implemented, in a real-time online experiment, the adaptive algorithm developed in Aims 1 and 2. I conducted experiments on amputees using a powered leg prosthesis across multiple experimental sessions. The working hypothesis is that the adaptive algorithm would learn to re-incorporate EMG into its predictions, and as a result, algorithm error rate would decrease over time. The online adaptive algorithm was also used in experiments evaluating across-user adaptation, wherein new mechanical sensor data from a novel user are incorporated over time (discussed in a preliminary study included in the appendix).

Chapter 4 provides a description the control system used in the online adaptation experiments, which is important to understanding and interpreting the results of those experiments. Chapter 5 addresses Aim 3 by describing the online adaptation experiments for single-user adaptation of EMG.

1.4 Dissertation Overview

Chapter 2 is an article published in the IEEE Transactions on Neural Systems and Rehabilitation Engineering that details the mechanism for detecting and compensating for disturbances in EMG signals for a pattern recognition algorithm used to control a powered leg prosthesis (Specific Aim 1). Chapter 3 is a manuscript that describes and evaluates the backwards estimation strategy that labels novel data that are used to update the algorithm, and simulates the adaptive algorithm using data from amputees collected in multiple experimental sessions (Specific Aim 2). Chapter 4 is an article in accepted by the IEEE Transactions on Neural Systems and Rehabilitation Engineering that details the overall control system (i.e., state machine control, classification architecture) of the prosthesis used in the online implementation of the algorithm. This article, which does not investigate adaptive control, was included because the powered prosthesis used in the online studies was different from that used in the offline simulations, and the included information on the overall control system is helpful in understanding the results of the online studies. While I was not the first author of this manuscript, I did provide the pattern recognition results that are discussed in the study, and are important for understanding the results of this dissertation. Chapter 5 is a manuscript detailing the results from the online implementation of the adaptive algorithm, specifically within-subject adaptation of EMG signals across experimental sessions. Chapter 6 contains a discussion of the dissertation work as whole. Appendix A is an additional study that was submitted and accepted to the 2016 IEEE Engineering in Medicine and Biology Conference which discusses preliminary results for across-user adaptation of mechanical sensor data. This submission demonstrates the potential to use adaptation as a means to improve algorithm performance across users, and also to train an intent recognition algorithm without the need for completing the long and burdensome protocol to collect training data.

2 Detection of and Compensation for EMG Disturbances for Powered Lower Limb Prosthesis Control

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2.1 Abstract

Myoelectric pattern recognition algorithms have been proposed for the control of powered lower limb prostheses, but electromyography (EMG) signal disturbances remain an obstacle to clinical implementation. To address this problem, we used a log likelihood metric to detect simulated EMG disturbances and real disturbances acquired from EMG containing electrode shift. We found that features extracted from disturbed EMG have much lower log likelihoods than those from undisturbed signals and can be detected using a single threshold acquired from the training data. We designed a linear discriminant analysis (LDA) classifier that uses the log likelihood to decide between using a combination of EMG and mechanical sensors and using mechanical sensors only, to predict locomotion modes. When EMG contained disturbances, our classifier detected those disturbances and disregarded EMG data. Our classifier had significantly lower errors than a standard LDA classifier in the presence of EMG disturbances. The log likelihood classifier had a low false positive threshold, and thus did not perform significantly differently from the standard LDA classifier when EMG did not contain disturbances. The log likelihood threshold could also be applied to individual EMG channels, enabling specific channels containing EMG disturbances to be appropriately ignored when making locomotion mode predictions.

2.2 Introduction

Surface electromyographic (EMG) signals have been used for decades to provide control information for powered upper limb prostheses [41], but have yet to be clinically implemented in lower limb prostheses because most commercially available devices are passive [42], [43]. Advances in onboard computers and electromechanical motors have led to the design of powered lower limb prostheses [6], [7]. Unlike passive prostheses, which cannot generate net positive mechanical work, powered devices are driven by electric motors that can generate the work required at the knee and ankle to complete important functional tasks such as stair climbing or walking uphill [44]. Powered prostheses typically use finite-state machines to appropriately control the impedance of the knee and ankle joints at different points (or states) of the gait cycle, as well as the impedances of those states in different locomotion modes (e.g., level walking, stair ascent, ramp descent) [6], [7]. The increased functionality of powered devices requires more advanced controllers that could be improved by the inclusion of neural information. The key to effective control of powered lower limb prostheses is to correctly determine user intent in order to transition the device between desired locomotion modes. Thus, EMG signals, which precede force generation at the joint [26], could be used to identify user intent and predict the desired locomotion mode.

Pattern recognition algorithms have been proposed to allow seamless and automatic transitioning between locomotion modes [9], [10], [23]. These algorithms eliminate the need for manual switching between modes (which requires, for example, use of a key fob or the user performing a specific, unnatural movement). Using pattern recognition to interpret kinematic and kinetic data from embedded mechanical sensors has been shown to accurately transition the prostheses between level-ground walking, sitting, and standing [9]. Recent studies have shown that incorporating neural information into the control system helps to identify user intent and to accurately predict upcoming locomotion modes. Adding EMG signal information to the information provided by mechanical sensors significantly reduces the error rates of the pattern recognition system and allows prediction of more locomotion modes [10]. However, disturbances in EMG signal quality — including changes in electrode position [15], loss of electrode-skin contact, variations in electrode/skin impedances, or muscle fatigue [16] — degrade its value for pattern recognition. If the pattern recognition system does not compensate for disturbances in EMG signals, this results in deterioration of locomotion mode prediction accuracy over time [17]. Thus, while EMG signals clearly add important neural control information, challenges remain in incorporating these signals within a control system that is clinically viable for long-term use.

Pattern recognition algorithms typically involve a training phase, where the algorithm is calibrated using labeled EMG patterns (or training dataset), and a testing phase, where the calibrated algorithm is used to classify novel patterns (testing dataset). One solution for reducing the effect of EMG signal disturbances due to changes in electrode location is to collect EMG signals from various potential electrode locations to create a more robust training dataset. Including EMG data from multiple plausible electrode locations allows the algorithm to learn many possible signal patterns and thus to accurately classify novel EMG data resulting from similar electrode location changes [15]. Similarly, others have proposed building and switching between probabilistic models of EMG signals to compensate for the changes in the signal characteristics [45]. However, these approaches require acquiring a large amount of training data that is both difficult and time-consuming to gather, particularly for lower limb applications. In addition, the ability to collect adequate training data depends on the skill of the prosthetist to determine all plausible displacement locations of EMG electrodes within the socket. Furthermore, these approaches would not be useful for EMG disturbances that lead to a total loss of information, such as short circuits or loss of electrode contact with the skin; in these situations, it would be most appropriate to ignore the affected channels. As an alternative to training with large data sets, an algorithm that automatically detects any EMG disturbance, and adapts the classification approach accordingly, would increase the clinical viability of EMG-based lower limb prosthesis control.

An adaptive system must be able to both detect EMG disturbances—to determine if it is appropriate to use that EMG data for locomotion mode prediction—and to ignore disturbed EMG data to prevent prediction errors. To date, no published methods have accomplished this goal for lower limb prostheses. Sensinger et al., 2009 [17], Fukuda et al., 2003 [32], and Du et al., 2013 [30] used the entropy associated with each classification decision as a measure of the algorithm decision confidence. This was done to identify examples of variable EMG patterns (i.e., decisions associated with high entropy) and add them to the training dataset. However, these studies have several limitations. The confidence metric, entropy, can only detect whether a pattern is close to the border between classes in feature space, where the class decisions have similar probabilities. This means that entropy cannot be used to detect EMG disturbances that result in patterns that are far from each of the class clusters but not necessarily at the class borders. Moreover, the proposed systems in these studies did not attempt to make the correct classifier decision despite encountering potentially noisy EMG signals. Rather, the novel pattern was added to the training dataset, and then the algorithm was retrained. This is problematic because predictions made with EMG signals containing disturbances are often inaccurate and potentially unsafe for the patient. Furthermore, adding incorrectly labelled data to the training set may result in significant deterioration of classification performance [17]. Thus, while batch retraining may decrease algorithm errors in the long-term, a method is needed in which the correct mode is predicted immediately, despite EMG disturbances. Some studies, using pattern recognition to control upper limb devices, addressed this issue by removing channels that were identified as containing disturbances [31], [46]. We extend this work to powered lower limb applications and offer the following improvements: (1) we use a metric that only depends on the EMG data collected during the initial training session. Thus, our proposed method requires no extra time to collect data for developing models of EMG containing disturbances, nor the development of an external detector which needs to be built and calibrated, as was done in [31] and [44]; (2) we use data from mechanical sensors embedded in the prosthesis as an alternative means of making locomotion mode predictions when EMG channels that are identified as containing disturbances are removed.

The objective of this study was to create a pattern recognition system for a powered leg prosthesis that is more robust to EMG disturbances. We accomplished this by enabling the algorithm to choose whether EMG data should be incorporated in mode predictions using a log likelihood metric. This metric can detect patterns that are far from each of the class clusters as well as those close to the class borders, whereas an entropy metric can only detect the latter. In the event that EMG disturbances are encountered, the algorithm ignores this data and uses only the onboard mechanical sensors to make a mode prediction. We expect our implementation to maintain adequate prediction accuracy despite removing EMG channels, because mechanical sensors can be used as an alternative means of making locomotion mode predictions.

Within this dissertation, this chapter will describe a method to identify EMG disturbances and prevent the resulting mode prediction errors. This addition is important to the overall development of an adaptive algorithm because it helps ensure that the user can ambulate safely while the algorithm learns from changed EMG signals. It is a significant improvement for EMG-based pattern recognition systems, whose performance decreases in the presence of EMG disturbances. The lack of a method to detect signal changes in lower limb prosthetic applications also makes this an innovative development in the field.

2.3 Methods

2.3.1 Experimental Protocol

Eight subjects with unilateral transfemoral amputations and two subjects with knee disarticulation amputations completed the experiment, which was approved by the Northwestern University Institutional Review Board. Subjects' ages ranged between 30 and 66 years; heights were between 1.65 m and 1.87 m; and weights between 52.2 kg and 111.6 kg. All subjects were community ambulators (K3 or K4 level).

The data collection procedure has been described previously [24] and is briefly summarized below for convenience. A physical therapist identified the following muscle sites on the residual limb via palpation: semitendinosus (ST), biceps femoris (BF), tensor fasciae latae (TFL), rectus femoris (RF), vastus lateralis (VL), vastus medialis (VM), sartorius (Sart), adductor magnus (AM), and gracilis (Grac). Six subjects had a custom-made skin-fit socket to attach to the prosthesis. Stainless-steel dome electrodes were embedded within these sockets at the identified muscle locations. Two subjects wore their own sockets; for these subjects, low-profile, self-adhesive silver-coated carbon electrodes (Arrowhead Medical Resources, Minnesota) were used and placed on the skin over the appropriate muscle locations. A powered knee and ankle prosthesis was aligned and attached to the subjects' sockets by a certified prosthetist at the Rehabilitation Institute of Chicago. The prosthesis was designed by the Center for Intelligent Mechatronics at Vanderbilt University [8].

Subjects gained experience using the device during pre-experimental sessions in which the prosthesis was tuned for the subject. Impedance parameters for the knee and ankle were tuned for each locomotion mode based on previously published strategies [9], [44], [47]. A physical therapist was present to ensure patient safety and to instruct the subject. Each subject completed 20 repetitions of a locomotion circuit that included level-ground walking, ramps, and stairs. The experimenter triggered all transitions between prosthesis locomotion modes at heel contact or toe-off, depending on the mode. Four of the participants also completed the protocol again in a second experimental session.

Signals from 13 mechanical sensors on the prosthesis—including kinematic sensors, kinetic sensors, and inertial sensors—were recorded at 500 Hz. A low pass filter with a cutoff frequency of 20 Hz smoothed the load cell signal. A custom-built EMG recording system, incorporating a Texas Instruments TI-ADS1299 instrumentation chip was used to record all EMG signals at 1000 Hz per channel. Both EMG signals and mechanical sensor signals, recorded while the subject completed the 20 repetitions of the circuit, were used for gait classification.

Data were segmented into analysis windows of 300 ms before heel contact and toe off [23]. The signal mean, maximum, minimum, and standard deviation were extracted from each analysis window for each mechanical sensor [7]. The mean absolute value, waveform length, zero crossing, slope sign changes, and the first two autoregressive coefficients of third order autoregressive model were extracted from each analysis window for each EMG channel [15], [48]. Thus, each step was represented by a vector of features that were used to calibrate or test a classifier.

2.3.2 Evaluation of Quality of EMG Signals

The log likelihood was used to determine the similarity between a new vector of EMG features, and those included in the training set. Log likelihood is the log probability of observing a multivariate point given a multivariate distribution. In this study, the point was the new test vector of EMG features, $\boldsymbol{x}_{EMG}$, and the multivariate distribution was estimated from the collection of all EMG feature vectors in the training set. The training data were modeled as a Gaussian distribution with mean μ_{EMG} and covariance Σ_{EMG}; the log likelihood for a new feature vector is given by Equation 2.1. A new EMG feature vector was characterized as being substantially different from the training data set if its log likelihood was more than three standard deviations from the average log likelihood of the feature vectors in the training set. Thus, only one threshold calculated from the EMG training data was used to detect the types of EMG disturbances in this study.

$$\ln p(\boldsymbol{x}_{EMG}|\mu_{EMG}, \Sigma_{EMG}) \propto -\frac{1}{2}(\boldsymbol{x}_{EMG} - \mu_{EMG})^t \Sigma_{EMG}^{-1}(x_{EMG} - \mu_{EMG}) \qquad (2.1)$$

In a separate analysis, we also investigated whether a log likelihood threshold could be applied to individual EMG channels with the intention of removing only those channels with potential disturbances from locomotion mode predictions. In this case, the threshold not only revealed whether EMG disturbances occurred, but also in which channel they occurred. This technique operated like the ensemble method described above, but was implemented on individual EMG channels. Thus, for each channel, likelihood models were trained, and the log likelihood of EMG features relative to the distribution of EMG features in the training dataset was determined. For each channel, if the likelihood was outside three standard deviations from the average log likelihood of the training set patterns for that channel, that channel was assumed to contain disturbances.

2.3.3 Classification

Three different classification strategies to predict the locomotion mode from the available EMG and mechanical sensor data were tested. All used linear discriminant analysis (LDA), which has been demonstrated to be useful for user intent recognition in lower limb prostheses [23]. The first approach (*FULL*) always classified the locomotion mode using a feature vector that incorporated information from all available EMG and mechanical sensor data (i.e., the full data set). The second approach (*LLT*, Figure 2.1) incorporated a log likelihood threshold on the EMG feature vector to determine whether to use both EMG and mechanical sensor data for classification (i.e., identical to the *FULL* approach), or only mechanical sensor data. The third approach (*LLTsc*) was identical to LLT, except that the log likelihood was computed for each EMG channel, and only channels that differed substantially from the training set were omitted from the classification process. For both the LLT and LLTsc approaches, EMG channels not

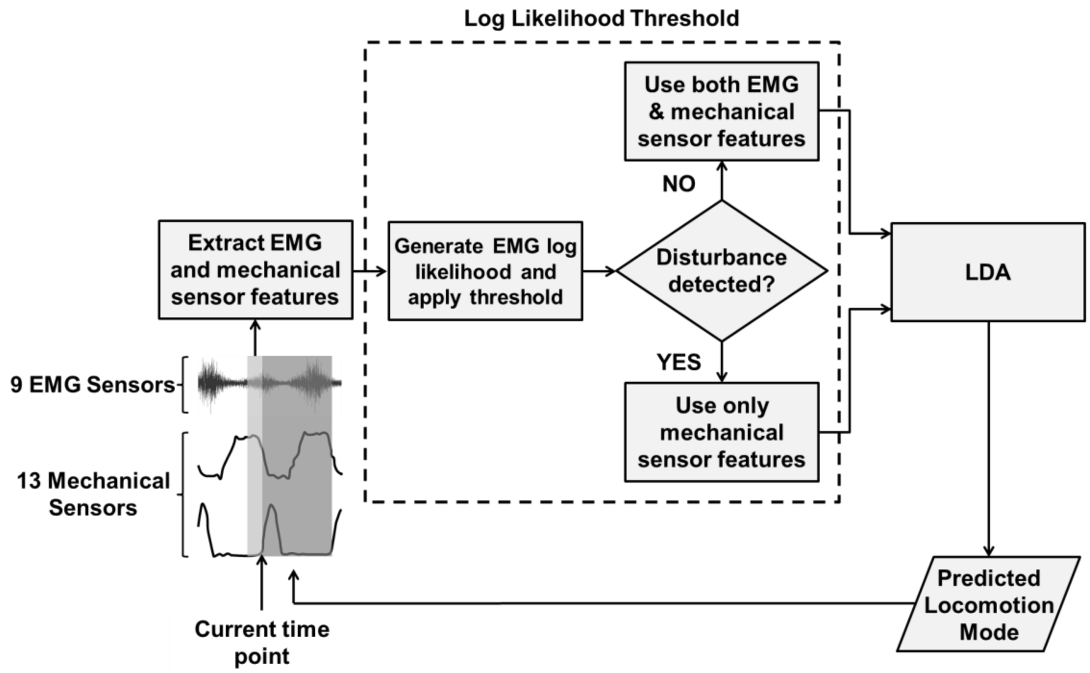

Figure 2.1: Flow chart representing the LLT algorithm. Features from EMG and mechanical sensors were extracted from 300 ms analysis windows prior to mode transition points. A threshold was applied to the log likelihood of the EMG pattern to determine whether the EMG signal contained disturbances. If disturbances were detected, only mechanical sensor features were used by the LDA algorithm to predict the locomotion mode of the upcoming step. Otherwise, both features from both EMG and mechanical sensors were used (i.e., the FULL strategy).

used for classification were eliminated by removing their features from the mean feature vector and from the appropriate rows and columns from the covariance matrix [31].

2.3.4 Algorithm Evaluation

To evaluate the performance of the classification strategies, we observed error rates when the input EMG data either had disturbances or had no disturbances. We simulated two types of disturbances: electrode liftoff (Figure 2.2) and electrode short-circuit, representing two extreme situations that might occur during daily use. Liftoff was simulated by embedding a 60Hz, 2 volt peak-to-peak sinusoid in a single random EMG channel, and EMG electrode short-circuits were simulated by embedding zeros into a single random EMG channel (Figure 2.3). We also evaluated the algorithm's performance on experimental data collected across two separate days.

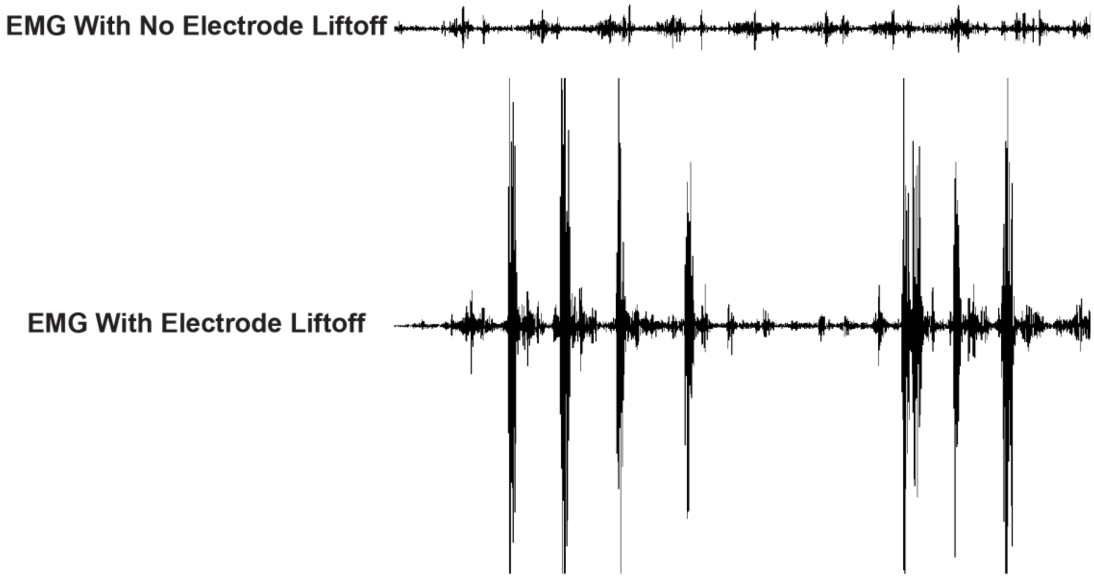

Figure 2.2: Example of a real EMG signal with and without electrode liftoff. The EMG signals shown were from the adductor magnus muscle. Both signals were acquired as the patient was using the prosthesis to walk on level ground. Electrode liftoff was observed during swing phase, resulting in large changes in the EMG signal.

This data set was used to approximate the shift in electrode placement that can occur with slippage or when donning and doffing a system. These EMG data was acquired from the four subjects that completed the protocol a second time in a separate experimental session.

The number of prediction errors was determined using 5-fold cross validation with the 20 circuit trials (i.e., using 16 trials in the training set and 4 trials in the test set, repeated 5 times such that each set of 4 trials was in the test set once). The analysis evaluating performance with simulated disturbances was completed with a testing dataset that (a) had simulated EMG disturbances in all of the testing trials, and (b) one that had no simulated disturbances. The analysis evaluating performance across experimental sessions was completed with a testing dataset that (a) that was acquired from a separate experimental session (i.e., the testing data came a session that was different from the first session where the training data was acquired), and (b) one that was acquired from the same experimental session (i.e., the testing data came a session

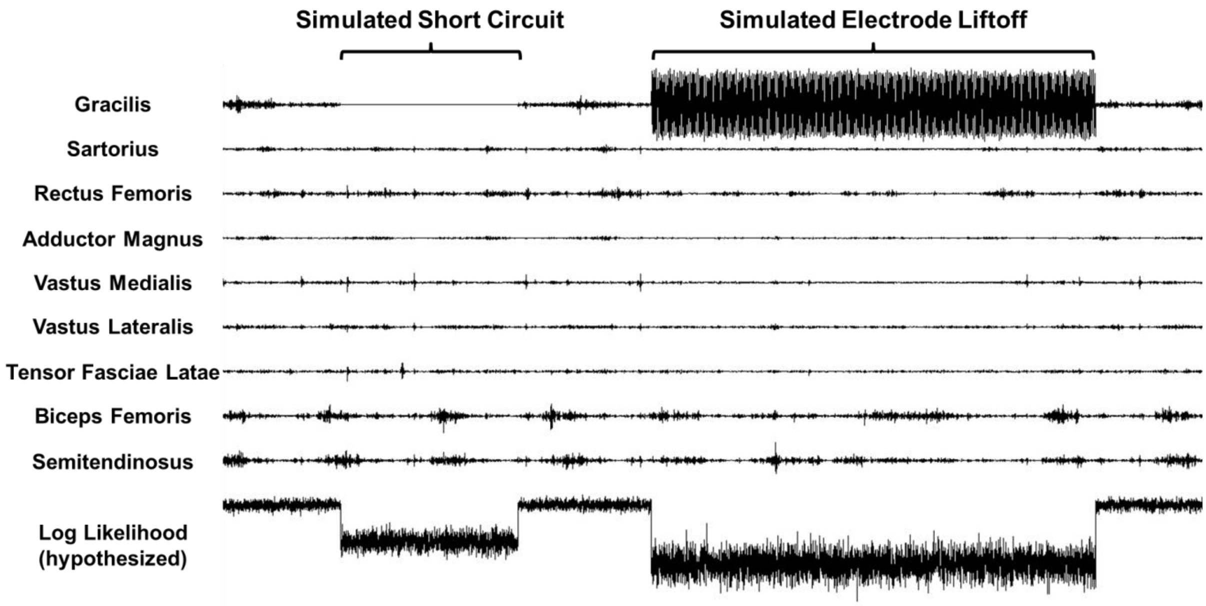

Figure 2.3: Examples of simulated disturbances embedded within real EMG data and the expected impact on the log likelihood. EMG data from nine leg muscles were collected as the subject was walking on level ground. Zero values are embedded into a single channel to simulate an electrode short circuit. A 60Hz, 2-volt peak-to-peak sinusoid is embedded into the channel to simulate electrode liftoff. The expected log likelihood of the features extracted from the EMG data is also plotted. The log likelihood of features extracted from EMG data with disturbances is expected to be much lower than that of EMG data without disturbances.

that was the same as the session where the training data was acquired). Performance was reported in terms of misclassification rates at heel contact and toe off, which are the critical points for transitioning between locomotion modes [24]. Misclassifications were categorized as either steady-state or transitional errors [24]. Steady-state error was the percentage of misclassified steps occurring when the device remained in the same locomotion mode. Transitional error was the percentage of misclassified steps occurring when the device was switching between different locomotion modes.

The analysis evaluating performance with real or simulated disturbances featured testing datasets that had (i) no EMG disturbances, (ii) simulated electrode liftoff inserted in a randomly selected EMG channel, and (iii) simulated EMG electrode short-circuits inserted in the same randomly selected EMG channel (Figure 2.3). The analysis evaluating performance across experimental sessions featured testing datasets that had (i) no electrode shift (i.e., the testing dataset came from the same experimental session as the training dataset), and (ii) electrode shift (i.e., the testing dataset came from a different experimental session as the training dataset). The average log likelihood of the patterns in each of the testing datasets was compared to that of the training dataset to determine whether EMG signal disturbances resulted in detectable changes in the log likelihood. The number of false positives and false negatives were calculated to determine how well the log likelihood threshold could detect electrode liftoff, electrode short-circuits, and electrode shift for both steady-state and transitional errors. Comparisons were made between the error rates of the FULL and LLT strategies using testing sets with and without simulated EMG disturbances. A repeated measures ANOVA was performed for both steady-state and transitional error with classification error as the response and testing set type and classification strategy as fixed within-subject variables with interaction terms. Variances between groups were not homogeneous based on a Levene’s Test, thus all the data were log transformed to fit the homogeneity assumption for ANOVA. Post-hoc tests (pairwise comparisons with Bonferroni corrections) were conducted on statistically significant variables of interaction. Another repeated measures ANOVA was performed to compare the error rates of the FULL and LLT strategies using testing sets acquired from the same and different experimental sessions from that of the training set (i.e., with and without electrode shift). Lastly, relative percent changes in error rates between the FULL and the LLT strategies are presented.

To evaluate the LLTsc strategy, electrode liftoff was sequentially added to each of the nine EMG channels (i.e., starting with no disturbances in any of the channels and ending with disturbances in all channels), and the log likelihood threshold was applied to each EMG channel to determine whether that channel should be used for locomotion mode prediction. This analysis was performed separately by calculating new steady-state and transitional error sets for locomotion mode prediction, averaged across subjects, after embedding disturbances in each additional EMG channel. The order of selection from first to last was: BF, Sart, AM, VL, TFL, RF, ST, Grac, and VM. The rationale for this order comes from previous literature [13], that determined which EMG channels reduced error rates the most as they were sequentially added. Thus, disturbances were added to the most important channels first.

2.4 Results

2.4.1 Effect of EMG Disturbances on the Log-Likelihood

Including simulated disturbances in the EMG signals resulted in changes in the log likelihood that could be readily detected by our proposed threshold. The average log likelihood of the training dataset was the highest, and that of the testing data with no simulated disturbances was within 1 standard deviation ($<1\sigma$) (Table 2.1). The average log likelihoods of the testing data with simulated liftoff and with simulated electrode short-circuit were much lower than that of the other two datasets ($>3\sigma$). For subjects who completed the protocol again in two separate sessions, the average log likelihood of the training dataset was again the highest, and that of the testing data coming from the same experimental session was within 1 standard deviation ($<1\sigma$) (Table 2.2). The average log likelihoods of the testing data coming from a different experimental session were much lower than that of the other two datasets ($>3\sigma$).

Our chosen threshold resulted in very few errors in the detection of simulated disturbances. There were few false positives (i.e., where simulated EMG disturbances were "detected" when none were present). Importantly, there were no false negatives, meaning that the threshold was able to detect all simulated EMG faults representing both electrode liftoff and short-circuits (Figure 2.4). Because all simulated disturbances were detected, the classification results for the reduced data sets involving the log likelihood threshold are identical. For subjects who completed the protocol again in two separate sessions, the chosen likelihood resulted in a majority (>90%) of EMG data coming from the same experimental session as those in the training set being used to make locomotion mode predictions (Figure 2.5). Most EMG data acquired from the second experimental session were not used to make locomotion mode predictions when the log likelihood threshold was used, though some EMG data (approximately 30%) was incorporated into the predictions.

TABLE 2.1: AVERAGE LOG LIKELIHOOD FOR SIMULATED DISTURBANCES

Dataset	**Average Log Likelihood (1σ)**
Training	–14.88 (22.37)
Testing (no simulated disturbances)	–23.65 (48.85)
Testing (simulated electrode liftoff)	–1.40e4 (1.04e3)
Testing (simulated electrode short-circuit)	–301.50 (94.21)

TABLE 2.2: AVERAGE LOG LIKELIHOOD OF EMG ACQUIRED ACROSS SESSIONS

Dataset	**Average Log Likelihood (1σ)**
Training	–1.56 (15.73)
Testing (same experimental session)	–12.56 (13.48)
Testing (different experimental session)	–493.16 (736.50)

Experimental Session	Used In Locomotion Mode Prediction	Not Used In Locomotion Mode Prediction	Used In Locomotion Mode Prediction	Not Used In Locomotion Mode Prediction
#1	95.54%	4.46%	92.99%	7.01%
#2	32.68%	77.32%	31.24%	68.76%

Figure 2.5: Proportion of steps where EMG was used to make a locomotion mode prediction using a log likelihood threshold. The rows of the matrix represent the experimental session, and the columns represent whether or not the EMG data was used to make a prediction. Steady-state and transitional steps are in the left and right matrices, respectively. Data are averages of four subjects.

2.4.2 Effect of Using a Log-Likelihood Threshold

Including a log likelihood threshold did not reduce classifier performance when no simulated disturbances were present. In comparison with the FULL strategy, the LLT strategy reduced both steady-state and transitional error (by 3.22% and 0.6%, respectively) when the testing set contained no simulated disturbances (Figure 2.6), although neither difference was significant ($p>0.05$). The presence of simulated disturbances caused significant problems for the FULL strategy. The FULL error rate significantly increased ($p<0.0001$) when test data had simulated electrode liftoff for both steady-state ($p<0.0001$) and transitional errors ($p<0.0001$).

	Detected As		Detected As	
True State	Without Simulated Changes	With Simulated Changes	Without Simulated Changes	With Simulated Changes
Without Simulated Changes	95.20%	4.80%	93.08%	6.92%
With Simulated Changes	0%	100%	0%	100%

Figure 2.4: Confusion matrices for detection of simulated EMG disturbances using a log likelihood threshold. The matrix shows the proportion of steps that are true or false negatives or positives. The rows of the matrix represent the instances of the true state, and the columns represent the instances of the detected state. Positive and negative refer to detecting and not detecting disturbances, respectively. Information represents grouped data from both types of simulated disturbances. Steady-state and transitional steps are in the left and right matrices, respectively. Data are averages of eight subjects.

Simulated short-circuiting also caused a significant increase in both steady-state ($p<0.001$) and transitional errors ($p<0.0001$). Simulated short-circuits caused fewer errors than simulated electrode liftoff did, for both steady-state ($p=0.04$ and transitional errors ($p<0.0001$). However, including the log likelihood threshold prevented many of these errors. The LLT strategy had a significantly lower error rate than the FULL strategy in the presence of simulated electrode liftoff for both steady-state ($p<0.0001$) and transitional steps ($p<0.0001$) (a relative reduction of 92.55% and 69.55%, respectively). The LLT strategy also reduced steady-state and transitional error rates in the presence of simulated short-circuits (by 54.55% and 22.38%, respectively); only the latter was found to be statistically significant ($p=0.03$). In the presence of simulated disturbances, where the LLT strategy only used mechanical sensors to make predictions, the LLT strategy did not achieve the same level of performance as the FULL strategy when there were no simulated disturbances. In the presence of simulated EMG disturbances, the LLT strategy had significantly higher error rates for transitional steps than the FULL and LLT strategies had when there were no simulated EMG disturbances ($p=0.005$ and $p=0.004$, respectively).

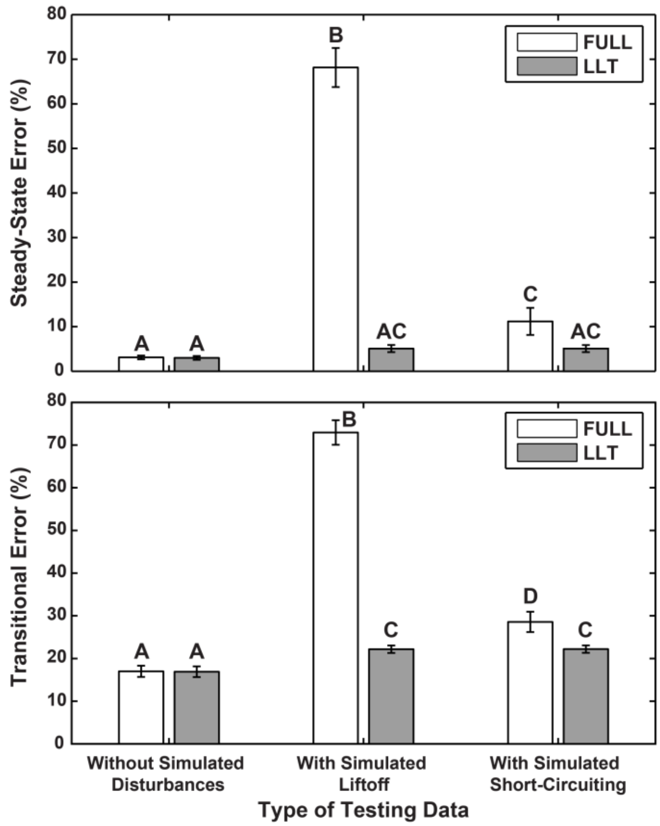

Figure 2.6: Effect of classification strategy and testing sets with and without simulated disturbances on classification error. Classification strategies were an LDA classifier (FULL) and an LDA classifier with a log likelihood threshold (LLT). Simulated disturbances were electrode liftoff and short-circuiting. Classification error rates for both steady-state (top) and transitional (bottom) steps are shown. Data are averages of eight subjects and error bars represent +/- 1 SEM. Groups that do not share a letter are statistically different.

Including a log likelihood threshold did not significantly change classifier performance when the testing day came from the same experimental session as that of the training data (Figure 2.7). In comparison with the FULL strategy, the LLT strategy reduced the steady-state error (a relative reduction of 5.61%) when the testing set was acquired from the same session, but there was a slight increase in the transitional error (a relative increase of 1.19%). Neither of these differences was found to be statistically significant ($p>0.05$). When the testing data came from a separate experimental session, both the steady-state and transitional error increased for the FULL strategy. Only the increase in the steady-state error was found to be significant

($p<0.01$). The LLT strategy prevented many of the across session errors, and reduced steady-state and transitional error rates (68.31% and 17.42% relative decrease, respectively), though these reductions were not found to be statistically significant from the FULL strategy ($p>0.05$). Using the LLT strategy resulted in most but not all EMG data acquired from a separate experimental session not being incorporated into the locomotion mode prediction. Thus, predictions made using data from a different experimental session were not always made with just mechanical sensor information. As a result, the LLT strategy performed differently from a system that only used mechanical sensors in the second experimental session. The LLT strategy had error rates of 5.88% and 21.76% in the second experimental session for steady-state and transitional steps, respectively, while a system using only mechanical sensors had error rates of 5.80% and 23.35%, respectively. Both the steady-state and transitional error rate of the LLT strategy in session 2 was higher than the FULL strategy in session 1 (74.77% and 29.76% relative increase, respectively). Neither difference was found to be statistically significant ($p>0.05$).

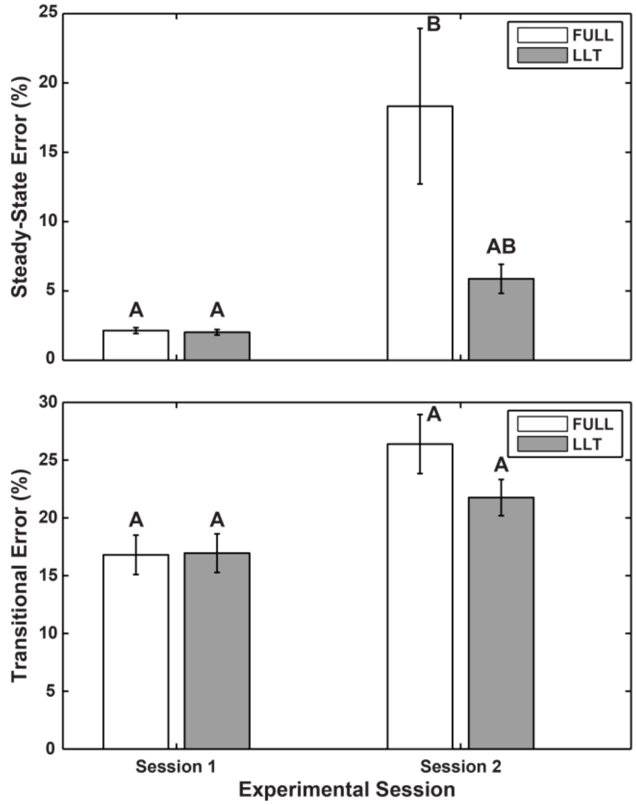

Figure 2.7: Effect of classification strategy and testing sets from different experimental sessions on classification error. Classification strategies were an LDA classifier (FULL) and an LDA classifier with a log likelihood threshold (LLT). Testing sets contained data that came from the same or different session than that of the training data. Classification error rates for both steady-state (top) and transitional (bottom) steps are shown. Data are averages of eight subjects and error bars represent +/- 1 SEM. Groups that do not share a letter are statistically different.

2.4.3 Effect of Using LLTsc

The channel-specific LLTsc strategy removed channels that were identified as containing disturbances, but kept those where no disturbances were detected. This resulted in error rates that were much lower than a system that could not compensate for such disturbances. Sequential selection of the nine EMG channels was performed starting with no liftoff in any of the channels and ending with liftoff in all channels. The error rates of the classifier for both steady-state and transition steps increased as more EMG channels were embedded with simulated electrode liftoff

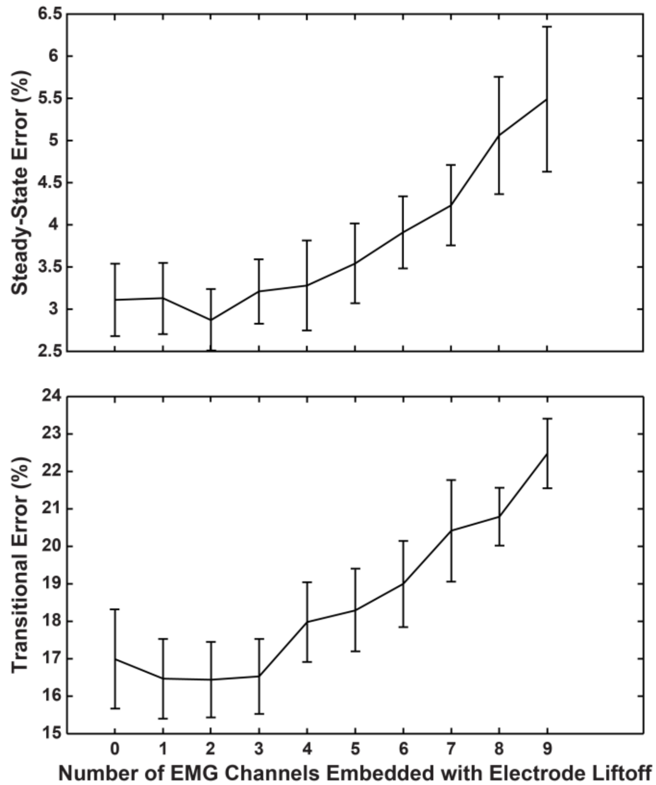

Figure 2.8: Effect of channel specific log likelihood thresholding (LLTsc) on locomotion prediction error rates. EMG channels were embedded with simulated electrode liftoff one by one and the error rate was averaged across all eight subjects. Classification error rates for both steady-state (top) and transitional (bottom) steps are shown. Sequential selection starts with no liftoff in any channels and ends with lift embedded in all channels.

for steady-state and transition steps (Figure 2.8). The error rates were highest when all channels contained disturbances, but the maximum error rate did not increase beyond that of the LLT system, which only used mechanical sensors when any disturbance was detected.

2.5 Discussion

The purpose of this study was to develop a method for detecting and compensating for EMG disturbances, with the intent of improving locomotion mode prediction in a powered lower limb prosthesis. Our results suggest that the log likelihood is a good metric for identifying EMG disturbances. Simulated electrode liftoff and electrode short-circuit disturbances were readily detected by our method, and most EMG data acquired from a different experimental sessions would not be incorporated into a locomotion mode prediction using the threshold. Moreover, the log likelihood metric was found to be stable, as the results were similar for the training and testing datasets without simulated disturbances, as well as training and testing datasets acquired from the same experimental session. The average log likelihood of the training patterns relative to the training dataset is a useful metric because it provides information about which EMG signals should be used to make locomotion mode predictions for a powered lower limb prosthesis. The log likelihood threshold detected and prevented errors associated with not only the simulated disturbances, but also disturbances related to the electrode shift that occurs across experimental sessions. Thus, we expect that the log likelihood threshold could also detect degradations in EMG quality due to other events such as variations in electrode/skin impedances and muscle fatigue. The log likelihood of patterns containing these disturbances is likely much lower than those of the training dataset. Thus, we expect our strategy to have a broad impact on the implementation of robust EMG controllers for lower-limb prostheses. In addition, the threshold we used only requires typical EMG training data, and does not need any additional data collection or external detectors.

Our design allowed the algorithm to choose which set of sensors was used for locomotion mode predictions (i.e., mechanical sensors alone vs. mechanical sensors and EMG) with the intention of preventing errors due to disturbances. Both the steady-state and transitional error significantly increased when the FULL strategy was tested on EMG data that contained simulated disturbances. Testing patterns that contain disturbances are very different from training patterns, and, as a result, are more likely to cause classification errors. Simulated short-circuits produced fewer errors than simulated electrode liftoff. It is possible that the simulated short-circuits were randomly inserted into a channel where there was little EMG activity. This would have generated an EMG pattern that was more like training EMG patterns and thus resulted in more accurate locomotion mode predictions. Using the LLT strategy significantly reduced steady-state and transitional error rates in the presence of simulated EMG disturbances. When EMG patterns in the testing dataset contained simulated disturbances, all EMG data were excluded from the algorithm’s predictions. Thus, the performance of the LLT was equivalent to that of a LDA classifier that only used mechanical sensors for its predictions. The method with which we developed the LLT ensures this baseline level of performance. It is worth nothing that the error rate of the LLT strategy in the presence of simulated EMG disturbances was higher than that of the FULL strategy when there were no disturbances. This difference highlights the benefits of incorporating EMG (when it is undisturbed) into locomotion mode predictions (particularly for transition steps), compared to using only mechanical sensors (i.e., LLT in the presence of EMG disturbances).

Moreover, the LLT strategy did not perform significantly worse than the FULL strategy when the EMG signals contained no simulated disturbances, meaning the LLT was able to incorporate undisturbed EMG into its predictions appropriately. This is supported by the very low false positive rates generated by the log likelihood threshold; very few undisturbed patterns were identified as having disturbances. This indicates that useful EMG data was rarely excluded from predictions. Even so, in the case of a false positive, the locomotion mode prediction made only by the mechanical sensors is likely to be correct. Interestingly, the LLT strategy had slightly lower error rates than the FULL strategy when the EMG signals contained no disturbances. It is likely that a small amount of EMG data produced a prediction error despite being in the testing dataset without disturbances. The log likelihood threshold could still detect disturbances within this dataset, and removing that EMG data resulted in a correct prediction using the mechanical sensors alone.

The log likelihood threshold proved effective in preventing errors caused by disturbances that were not simulated. Using the LLT strategy on data from a different experimental session reduced both steady-state and transitional error rates when compared to the performance of the FULL strategy in the same scenario. In this case, the LLT strategy did not completely disregard all EMG data as was done with simulated disturbances. Rather, the system using the LLT strategy incorporated EMG into its predictions in approximately 30% of the steps. This highlights the difference between electrode shift and disturbances where there is a total loss of information, such as electrode liftoff. EMG data acquired from a different experimental session was not always completely different from the training data according to our log likelihood metric. It is possible that the positions of the electrodes in the second experimental session produced data that was still similar to those in the training set. This resulted in a system that didn’t always use only mechanical sensors, and thus the LLT strategy performed better than a system that only used mechanical sensors for transitional steps. Moreover, the LLT strategy again did not perform significantly worse than the FULL strategy when the EMG signals in the testing dataset came from the same experimental session as the training data, meaning the LLT incorporated undisturbed EMG into its predictions appropriately.

Using only mechanical sensors is a much better alternative than incorporating EMG data with disturbances into the locomotion mode prediction, which results in a very high error rates (Figure 2.6 and Figure 2.7). This presents an improvement over closely related work with adaptive EMG-based control algorithms. Fukuda et al., 2003 [32]; Sensinger et al., 2009 [17]; and Du et al., 2013 [30] all used a retraining strategy when encountering EMG disturbances. In these studies, the pattern in question would be added to the training set and the algorithm would be retrained with the updated dataset. While this strategy may be viable in upper limb applications where errors do not significantly endanger the user, it may cause problems in lower limb applications where errors may present a risk of falling. Classification accuracy would likely improve for future testing patterns after many EMG patterns have been collected, but this strategy does not prevent the algorithm from using these patterns for mode prediction prior to adding them to the training set, resulting in lower classification accuracies that would not be suitable for real-time use. Our proposed LLT strategy would improve on these studies by allowing the algorithm to ignore EMG signals and only use the onboard mechanical sensors to make predictions in the event that EMG signal disturbances are detected. Thus, the LLT method is more suitable for real-time use, where immediate accurate predictions must be made in the presence of EMG disturbances. Moreover, this method does not exclude the possibility of retraining. After disturbed EMG has been identified, the pattern in question could be added to the training set. However, a retraining strategy would be more appropriate for disturbances involving electrode shift rather than the conditions simulated in this study. The pattern recognition system would benefit from adding EMG patterns acquired from shifted electrodes, whereas the simulated disturbances in this study contain little useful information. Our proposed strategy is viable because the powered device used in this study was equipped with mechanical sensors that can make accurate locomotion mode predictions. However, a passive device could be equipped with a less comprehensive mechanical sensor set, as in Huang's 2011 study [10] in order to implement our strategy.

We have also shown that the log likelihood threshold could be applied to each EMG channel to determine which EMG channel contains disturbances (LLTsc). This technique allowed us to remove individual electrodes that were likely to contain disturbances and thus more likely to cause a locomotion mode prediction error. One can easily remove features associated with disturbed EMG channels from the mean feature vector and the covariance matrix, resulting in a feature vector of mechanical sensor features plus the remaining, undisturbed EMG features. Using this technique has the advantage of not only removing EMG that is potentially detrimental, but also keeping the remaining EMG features that improve algorithm performance over using mechanical sensors only (Figure 2.8). The results of this study show that, in general, including more (undisturbed) EMG channels decreases prediction errors, which is in accordance with the findings from other studies [10]. Studies involving adaptive upper limb systems have also shown that removing channels that contain disturbances is beneficial. However, these studies are limited in that removing too many EMG channels could result in an inadequate number of remaining channels to provide accurate user intent recognition [31], [46]. Our implementation of a channel-specific threshold has the added benefit of including mechanical sensors in the locomotion mode prediction. The added information from mechanical sensors both increases prediction accuracy and mitigates the negative impact of removing too many EMG channels.

This study marks a step forward in the development of clinically viable EMG-based control systems for lower limb devices by compensating for variations in EMG signals that degrade algorithm performance. It is also a significant step towards developing an adaptive EMG-based control system for powered lower-limb devices. By enabling the algorithm to choose when to incorporate EMG data into its decisions, we not only mitigate the effects of EMG signal variation, but we can also determine a good starting time point for adaptation. In other words, if the threshold detected many EMG signals with disturbances for an extended period of time, this might indicate that the algorithm needs to be updated via retraining or other adaptive strategies.

3 Simulation of Adaptive Neural Control in Powered Lower Limb Prosthesis

Authors: John A. Spanias, Eric J. Perreault, and Levi J. Hargrove

3.1 Abstract

Using electromyography (EMG) to improve intent recognition algorithms for powered lower limb prostheses has shown promise, yet clinical implementation remains an obstacle because the EMG signals change over time. The objective of this study was to develop an adaptive pattern recognition algorithm that learns novel EMG data to maintain low error rates over long-term use. We required our algorithm to 1) prevent errors associated with disturbances in EMG signals, 2) associate EMG patterns with the correct class label, and 3) update the classifier using the automatically labeled patterns. Data acquired from four amputees walking with a powered knee-ankle prosthesis in multiple sessions were used to evaluate our algorithm. We show that our algorithm accurately labeled new data by comparing mechanical sensor information to characteristic gait profiles generated during ambulation, and that these low error rates did not change significantly (p=0.36) across sessions. Our algorithm adapted its parameters by adding new data to the initial training dataset, resulting in significantly decreased classification error rates (p=0.049). These results suggest that an adaptive EMG-based pattern recognition algorithm is useful for enhancing and maintaining long-term performance.

3.2 Introduction

Powered prosthetic legs are now commercially available and several advanced prototypes have been developed [5], [6], [49]. However, implementing a robust control system in these devices remains challenging, limiting further development and distribution. Most current systems use a hierarchical controller and accommodate several modes of locomotion (e.g. level ground walking, stair ascent, ramp descent). This typically consists of a finite state machine to control the switch between portions of the gait cycle (e.g. stance, swing,) and a low-level controller to appropriately actuate motors at the knee and ankle joints using state-specific impedance parameters [49]–[51]. A key challenge is identifying the desired mode of locomotion to allow for seamless transitions between the user's desired functions. Meeting this challenge requires correctly identifying the user's intended mode prior to the user taking the next step with the prostheses, a process we term *forward prediction*.

The performance of any forward prediction algorithm depends on the available signals used in the decision making process [12], [24], [51]. Much can be inferred from mechanical sensors located on the prostheses, such as those that measure kinetic and kinematic information. Neural signals, such as electromyograms (EMGs), add important information that significantly reduces forward prediction error rates [10], [13], [14], [23], [25]. These benefits have been observed offline, when examining data collected from previous walking sessions, and online when incorporated into a real-time controller. A difficulty with incorporating EMGs is that their quality can change from day-to-day due to shifts in the placement of electrodes relative to the muscles of interest, loss of skin-electrode contact, variations in electrode/skin impedance, or anatomical changes over time [15]. These issues could influence the utility of EMG signals for long-term use.

The research on long-term use and stability of prosthetic systems incorporating EMGs is limited. Most studies that have evaluated EMG-based forward prediction algorithms for lower limb prostheses have been performed within a single day [14], [25]. Algorithms that use only mechanical sensor data have been shown to be relatively robust across days, presumably because the mechanical sensors do not change their behavior significantly over time [52]. In limited research evaluating across-day performance, we have found that forward prediction performance deteriorates significantly between days when using EMG signals [53]. This is likely because we used a static decoder that was unable to compensate for EMG signal changes. We later developed a technique in Chapter 2 that used the log-likelihood of the observed EMG signals to detect changes in signal quality, and reverted to using only mechanical sensors when significant changes in EMG were detected [53]. This prevents major classification errors, but also eliminates the benefits associated with using EMGs in forward prediction process. Here we develop a complementary algorithm that adapts the forward predictor when changes to the information content of the EMG signals are detected, thereby restoring the benefits of EMG.

Adaptive pattern recognition algorithms have been developed for numerous applications, but have seldom been used successfully in the area of myoelectric control [17], [32], [54]. Most studies focus on upper-extremity prostheses and rely on adaptation paradigms that are supervised, meaning that patterns must be paired with a class label representing the intent of the user to calculate classifier boundaries. In these studies, the output of the classifier used in forward prediction was also used to label new data [17]. This approach can be problematic because a pattern recognition algorithm that is presented altered EMG is likely to make misclassifications, resulting in new patterns being paired with the wrong class label. Data that are incorrectly labeled could cause significant deterioration in forward prediction performance if they are added to the training set [17]. For lower extremity applications, we can take advantage of the cyclic nature of human ambulation and rely on knowledge of the leg's programmed gait profiles to help supervise adaptation of our forward prediction. After the user completes a stride, mechanical sensor data acquired from the entire stride are compared to characteristic gait profiles to determine the mode of the last stride taken, a process we term *backwards estimation*. This strategy is in contrast to the forward prediction needed for real-time control which must make predictions based on data obtained before the stride of interest. Preliminary results have shown that fewer data are labeled incorrectly when backwards estimation is used [52]. What remains incomplete is the evaluation of an adaptive forward prediction algorithm that combines reliable EMG disturbance rejection with accurate labeling of novel data.

The objective of this study was to develop a forward prediction algorithm for a powered lower limb prosthesis that safely incorporates new data to adapt to changes in EMG information content. This algorithm had to: 1) be robust to EMG disturbances; 2) accurately label new EMG data; and 3) correctly update algorithm parameters. Thus, this chapter combines the log-likelihood threshold developed in Chapter 2 with an adaptive algorithm that can learn from new EMG signals when changes are detected. We evaluated robustness to EMG disturbances by testing the algorithm with data acquired from multiple experimental sessions. Backwards estimation was used to label new patterns from newer sessions with the correct class before they were used to update the forward predictor. We evaluated our adaptive algorithm with data that the algorithm would encounter outside a controlled experimental environment, providing an accurate simulation of how the proposed algorithm would behave in practice. We hypothesized that our algorithm would not only improve performance across experimental sessions when compared to a non-adaptive algorithm, but would also outperform an algorithm that only uses mechanical sensors data to make forward predictions, which is a significant improvement over prior results.

Within this dissertation, this chapter provides an offline simulation of the adaptive algorithm. It expands the work completed in Chapter 2 by allowing the forward predictor to learn from new EMG signals after identifying changes within the EMG. Adaptation is accomplished through accurate labeling of new patterns, which is completed via the backwards estimation strategy explained in this chapter. This strategy takes advantage of the cyclic nature of ambulation, making it an innovative method for automatically labeling new training data.

3.3 Methods

3.3.1 Experimental Protocol

Four subjects with unilateral transfemoral amputations completed the experiment, which was approved by the Northwestern University Institutional Review Board. Subjects' ages ranged from 30 to 66, heights from 1.75 and 1.87 m, and weights from 77.1 and 96.6 kg. Written and verbal consent was obtained from each subject involved.

Each subject was fitted with a custom-made skin-fit suction socket that had embedded stainless-steel dome electrodes that recorded surface EMG signals from nine muscles: semitendinosus, biceps femoris, tensor fasciae latae, rectus femoris, vastus lateralis, vastus medialis, sartorius, adductor magnus, and gracilis. A clinician identified the muscle sites via palpation, and the electrodes were inserted into the socket based on the identified locations. The Center for Intelligent Mechatronics at Vanderbilt University designed the powered knee and ankle prosthesis used for this experiment (Figure 3.1) [8]. A certified prosthetist attached and aligned the prosthesis to the subject's socket. Prior to completing the protocol for this study, each subject participated in tuning sessions where the leg's state-based impedance parameters were tuned in each of the five modes investigated in this study (level walking, stair ascent/descent, ramp ascent/descent) as described in previous studies [6], [44], [47], [51].

The general experimental paradigm used to collect the data in this study has been described in previously published literature [28]. Briefly, after the prosthesis was tuned for each subject, the subject participated in two different experimental sessions completed across two days. In both sessions, the subject completed a set of offline supervised locomotion circuits, where the subject completed 20 repetitions of a circuit that included level-ground, ramps, and stairs (Figure 3.2). During this offline portion, an experimenter triggered the prosthesis between

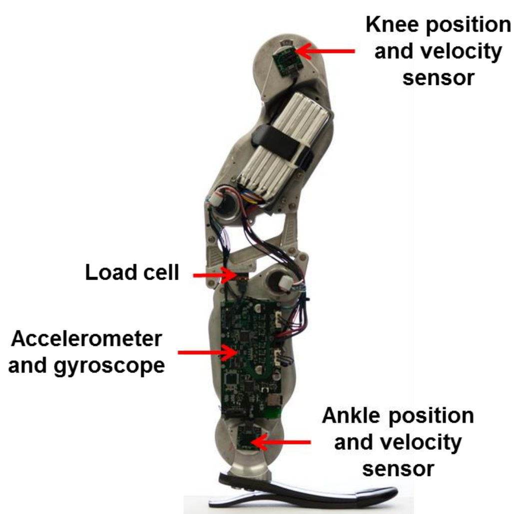

Figure 3.1: Powered lower limb prosthesis used by amputee subjects. Subjects used the prosthesis to complete the experimental protocol. The figure also shows the embedded mechanical sensors that were used to acquire kinetic and kinematic data from the subjects.

Level Walking Ramp Ascent Ramp Descent Stair Ascent Stair Descent

Figure 3.2: Photographs of amputee subjects completing the locomotion circuits with the programmed locomotion modes. The figure shows examples of the different modes of the powered lower limb prosthesis. The prosthesis transitioned between these modes as the amputee subjects completed the locomotion circuits.

modes at heel contact and toe-off using a key fob. Therefore, the prosthesis was always in the correct mode during the completion of the supervised circuits. All mechanical sensor data, EMG signal data, and locomotion mode labels were recorded as the subject completed the offline portion. In the second experimental session, in addition to the 20 offline locomotion circuits, subjects also completed two sets of 10 trials where an online forward predictor controlled the mode of the prosthesis. Each set of 10 trials used a different type of forward predictor: First, a forward predictor where both EMG and mechanical sensor data were classified by a Dynamic Bayesian Network (DBN) classifier (described below) [14], [24]. Secondly, only mechanical sensor data were classified by a Linear Discriminant Analysis (LDA) classifier. It is important to note that the forward predictors sometimes made classification errors and transitioned the leg into the incorrect mode during these online sessions. In summary, the subjects completed the offline portion of the experiment in both sessions, and completed the online portion only in the second session. The entirety of these datasets was used to run an offline simulation of our proposed adaptive algorithm.

Signals from 13 mechanical sensors embedded within the prosthesis were recorded at 500 Hz. These included signals from kinematic, kinetic, and inertial sensors. Kinematic sensors recorded the relative positions and velocities of the knee and ankle joint. Kinetic sensors recorded torques (measured with the motor current) delivered to the knee and ankle, as well as information from the axial load cell. The signal from the load cell was smoothed using a low pass filter with a cutoff frequency of 20 Hz. All EMG signals (nine channels in total, for each investigated muscle) were recorded at 1000 Hz per channel using a custom-built EMG recording system that incorporated a Texas Instruments TI-ADS1299 instrumentation chip.

3.3.2 Forward Prediction Algorithm

In this study, we used a DBN for forward prediction [24], which predicted the locomotion mode of the prothesis. Mechanical sensor data and EMG data were segmented into analysis windows of 300 ms before eight different gait events (Figure 3.3), where the gait events were 0/25/50/75% of both stance and swing phases (0% of stance was heel contact and 0% of swing was toe off) [24]. Mechanical sensor features were extracted from each window for each sensor and were the signal mean, standard deviation, maximum, minimum, initial, and final values [9], [24]. The EMG features were the mean absolute value, waveform length, zero crossing, slope sign changes, and the first two autoregressive coefficients of third-order autoregressive model extracted from each window for each EMG channel [13], [55], [56]. The DBN generated posterior probabilities for each gait event (which were detected with the state machine of the

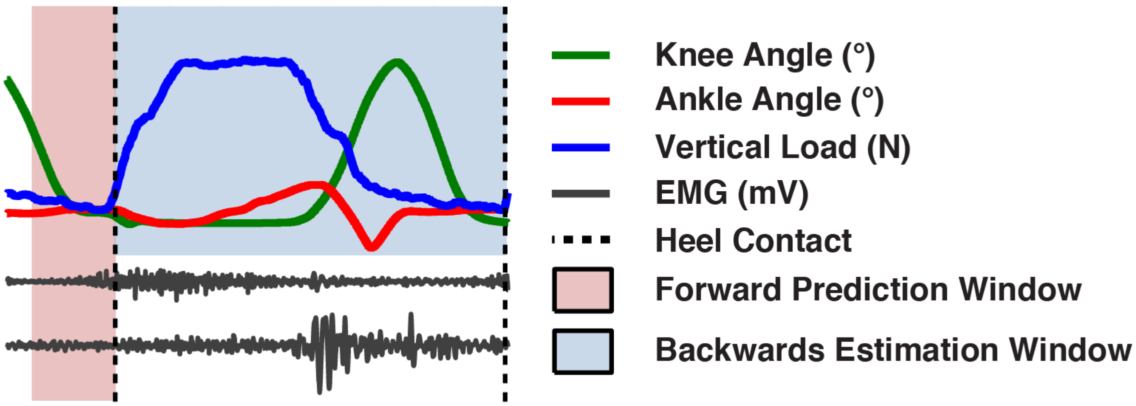

Figure 3.3: Examples of real data, and windows used for forward prediction and backwards estimation. The figure shows representative data from a single stride acquired from a single subject, including the measured knee angle, ankle angle, load cell reading, and two channels of EMG data. Also shown are the windows used for forward prediction and backwards estimation. Forward prediction used a 300ms window (the red shaded window) of data that began before a gait event (heel contact in this figure). The backwards estimator used the entire window of data between gait events (the blue shaded window from heel contact to heel contact in this figure), and classified this data to provide a label for the pattern that updates the forward predictor.

prosthesis), and which were then transformed into prior probabilities for the next gait event. More information on DBNs with lower limb prostheses can be found in [24].

The DBN also used a threshold based on the log-likelihood of the EMG feature vector to determine whether it is appropriate to use EMG to make its predictions [53]. The log-likelihood is the log probability of observing a multivariate point given a multivariate distribution. The multivariate point was an EMG feature vector, and the multivariate distribution was the collection of all EMG feature vectors in a training dataset modeled as a Gaussian distribution. If the log-likelihood of a novel EMG feature vector from the testing dataset was more than three standard deviations from the average log-likelihood of the feature vectors in the training set, that novel vector was assumed to be different from those of the training data set [53]. The primary purpose of using this metric in this study was to automatically determine if the EMG data measured during one experimental session were different from those measured during another session. When they were not different, the forward predictor used EMG data. Otherwise, only mechanical sensor data were used. The forward predictor classified data into one of five classes representing the different mode of the leg (level walking, stair ascent, stair descent, ramp ascent and ramp descent).

3.3.3 Backwards Estimation Algorithm

For backwards estimation, we wait until after the stride has been completed and then attempt to recognize the performed gait pattern. To achieve this, only mechanical sensor data were segmented into two windows representing the swing phase (toe off to toe off) and stance phase (heel contact to heel contact) within a single stride (Figure 3.3) [52]. The backwards estimator used in this study also used a DBN to classify the completed gait pattern [24]. The mechanical sensor features extracted for backwards estimation were once again signal mean, standard deviation, maximum, minimum, initial, and final values. The output of the backwards estimator provided a class label for the pattern of data used by the forward predictor before the stride. The backwards estimator classified gait patterns into one of the same five classes as the forward predictor.

3.3.4 Algorithm Evaluations and Statistical Comparisons

For supervised adaptation, it is important to accurately assign class labels to patterns of new data, and these class labels need to be generated automatically to be suitable for online implementation. In this study, we were interested in presenting backwards estimation as an accurate and automatic labeling strategy for an adaptive EMG-based forward prediction algorithm. Specifically, we hypothesized that backwards estimation was a superior labeling strategy when compared to using the output of the forward predictor to label new data. Thus, we investigated the following:

- The performance of the forward predictor and the backwards estimator within and across experimental sessions
- The performance of the backward estimator when evaluated with data where the prosthesis was controlled by the online forward predictor
- The performance of an adaptive forward predictor that used backwards estimation to label new data added to the training dataset
- Whether the aforementioned adaptive forward predictor could learn to re-incorporate EMG into its predictions as more new data were added to the training dataset

In this study, error rates are reported as pooled misclassification rates at heel contact and toe-off, as these are the time points where the prosthesis was allowed to transition between locomotion modes. Variances between groups were not homogeneous based on a Levene's Test; thus error rates were log transformed to fit the homogeneity assumption for ANOVA. Post-hoc tests were conducted on statistically significant variables of interest ($p < 0.05$).

3.3.4.1 Evaluation of Labeling Strategies Across Sessions

We investigated the performance (quantified by the classification error rate) of the forward predictor and the backwards estimator within and across experimental sessions by using data collected from the offline supervised trials. Training and testing datasets for the forward predictor and the backwards estimator were created by using leave-one-trial-out cross validation with the data collected from the 20 offline supervised trials (i.e., using 19 trials in the training set and one trial in the test set, repeated 20 times such that each trial was in the test set once). Both the forward predictor and the backwards estimator were trained with data acquired from the offline portion of the first experimental session, and were tested under two conditions: 1) the testing data came from the same experimental session as the training data; and 2) the testing data came from a different experimental session. A repeated measures ANOVA was performed with classification error rate as the response and the experimental session and type of classifier (forward prediction or backwards estimation) as fixed within-subject variables with interaction terms.

3.3.4.2 Evaluation of Labeling Strategies During Online Trials

We also investigated the error rate of the backward estimator during trials where the prosthesis was controlled by the online forward predictor. This was determined by using data collected from the online trials. We trained the backwards estimator using the offline data from the first experimental session (20 training trials), and evaluated it on data acquired from the online portion of the second experimental session (10 testing trials). The error rates of the online forward predictor and the backwards estimator were compared using a paired t-test.

3.3.4.3 Evaluation of the Simulated Adaptive Forward Predictor

We simulated adaptation of the forward predictor by adding novel data to its original training dataset and updating algorithm parameters (for a DBN, these included class means and covariances). A forward predictor and a backwards estimator were trained with all 20 trials of the supervised offline circuits from the first experimental session for each subject. We created an adaptation dataset comprised of data collected from the 10 trials of the online portion of the second session (i.e., when mode transitions were controlled by a static online forward predictor that could make errors and transition the leg into the incorrect mode). Thus, the adaptation dataset contained data where the user was ambulating with the online forward predictor, and consequently contained data of the mistakes made by the forward predictor. We also created a testing dataset comprised of data collected from the offline supervised circuits from the second experimental session (20 testing trials). To simulate adaptation of the forward predictor, we added data collected from the adaptation dataset to the training dataset, updated the predictor's parameters, and observed the predictor error rates on this testing dataset. We used sequential estimation to update the parameters of the forward predictor, including the class means, μ_c, and covariances, Σ_c, of each classifier; *c* corresponds to the specific class. Equations 3.1 and 3.2 describe sequential estimation of a class mean, μ_c, and class covariance, Σ_c, based on *N* observations and given the contribution of the newest pattern, x_N.

$$\mu_{c,N} = \mu_{c,N-1} + \frac{1}{N}\left(x_{c,N} - \mu_{c,N-1}\right) \qquad (3.1)$$

$$\Sigma_{c,N} = \Sigma_{c,N-1} + \frac{1}{N}\left(x_N {x_N}^T - \Sigma_{c,N-1}\right) - \mu_{c,N}{\mu_{c,N}}^T \qquad (3.2)$$

These updated class means and covariances were then used to update the weights of DBN classifiers, which are used to classify patterns of data. The class covariances were then pooled to create a single covariance matrix for the data, Σ, and weights, $\boldsymbol{W_c}$, and biases, w_c, for each class were calculated. These weights and biases represent updated DBN classifiers. The equations for updating the weights and biases are found in Equations 3.3 and 3.4:

$$W_c = \Sigma^{-1}\mu_c \qquad (3.3)$$

$$w_c = -\frac{1}{2}\mu_c^t \Sigma^{-1}\mu_c \qquad (3.4)$$

We evaluated the adaptive forward predictor by observing the overall error rates before adaptation, and after adding data from the adaptation dataset given a specific labeling strategy. For this evaluation, we considered adaptation given that all labels were correct, or labels are provided by the backwards estimator. A repeated measures ANOVA was performed with classification error rate as the response and initial/final performance as a fixed within subject variable. We reported error rates after adding the lowest common number of steps in the adaptation datasets of each subject (455 steps).

3.3.4.4 Reincorporating EMG

Lastly, we present the percentage of steps in the testing dataset where EMG was used as more novel data were added to the training set. We added data from the adaptation dataset one step at a time and in random order. As each step was added, we calculated the percentage of steps in the testing dataset where EMG was used.

3.4 Results

3.4.1 Performance of Automatic Labeling Strategies

The backwards estimator outperformed the forward predictor in both experimental sessions (Figure 3.4). When evaluated on data from Session 1, the backwards estimator had an error rate that was 2.26% [0.91%], mean [standard deviation], lower than that of the forward predictor ($p < 0.001$). In Session 2, the error rate of the backwards estimator was 4.88% [2.11%] lower than that of the forward predictor ($p < 0.001$).

The backwards estimator was also more consistent across experimental sessions than the forward predictor was (Figure 3.4). When compared to Session 1, the error rate of the backward estimator in Session 2 increased by 0.43% [0.80%], and this increase was not found to be statistically significant ($p = 0.36$). In contrast, the error rate of the forward predictor significantly increased by 3.05% [3.49] ($p < 0.001$) across experimental sessions.

Backwards estimation remained the superior labeling strategy even when the online forward predictor controlled the leg and sometimes transitioned it into the incorrect mode (Figure 3.5). Online forward prediction errors caused the backward estimator to make errors at a higher rate, but the error rate of the backwards estimator was 5.70% [6.88%] lower than that of the online forward predictor (p = 0.049).

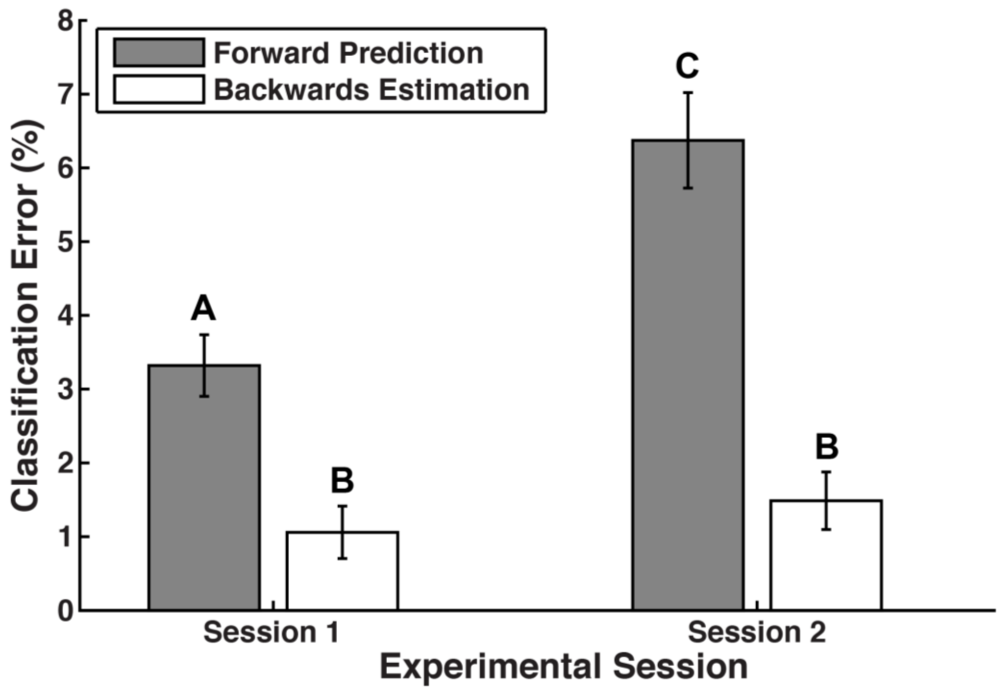

Figure 3.4: Effect of classification strategy and experimental session on classification error. Classification strategies were a forward predictor and a backwards estimator. Testing sets contained data that came from the same (Session 1) or different session (Session 2) as that of the training data. Data are averages of four subjects and error bars represent ±1 standard error of the mean (SEM). Bars that do not share a letter are statistically different (p < 0.05).

3.4.2 Influence of Labeling Strategy on Algorithm Adaptation

The good performance of the backwards estimator as a labeling strategy was reflected in the error rate of the adaptive forward predictor (Figure 3.6). The adaptive forward predictor that was supervised using the backwards estimation significantly reduced error rates by 2.02% [1.86%] (p = 0.049) when compared to its starting error rate (i.e. before any adaptation). The ending error rate of the adaptive forward predictor that used backwards estimation as a labeling strategy was also not significantly different from the adaptive forward predictor that had perfect labels (0.65% [0.98%] increase, $p = 0.59$).

3.4.3 Influence of Amount of Added Data on Incorporating EMG into Forward Predictions

Consistent with our previous findings [53], the forward predictor used EMG signals to make predictions in 30.5% [0.0%, 86.1%], mean 95% CI [lower bound, upper bound], of the testing data before being updated (Figure 3.7). As more data were added, the percentage of steps in the testing dataset where EMG was used to make forward predictions increased. After all novel data were added, the updated forward predictor used EMG in almost 90% [73.2%, 98.6%] of the testing data.

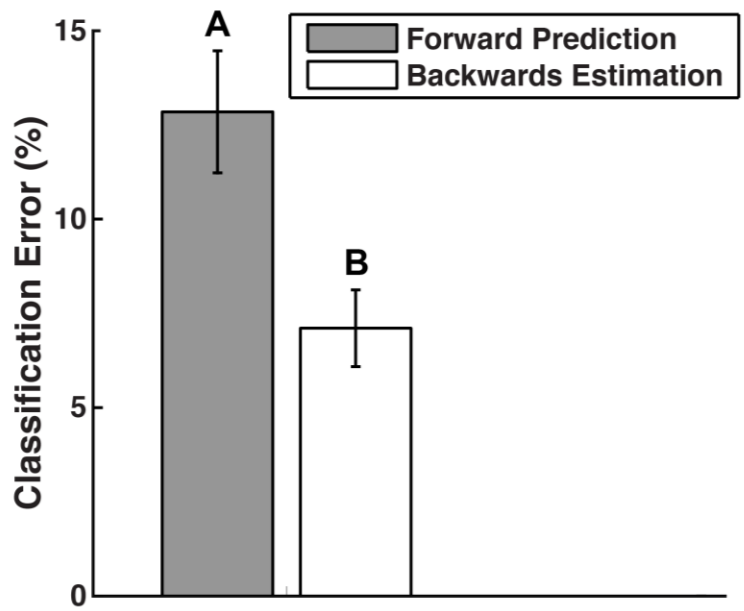

Figure 3.5: Error rates of the online forward predictor and the backwards estimator when tested on data acquired during trials where the online forward predictor was used to control the prosthesis. Data are averages of four subjects and error bars represent ±1 SEM. Bars that do not share a letter are statistically different ($p < 0.05$).

3.5 Discussion

The purpose of this study was to develop and evaluate an adaptive EMG-based forward prediction algorithm for a powered prosthetic leg. Our simulations showed that our algorithm completed the outline objectives, and 1) was robust to EMG disturbances via use of a log-likelihood threshold for EMG data; 2) could accurately label new EMG data using a backward estimator; and 3) correctly update algorithm parameters using sequential estimation. The data used to evaluate our algorithm represent a common problem for EMG-based forward prediction algorithms because they were acquired across multiple experimental sessions, and are similar to those that would be acquired if a patient were to don and doff the prosthesis. Moreover, the adaptive algorithm was evaluated with data that were acquired when the forward predictor

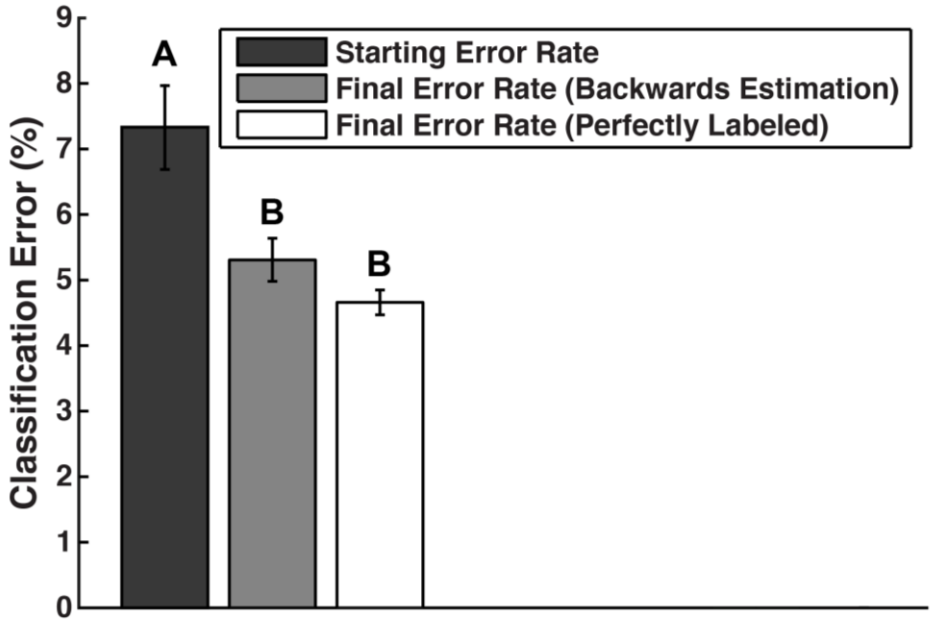

Figure 3.6: Classification error rates of the forward predictor before and after data from the adaptation dataset are added to the training dataset. Data were added to the training set under two conditions: 1) a backwards estimator labeled all data; and 2) all novel data were correctly labeled (perfectly labeled). Data are averages of four subjects and error bars represent ±1 SEM. Bars that do not share a letter are statistically different ($p < 0.05$).

occasionally transitioned the leg into the incorrect mode, an event that occurs during real-time use. Thus, we believe that this study presents a realistic simulation of an adaptive algorithm.

Forward prediction algorithms are typically trained using supervised learning algorithms that require new data to be paired with a class label [10], [14], [50]. Manually collecting labelled training data is inconvenient and time-consuming. Thus, we investigated techniques for implementing unsupervised adaptation, meaning that all data are automatically labeled by the adaptive algorithm even though the true intent of the user (i.e. the class labels) is unknown. Previous studies have used the output of the forward predictor as a label for new data that were used to update the predictor [17]. This strategy is problematic, specifically for our application, where the EMG signal degradation hurts forward prediction performance [53], and would result in more data being mislabeled as shown in the across session changes of the forward predictor in

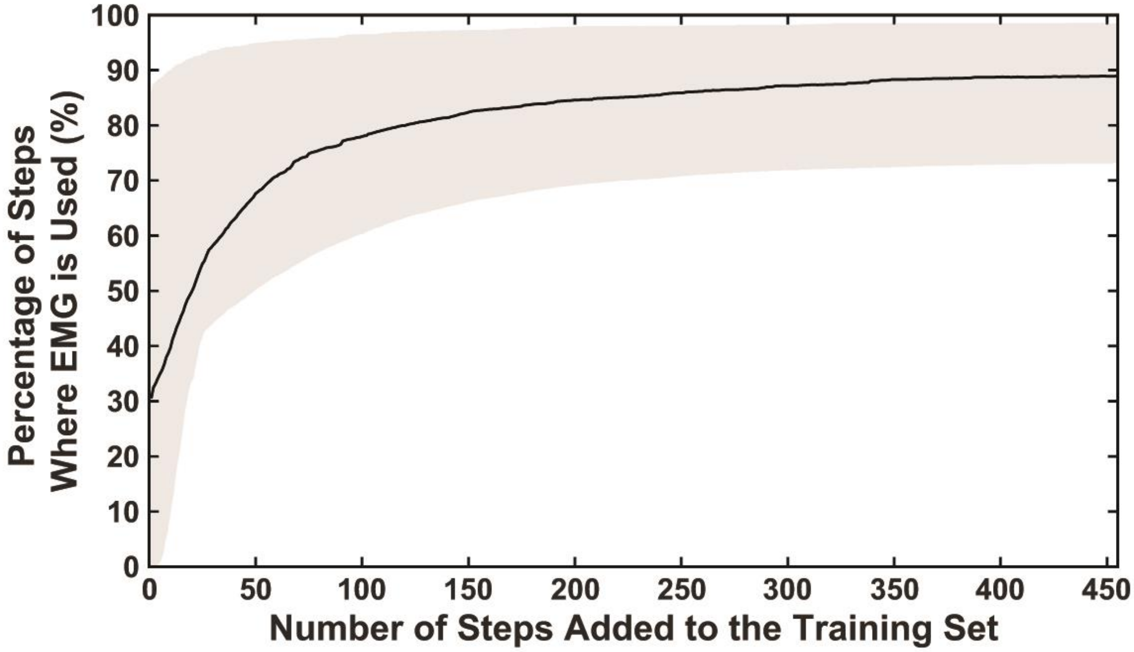

Figure 3.7: Percentage of EMG incorporated into locomotion mode predictions as more novel data were added to the training set. A forward predictor with a log-likelihood threshold was trained on offline data from the first experimental session and tested on offline data from the second experimental session. Novel data from the online portion of the second experimental session were added to the training set one step at a time. The graph shows the percentage of steps within the testing set where EMG was incorporated as more steps were added to the training set. Data are averages of four subjects and error bars represent 95% confidence intervals.

Figure 3.4. Mislabeled data have been shown to negatively impact adaptation in studies investigating myoelectric control for upper-limb prostheses [17].

To address these limitations, we developed a backwards estimator to recognize which programmed gait profiles were executed by the user. These data contain longer recordings than those used by forward prediction (approx. 1.5 second windows compared to 0.3 seconds), and are acquired from only mechanical sensors, which do not suffer from the signal quality degradation that we observe with EMG [53]. We found that backwards estimation had lower error rates than those of forward prediction within a single experimental session and across sessions (Figure 3.4). Moreover, the performance of the backwards estimator did not change across experimental sessions, making it a reliable labeling strategy that works over many days. Thus, we found that it is easier to determine what the subject did (backwards estimation) than to determine what the user wanted to do (forward prediction).

We also evaluated the backwards estimator with data where the prosthesis was sometimes in the incorrect mode. Misclassifications by the forward predictor sometimes produce gait patterns that are unlike those generated when the leg is operating within the correct mode. Prior to this study, it was unclear how these misclassifications would impact the performance of the adaptive algorithm. We addressed this limitation by evaluating the performance of the backwards estimator with data where the prosthesis was controlled by the online forward predictor (Figure 3.5). These data contained gait patterns where the leg was occasionally in the incorrect mode as a result of misclassifications. As expected, we observed that the error rate of the backwards estimator was higher when it was evaluated on these data.

However, the increased error rate of the backwards estimator was still lower than that of the online forward predictor, Furthermore, the adaptive forward predictor that used backwards estimation as a labeling strategy did not perform differently from one that used perfect labels, and the adaptive algorithm had significantly decreased error rates when compared to the starting error rate (Figure 3.6). Still, it may be possible to further improve the performance of backwards estimation by collecting data where the leg is in the incorrect mode, and using those data to train the backwards estimator to recognize the true intent of the user despite misclassifications by the online forward predictor. For this study, we did not train the backwards estimator with data where the user was ambulating in the incorrect mode because the amputee subjects did not complete this type of walking in the first offline session.

The adaptive forward predictor also learned to reincorporate EMG as more data from the second experimental session were added to the training dataset (Figure 3.7). Initially, the adaptive predictor used EMG in approximately 30% of the steps in the testing dataset. This is most likely because the testing data contained changes associated with electrode shift caused by donning and doffing the prosthesis (though this shift was not explicitly measured). Our log-likelihood threshold determined that most of the EMG was inappropriate for forward prediction, and instead relied on only mechanical sensors. However, unlike other EMG disturbances such electrode liftoff where there is a complete loss of information, the testing data in this study still contained some useful information that could be used for prediction. Thus, as we have seen in previous studies [53], our forward predictor initially used EMG in a small percentage of steps.

The percentage of steps where EMG was used in the testing dataset increased to almost 90% after data from 455 steps were added to the original training dataset. This likely contributed to the decrease in the error rate of the adaptive forward predictor because EMG has been shown to improve algorithm performance given that it has been appropriately trained [10], [14]. We expect that this percentage would continue to increase as more novel patterns are added to the training dataset, though it is clear that this positive rate decreases as more patterns are added. This is because new EMG data contribute less to the development of the model as more patterns are added to the training dataset. It is also possible that EMG data from the first experimental session kept the algorithm from completely learning the updated model of EMG features. In this study, new data were simply added to the training set, but it may be beneficial to “forget” data from previous sessions as the forward predictor is updated. This would result in a forward predictor that uses the most recent or most representative set of EMG data, though the benefit this provides for our algorithm is still unknown. On the other hand, it may be beneficial to include many days of EMG data, so that many unique exemplars are incorporated into the model of EMG. Though our proposed adaptive algorithm does not always use EMG, we believe that it is a safer alternative than always trusting the information that EMG provides, which may be corrupted by signal changes and inappropriate for forward prediction.

Another noteworthy limitation that was not explored in this simulation is that the online data used to update the forward predictor was not affected by adaptation (i.e., because this was an offline analysis, the performance of the updated forward predictor did not change the actual behavior of the leg). It would be more appropriate to look at the rate of convergence to a plateaued error rate, and the level of the plateau in a fully online system.

Even considering the aforementioned limitations, our data suggest that an adaptive forward predictor that uses a backwards estimator to label new data is a practical EMG-based forward predictor for powered prosthetic legs. Our algorithm could intelligently determine whether or not to use EMG in its forward predictions, automatically and accurately label new patterns of data via backwards estimation, and update algorithm parameters to improve performance over time. Moreover, we have evaluated our proposed algorithm with data that represent real-time use of the algorithm, and believe this to be a realistic offline simulation of the adaptive algorithm. This research represents a step forward for intent recognition algorithms for lower limb prostheses because it will prevent unintended prosthesis behavior due to the adverse effects of EMG signal variations, and maintain low error rates over long-term use.

4 Delaying Ambulation Mode Transition Decisions Improves Accuracy of a Flexible Control System for a Powered Knee-Ankle Prosthesis

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4.1 Abstract

Powered lower limb prostheses can assist users in a variety of ambulation modes by providing knee and/or ankle joint power. This study's goal was to develop a flexible control system to allow users to perform a variety of tasks in a natural, accurate, and reliable way. Six transfemoral amputees used a powered knee-ankle prosthesis to ascend/descend a ramp, climb a 3- and 4-step staircase, perform walking and standing transitions to and from the staircase, and ambulate at various speeds. A mode-specific classification architecture was developed to allow seamless transitions at four discrete gait events. Prosthesis mode transitions (i.e., the prosthesis' mechanical response) were delayed by 90 ms. Overall, users were not affected by this small delay. Offline classification results demonstrate significantly reduced error rates with the delayed system compared to the non-delayed system ($p<0.001$). The average error rate for all heel contact decisions was 1.65% [0.99%] for the non-delayed system and 0.43% [0.23%] for the delayed system. The average error rate for all toe off decisions was 0.47% [0.16%] for the non-delayed system and 0.13% [0.05%] for the delayed system. The results are encouraging and provide another step towards a clinically viable intent recognition system for a powered knee-ankle prosthesis.

4.2 Introduction

A new generation of lower limb prosthetic devices has emerged to restore function and mobility to individuals with a major lower limb amputation. Powered prosthetic knees and ankles can provide amputees with near physiological joint power at the knee and/or ankle [5], [6], [49], [57] and assist them in performing a variety of ambulation modes. Novel control strategies have been developed to assist amputee users during steady-state level-ground walking, inclined-surface walking, stair climbing, and standing up from a seated position. Control of these powered devices within an ambulation mode is often achieved through finite state machines; mechanical sensors embedded into the prosthesis can be used to identify different portions of the gait cycle (e.g., swing or stance phase) and modify the device’s response (e.g., provide resistance, generate power, etc.) [6], [21], [44], [47], [49], [51], [58], [59].

A challenge exists as to how to best transition these devices from one mode to another. Ideally, users should be able to transition between ambulation modes in a natural, seamless, and reliable way. The most basic, albeit cumbersome, ways include pressing a button on a key fob or performing an exaggerated motion with the residual limb [57], [60]. Recently, pattern recognition algorithms have been used for ambulation mode classification in lower limb prostheses; these systems predict an upcoming mode transition and transition the prosthesis appropriately. Studies have reported results using a range of mechanical sensors (e.g., goniometers, load cells, inertial measurement units) [28], [50], [61], electrophysiological sensors (e.g., electromyography) [6], [10], [23], environment sensors (e.g., vision) [12], [62], classification methods (e.g., support vector machine, linear discriminant analysis, dynamic Bayesian network) [10], [14], [24], [25], and classifier training mechanisms [9], [18], [28] for lower limb pattern recognition systems. Data classification has been performed at discrete points during each gait cycle (e.g., at heel contact or toe off) [14], [23] or continuously throughout the gait cycle [9], [10]. While these system results are promising, error rates with transfemoral amputee users remain relatively high when predicting mode transition steps compared to steady-state steps.

Investigations into ambulation mode transition steps highlight a critical timing window [10], [63] in which the prosthesis can safely switch from one ambulation mode to another. The more recent study [63] identified four to five gait phases (e.g., terminal double support, swing flexion, swing extension prior to the surface transition or initial double support after the surface transition) where a powered prosthesis could transition between level-ground walking and inclined-surface walking and not disrupt the user's balance. This new research suggests that delaying the ambulation mode transition by a small window of time may not affect user performance. Another study, which tested the effects of ambulation mode prediction system errors (i.e., misclassifications) on real-time performance of amputee users, demonstrated that depending on the ambulation mode and gait phase of the error, transfemoral amputee users either did not notice some errors or noticed them but still felt stable [64]. However, errors during other mode transitions, such as the transitions between level-ground walking and stair climbing, may result in more noticeable or substantial errors [14], [25]; the critical timing window for these transitions is not yet defined. These findings are important because delaying the timing of ambulation mode transitions by a small window may improve ambulation mode prediction accuracy without noticeably affecting the user's performance.

To further improve lower limb powered prosthesis control systems, studies need to account for wider variability within the collected data set. Many of the previously described systems required amputee users to be fairly deliberate in their ambulation during data collection. Multiple trials were recorded of users performing the same ambulation task in a similar way each time [28]. While these exemplars help to create a more accurate system representing the data collected, it may not translate to a more reliable system when the amputee user leaves the laboratory. System architectures need to be updated to account for user preferences in speed, various approaches to obstacles, and variability in the environment.

The goal of this study was to create a flexible and more accurate lower limb intent recognition system for powered knee-ankle prostheses. We refined our existing system [14] by incorporating a standing mode, a mode-specific classifier system [18], and additional prosthesis transitions that allowed users to ascend and descend even- and odd-numbered staircases from standing or walking at various approach angles. We investigated the effect that a 90 ms delay in ambulation mode transitions had on the accuracy of each mode-specific classifier which allowed transfemoral amputee users to transition between six modes (standing, level-ground walking, ramp ascent, ramp descent, stair ascent, and stair descent) at various discrete time points during the gait cycle. We hypothesized that the delayed system would result in fewer errors than a non-delayed system.

Within this dissertation, Chapter 4 serves to describe a newer prosthesis and its control system, both of which are different from those used in previous chapters. Specifically, this chapter describes a new state machine and classifier architecture, which both define the type of mode transitions the prosthesis is allowed to complete. Thus, the study in Chapter 4 provides a description of the prosthesis and control system that will allow the reader to contextualize and understand the results of later chapters, which describe the online adaptation experiments. These enhancements are significant contributions in the field of lower limb prosthetics because they improve control, ease of use, and pattern recognition performance.

4.3 Methods

4.3.1 Powered Knee-Ankle Prosthesis Control

A third generation powered knee-ankle prosthesis designed by Vanderbilt University [19], [49] was used in this study. Joint torques, τ_i, were modulated according to an impedance-based model (Equation 4.1):

$$\tau_i = -k_i(\theta_i - \theta_{ei}) - b\dot{\theta}_i, \qquad (4.1)$$

where i corresponded to the knee or ankle joint, θ was the joint angle, and $\dot{\theta}$ was the joint angular velocity. Impedance parameters, stiffness, k, equilibrium angle, θ_e, and damping coefficient, b, were modified according to a finite state machine. Relative joint angles and velocities were measured from a subset of the sensors embedded within the prosthesis. A complete list of sensors is available in Section 4.3.3.

The finite state machine, refined from previous versions [14], [44], [47], [49], [51], included a standing mode and five ambulation modes (i.e., level-ground walking, ramp ascent, ramp descent, stair ascent, and stair descent). Knee and ankle impedance parameters were modulated within each state according to previously defined control strategies [51], [58], and sensor data, evaluated in 30 ms increment windows, transitioned the prosthesis between states within a mode. The enhanced state machine architecture allowed the prosthesis to transition between modes at discrete time points during the gait cycle including heel contact, mid-stance, toe off, and mid-swing. Most between-mode transitions were initially governed by key fob input from the experimenter; however, some between-mode transitions were executed based on mechanical sensor data and/or timers, including transitions from:

- standing to level-ground walking based on axial shank force, prosthesis ankle angle, and shank inclination angle (Figure 4.1);
- level-ground walking to standing based on a timer or to standing swing phase based on axial shank force (Figure 4.1); and
- stair ascent to standing based on axial shank force and prosthesis knee velocity.

With this system, users had the ability to freely ambulate about a laboratory environment consisting of a level-ground walking surface, a 10 degree inclined surface, a 4-step staircase, and a 3-step staircase. When ascending and descending the 4-step staircase, only heel contact and toe off transitions were necessary to provide a seamless transition to and from level-ground walking. When ascending and descending the 3-step staircase, additional mode transitions (i.e., mid-swing and mid-stance, respectively) were necessary for the transitions from stair ascent or stair descent to level-ground walking. Users were also able to ascend or descend both staircases using a standing or a walking approach; previous systems had only allowed for a walking approach [24],

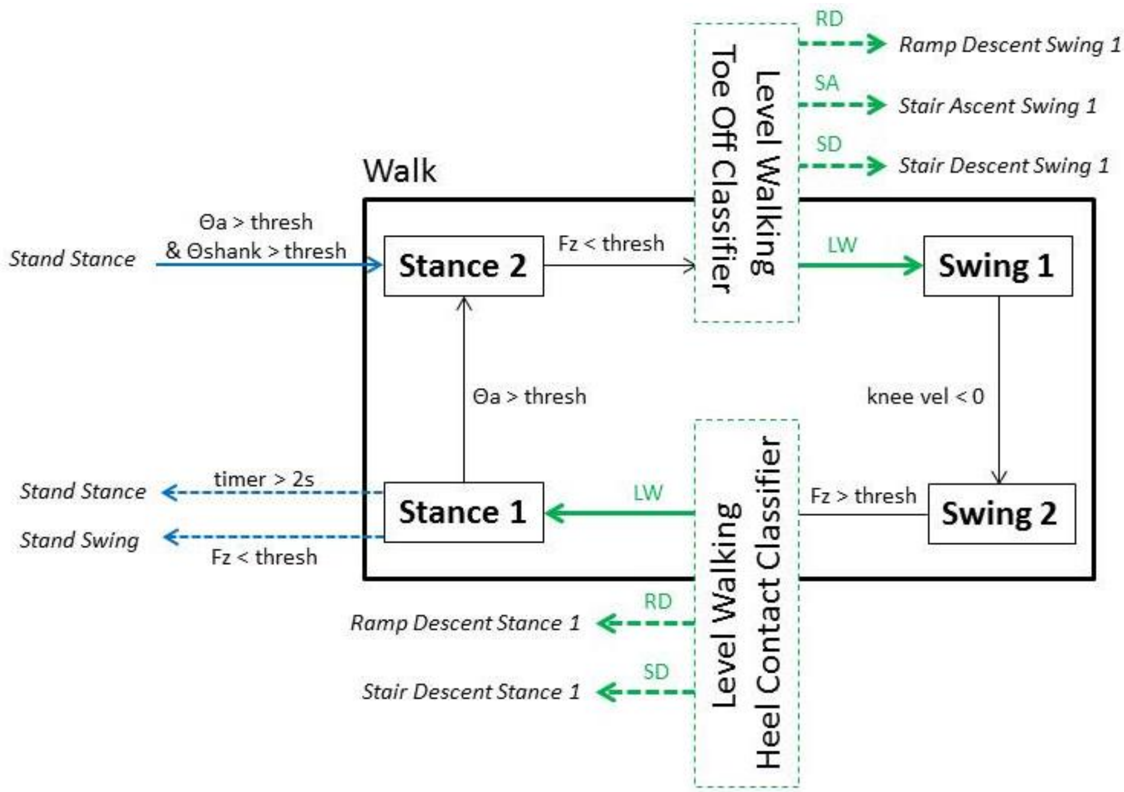

Figure 4.1: Example of finite state machine for a single mode. The figure shows a portion of the finite state machine for walking mode only. Within-mode transitions that occurred based on mechanical sensor data are shown with black arrows. Between-mode transitions that occurred based on mechanical sensors are shown with blue arrows. Between-mode transitions that occur based on the execution of a key fob or a pattern recognition classifier are shown with green arrows. Walking mode transitions are displayed with solid lines and all outgoing ambulation mode transitions from walking mode are displayed with dashed lines.

[28].

4.3.2 Experimental Protocol

Six individuals with a unilateral transfemoral or knee disarticulation amputation gave written informed consent to participate in this study (Table 4.1). All users were capable of community ambulation with Medicare functional classification levels K3 or K4. Users were fitted to the powered knee-ankle prosthesis by a certified prosthetist and had previous experience (minimum of 5 hours) ambulating on the device (Figure 4.2).

TABLE 4.1: SUBJECT DEMOGRAPHICS

User	Gender	Age (years)	Time Post-Amputation (years)	Weight (kg)	Etiology	Amputation Level
TF1	Male	57	45	83.9	Left Traumatic	Transfemoral
TF2	Male	66	39	86.2	Right Traumatic	Transfemoral
TF3	Female	23	8	52.2	Left Sarcoma	Transfemoral
TF4	Male	30	18	86.2	Left Sarcoma	Knee Disarticulation
TF5	Male	44	19	96.6	Left Traumatic	Transfemoral
TF6	Male	25	1	72.6	Right Sarcoma	Transfemoral
Mean [SD]	**-**	**40.8 [17.8]**	**21.7 [17.2]**	**79.6 [15.5]**	**-**	**-**

Figure 4.2: A transfemoral amputee wearing the powered knee-ankle prosthesis demonstrating various transitions from stair descent to level-ground walking.

Users were allowed to practice using the powered prosthesis for all ambulation modes prior to data collection. A physical therapist was present to assist them and ensure safety. Once users were comfortable and the device was properly configured for each mode [51], they performed a series of in-laboratory ambulation tasks while an experimenter manually triggered the powered prosthesis into the correct mode. In order to investigate both a delayed mode transition system and a non-delayed mode transition system, steady-state and between-mode transitions were delayed by 90 ms during data collection. Pilot tests revealed that users' performance and stability was not affected by delaying these transitions by 90 ms [65]. The tasks included:

- a circuit of level-ground walking approaches to and from ramp ascent and descent on a 10 degree inclined surface and stair ascent and descent on either a 4-step staircase (10 trials) or a 3-step staircase (10 trials);
- climbing stairs in a stairwell (4 flights);
- climbing up two steps, standing, climbing up two steps, standing, turning around, descending the steps in the same manner (20 trials);
- walking at various speeds, straight-line walking, and walking in circles (10 trials total); and
- standing including shuffle steps, turning, and quiet standing (5 trials).

Users led with their sound side for all stair ascent approaches, with their prosthesis side for all stair descent approaches, and with either side for ramp ascent and ramp descent approaches. To increase variability for all circuit trials, users approached the ramp and staircase from various angles (i.e., straight, 45 degrees, or 90 degrees). This protocol allowed for the collection of both the steady-state ambulation tasks and seamless mode transitions required to train a lower limb intent recognition system [28].

4.3.3 Pattern Recognition System Configuration and Evaluation

Data from 18 mechanical sensors embedded on the prosthesis were recorded at 500 Hz including: knee and ankle joint angles and velocities, motor currents, prosthesis acceleration and rotational velocity, calculated thigh and shank inclination angles, and 6-Degree Of Freedom

(DOF) forces and moments. The mode and state of the powered prosthesis were also recorded to serve as labels for the data.

A mode-specific classifier system was trained to predict transitions between ambulation modes (Table 4.2, Figure 4.1, and Figure 4.3) [18]. Level-ground walking and ramp ascent data were treated as one class. This data grouping was chosen because these two modes had similar impedance parameter settings [51], and previous systems have shown that ramp ascent mode can

TABLE 4.2: AMBULATION MODE CLASSIFIER DESCRIPTIONS

Gait Phase	Classifier	Active in	Description	Number of Classes
Heel Contact	HC_LW	Level-ground Walking	Predicted steady state and the transitions from level-ground walking to stair and ramp descent	3 (LW, RD, SD)
	HC_SD	Stair Descent	Predicted steady state and the transitions from stair descent to level-ground walking	2 (LW, SD)
	HC_RD	Ramp Descent	Predicted steady state and the transitions from ramp descent to level-ground walking	2 (LW, RD)
	HC_ST	Standing	Predicted steady state and the transition from standing to stair descent	2 (ST, SD)
Mid-Stance	MST_SD	Stair Descent	Predicted the transition from stair descent to level-ground walking when the first step on level ground was with the prosthesis (e.g., on 3-step staircase)	2 (LW, SD)
Toe Off	TO	Level-ground Walking, Ramp Descent, Stair Descent	Predicted steady state and the transitions from level-ground walking to stair ascent and between level-ground walking and ramp/stair descent	4 (LW, RD, SA, SD)
	TO_ST	Standing	Predicted steady state and the transition from standing to stair ascent	2 (ST, SA)
Mid-Swing	MSW_SA	Stair Ascent	Predicted steady state and the transition from stair ascent to level-ground walking when the first step on level ground was with the sound side (e.g., on 3-step staircase)	2 (LW, SA)

Gait Events, HC: heel contact; MST: mid-stance; TO: toe off; MSW: mid-swing;

Ambulation Modes, LW: level-ground walking; SD: stair descent; SA: stair ascent; RD: ramp descent, ST: stand

be incorporated into the walking class mode [47], [66]. The Toe Off (TO) classifier was not mode-specific (i.e., the same classifier was used at toe off during level-ground walking, ramp descent, and stair descent) because there were no trained mode transition examples at toe off from stair/ramp descent back to level-ground walking. Since the data were collected with a 90 ms delay for all ambulation mode transitions, simple post- processing was necessary to evaluate a non-delayed system using the same data set. For the non-delayed system, data were segmented into 300 ms windows immediately preceding gait events (e.g., from 300 ms before heel contact to heel contact). For the delayed system, data were segmented into 300 ms windows starting 210 ms before gait events (e.g., from 210 ms before heel contact to 90 ms after heel contact). A feature set including mean, standard deviation, maximum and minimum values and initial and final values was extracted from the data in each analysis window [9]. The dimensionality of this feature set was reduced from 120 features to 50 features using Principal Component Analysis [67]. Dynamic Bayesian Network (DBN) classifiers, which take into account the time history of signals over the entire stride, were trained [24] and evaluated according to their definitions in Table 4.2 using leave-one-out cross validation. Figure 4.3 shows an overview of the system architecture including trained mode transitions. Mode transitions which were highly unlikely to be encountered in real-time use (e.g., mode transition between ramp descent and stair ascent) were not allowed.

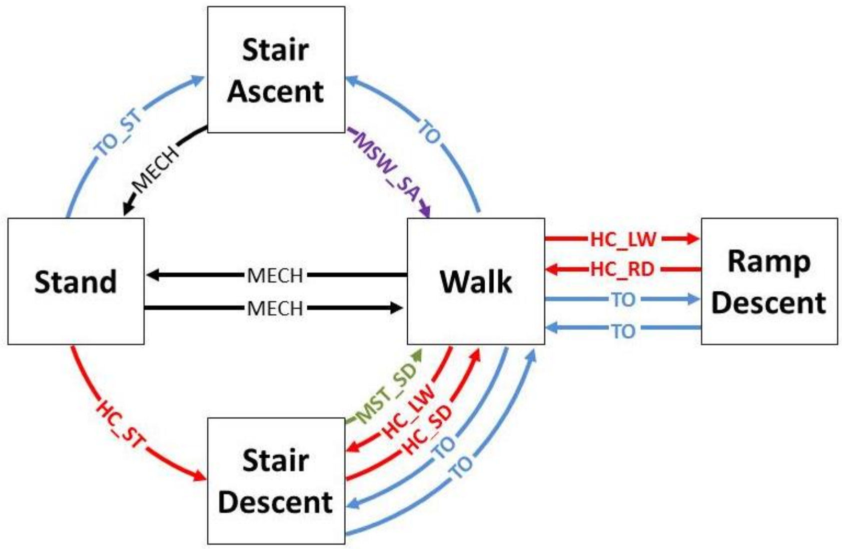

Figure 4.3: An overview of the mode-specific classifier architecture. State machine prosthesis modes are shown indicating the corresponding classifier (see Table 2 for descriptions) or mechanical trigger associated with each transition. Mechanical transitions are labeled in black, heel contact classifiers are in red, mid-stance classifier in green, toe off classifiers are in blue, and mid-swing classifier in purple. Ramp ascent data were grouped together with walking data.

Classifier performance in both the non-delayed and delayed system was evaluated using offline classification error. Classification error rates for each of the eight classifiers were calculated and averaged for each of the four main gait events (heel contact, mid-stance, toe off, mid-swing). Average error rates were then separated into steady state error—the percentage of steps that were misclassified when the user was not changing ambulation modes, and transition error—the percentage of steps that were misclassified when the user was transitioning between two ambulation modes. We performed a two-factor ANOVA to test for significant differences in error rates at each gait event. For each test, classification error rate was the independent measurement, subject was a random factor, and the delay condition (non-delayed, delayed) and type of error (steady-state, or transition) were fixed factors. An interaction term between delay condition and type of error was also included in the model.

System performance was evaluated by grouping the effect of each classification error. Since this study involved offline testing only, errors were grouped based on the effect they would have on user performance during an online test [64]. Errors that would have been noticeable but likely not impede ambulation (e.g., misclassifications at heel contact to ramp or stair descent during level-ground walking) were categorized as moderate perturbations and errors that would have greatly affected users' stability and would have required the experimenter to manually correct the error (e.g., misclassification at toe off to stair ascent during level-ground walking or misclassification at mid-stance to level-ground walking during stair descent) were categorized as substantial perturbations.

4.4 Results

All users were successful performing the instructed activities including climbing even- and odd-numbered step staircases, climbing stairs from a standing or walking approach, and approaching the ramp and staircase at various angles and walking speeds. Users did not notice the 90 ms mode transition delay at heel contact while transitioning between standing, level ground walking, ramp descent, and stair descent. There was a small noticeable delay for transitions that occurred at toe off (e.g., Stand to Stair Ascent), but this did not impede use of the powered prosthesis. Average stride time (i.e., heel contact to heel contact of the prosthesis) across all users and all modes was 1.97s [0.17s]. Therefore the 90 ms mode transition delay represented approximately 4.6% of the stride time. Figure 4.4 provides an example of the different data windows for a non-delayed vs. delayed system for a select number of mechanical sensors. There was additional class separation of mechanical sensor trajectories during the 90 ms delay window.

For the Non-Delayed System, the complete system average error rate was 0.98% (Table 4.3). The majority of error rates for the individual classifiers were below 2% except for the heel contact classifiers, of which the HC_RD classifier had an overall error rate of 6.8%. For the Delayed System, the complete system average error rate was 0.30%. All overall error rates for the individual classifiers were below 2%, The HC_RD classifier error rate was reduced to 0.86% in the Delayed System. The level-ground walking and ramp descent heel contact classifiers (HC_LW and HC_RD) showed the largest decreases in classification error for the delayed

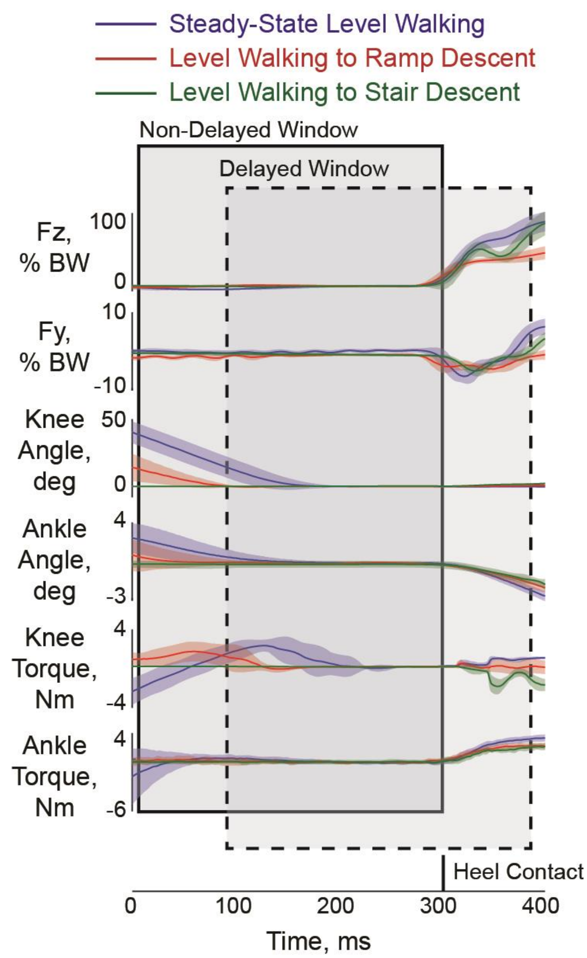

Figure 4.4: Example mechanical sensor data for the HC_LW classifier. The heel contact data window is shown for both the non-delayed and delayed system window for steady-state level-ground walking, level-ground walking to ramp descent transition and level-ground walking to stair descent transition. The delayed data window provides additional data after heel contact that is beneficial for separating classes.

TABLE 4.3: MODE-SPECIFIC CLASSIFIER ERROR

	Classifier								Complete
Error	HC_LW	HC_SD	HC_RD	HC_ST	MST_SD	TO	TO_ST	MSW_SA	System
Overall									
No. of decisions	754 [96]	112 [7]	90 [14]	511 [98]	116 [12]	1206 [97]	634 [98]	122 [3]	3545 [420]
Non-delayed, %	2.25 [1.75]	0.76 [0.90]	6.81 [4.60]	0.16 [0.25]	0.30 [0.47]	0.40 [0.15]	0.57 [0.24]	1.37 [0.68]	0.98 [0.39]
Delayed, %	0.53 [0.38]	0.92 [0.85]	0.86 [1.65]	0.16 [0.25]	0.17 [0.40]	0.19 [0.09]	0.03 [0.06]	1.39 [1.36]	0.30 [0.10]
Steady-State									
No. of decisions	723 [96]	72 [6]	67 [11]	497 [102]	106 [13]	1095 [96]	530 [102]	111 [3]	3182 [423]
Non-delayed, %	1.97 [1.68]	0.98 [1.28]	3.53 [3.01]	0.17 [0.26]	0.15 [0.37]	0.31 [0.13]	0.44 [0.20]	1.36 [0.51]	0.78 [0.63]
Delayed, %	0.44 [0.29]	1.22 [1.19]	0.54 [0.86]	0.17 [0.26]	0.19 [0.45]	0.15 [0.10]	0.03 [0.07]	1.52 [1.49]	0.27 [0.10]
Transitional									
No. of decisions	31 [7]	40 [2]	23 [4]	33 [6]	11 [1]	111 [4]	104 [6]	11 [1]	363 [36]
Non-delayed, %	8.46 [4.92]	0.40 [0.97]	16.75 [11.85]	0 [0]	1.52 [3.71]	1.34 [0.73]	1.27 [0.92]	1.67 [4.08]	2.65 [1.21]
Delayed, %	2.76 [2.94]	0.43 [1.05]	1.67 [4.08]	0 [0]	0 [0]	0.59 [0.46]	0 [0]	0 [0]	0.55 [0.24]

Gait Events, HC: heel contact; MST: mid-stance; TO: toe off; MSW: mid-swing

Ambulation Modes, LW: level-ground walking; SD: stair descent; SA: stair ascent; RD: ramp descent; ST: stand

system compared to the non-delayed system, particularly due to the decrease in transitional errors.

Comparing across gait events, delaying classification decisions by 90 ms significantly reduced the mode-specific classification errors compared to the non-delayed system for decisions made at heel contact and toe off ($p<0.001$) (Table 4.3). Transitional error rates were statistically higher than steady state error rates ($p<0.001$) (Figure 4.5). There was an interaction effect ($p<0.01$) indicating that there is a particular improvement for transitional error with the delayed system. No significant differences were found at mid-stance or mid-swing. The average error rate for all heel contact decisions (i.e., average of the HC_LW, HC_SD, HC_RD, and HC_ST classifiers) was 1.65% [0.99%] for the non-delayed system and 0.43% [0.23%] for the delayed system. The average error rate for all toe off decisions (i.e., the average of the TO and TO_ST classifiers) was 0.47% [0.16%] for the non-delayed system and 0.13% [0.05%] for the delayed system.

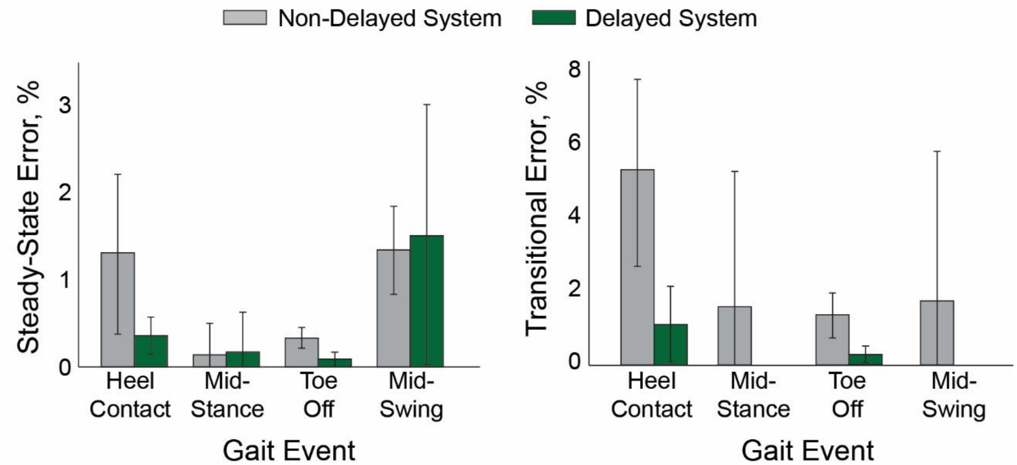

Figure 4.5: Average effect of non-delayed vs. delayed system on classification error. Error rates for steady-state and transitional steps are shown on the left and right, respectively. Heel contact error rates are the average of the HC_LW, HC_SD, HC_RD, and HC_ST classifiers. Toe off error rates are the average of the TO and TO_ST classifiers. Error bars indicate standard deviation. Note different vertical axis scaling between the left and right figures.

TABLE 4.4 CLASSIFICATION ERRORS GROUPED BY THE PERTURBATION TO THE USER

		Non-Delayed System				Delayed System			
User	**No. of Decisions**	**Un-noticeable**	**Moderate**	**Substantial**	**Total**	**Un-noticeable**	**Moderate**	**Substantial**	**Total**
TF1	3570	1	48	4	53	0	10	2	13
TF2	3885	0	40	6	46	0	8	2	10
TF3	3614	4	13	7	27	0	5	4	9
TF4	3595	1	17	4	22	1	11	2	14
TF5	3289	1	15	5	21	3	2	0	5
TF6	3402	0	36	7	43	1	12	2	15
Counts Mean [SD]	**3545 [219]**	**1 [1]**	**28 [15]**	**6 [1]**	**35 [14]**	**1 [1]**	**8 [4]**	**2 [1]**	**11 [4]**
% Mean [SD]	--	**0.03 [0.04]**	**0.79 [0.42]**	**0.16 [0.04]**	**0.98 [0.40]**	**0.024 [0.033]**	**0.23 [0.11]**	**0.06 [0.036]**	**0.31 [0.11]**

In terms of potential impact on the user, evaluating the system as a whole (i.e., the combined effect of all eight classifiers in combination with allowable mode transitions in the state machine) indicated that the majority of errors would have been of moderate consequence (i.e., users would notice them but did not considerably affect their balance) for both systems) (Table 4.4). The delayed system reduced errors that would have caused moderate or substantial perturbations compared to the non-delayed system.

4.5 Discussion

Users were able to successfully transition between all ambulation modes with ease and perform a wider variety of ambulation tasks than previously collected [14], [28] due to the enhanced state machine. With the addition of standing mode, all users could shift their weight with ease and remain confident that the knee will be stable and not buckle. Users transitioned between standing and walking mode when they desired on mechanical sensor data alone. This transition was not included as a separate class to the pattern recognition system because mechanical sensor thresholds and timers were sufficient to provide this seamless transition. With the addition of the standing mode heel contact and toe off classifiers, users could transition to stair ascent and stair descent from standing mode (something not available in our previous systems [14], [24]). Users could, if necessary, come to a stop before ascending/descending stairs or stop on a stair and then continue. Users commented on how they did not feel forced to approach the staircase in a certain way. They liked the flexibility to approach the staircase with a fast or slow speed, take long or short steps, and did not have to pace out their steps before reaching the first stair. The addition of the stair descent mid-stance and stair ascent mid-swing classifiers allowed users to successfully transition (ascending or descending) from an odd-numbered staircase to level-ground walking. Finally, with this flexible system, users were able to vary their speed and approach angles while still maintaining seamless transitions throughout the trials in the laboratory, hallway, and stairwell.

Even with increased variability, this data set with a non-delayed system resulted in improved accuracy rates compared to previous systems. Previous literature reports average error rates across five ambulation modes (level-ground walking, ramp ascent, ramp descent, stair ascent, stair descent), at 4.2% when using a DBN classifier with mechanical sensor data [14], 2% for steady-state and 20% for mode transitions in another similar study [24], and 2.1% for steady-state and 8.0% for mode transitions when a mode-specific classifier was incorporated [18]. This study's improved overall error rate for the non-delayed system of 0.99% (0.8% for steady-state and 2.7% for mode transitions) across five modes (standing, level-ground walking/ramp ascent, ramp descent, stair ascent, stair descent) was likely due to a few factors. This study included additional mechanical sensor data, specifically the 6-DOF load cell mounted between the knee and ankle and calculated thigh and shank inclination angles. The addition of these signals has been shown to significantly reduce error rates [61]. Also, in the previous systems there were a large number of misclassifications between the level-ground and incline walking classes. In this study they were treated as one class [66]. The mode-specific classification structure [18] has been shown to reduce errors over these previous systems. Another possibility for a reduction in error rate for our non-delayed system is the inclusion of feature reduction. Even with these improvements, transitional errors at heel contact for the non-delayed system remained high at an average over 5% (Figure 4.5).

Delaying classifier decisions by 90 ms following a gait event provided a significant reduction in errors over the non-delayed system's results. Overall classification error rates were reduced from 2.7% to 0.5% for transitions and 0.99% to 0.30% for steady state. To our knowledge, this is the first lower limb intent recognition system to reduce transitional errors for a powered knee-ankle prosthesis to under 1% for five modes. The reduction in error rates for the delayed system is likely due to further discriminating sensor data that appears immediately following a gait event (i.e., heel contact or toe off). Figure 4.4 demonstrates this qualitatively, as some of the mechanical sensor trajectories change following a gait event. Users and the prosthesis respond differently at heel contact during steady state walking, during the level ground walking transition to ramp descent, and during the level ground walking transition to stair descent. This small, 90 ms window of new data assisted in further separating the ambulation modes. While it is possible that delaying these decisions by more than 90 ms may further reduce error rates, much longer delays likely will have a negative impact on performance. Increased delays may be perceived by users as a functional delay (the 90 ms delay for toe off transitions was noticeable but did not impede users) or be past the critical timing in which the user's walking balance may be affected [63].

The delayed system reduced the amount of moderate and substantial system error rate (i.e., the errors that would have affected user performance if tested during real-time). The combination of the transitions allowed in the state machine and the mode-specific classifier architecture only allowed the relevant transitions out of the current locomotion. Therefore, misclassifications from ramp descent to any other mode except for level-ground walking (e.g., stair descent, stair ascent) were not possible in this system. Moderate errors, or errors that would be noticeable but not impede ambulation such as misclassifications between level-ground walking and ramp/stair descent (heel contact classifiers) and missed mode transitions from level-ground walking to stair ascent (toe off classifier) were reduced by a factor of 3. Substantial errors, or errors that had the potential to significantly affect users' stability such as misclassifications to stair ascent during steady-state level-ground walking (toe off classifier) and to level-ground walking during steady-state stair descent (mid-stance classifier) or steady-state stair ascent (mid-swing classifier), were also reduced by a factor of 3 with the delayed system compared to the non-delayed system. With the new addition of the mid-stance and mid-swing classifiers, these system errors likely affect users' stability in different ways than previously reported [14], [25], [64].

Although this study reports encouraging results for lower limb intent recognition of a powered knee-ankle prosthesis, there are limitations. The system still needs to be tested in real-time. We expect similar improvements for an online system since lower limb intent recognition systems have been shown to have carry over from offline to online performance [14]. Real-time results will allow us to evaluate how errors propagate through a delayed mode transition system. Previous work with a non-delayed mode transition system reported that when a step was misclassified, the subsequent steps were more likely to be incorrectly classified [14]. Future work may also include incorporating neural information from electromyography (EMG) data [10], [14], [23], [25]. In this study, error rates likely were already reduced due to the addition of mechanical sensors (6-DOF load cell, shank and thigh inclination angles) and a mode transition delay. EMG data may have the potential to further reduce these error rates, although to what extent is still unknown.

4.6 Conclusion

This study developed a flexible and more accurate lower limb intent recognition system by incorporating a mode-specific classifier with delayed mode transitions. Individuals with a transfemoral amputation successfully used a powered knee-ankle prosthesis to seamlessly transition between standing, level-ground walking, ascending/descending a ramp, and ascending/descending even- and odd-numbered staircases using a variety of approaches and speeds. The results demonstrate that delaying ambulation mode decisions (and thus delaying the prosthesis' mechanical response while transitioning between two different modes) by 90 ms significantly decreased prediction errors. Furthermore, this delay significantly reduced the amount of moderate and substantial system errors, thereby reducing the number of times a user's stability would be affected. The results of this study are encouraging and provide another step towards a clinically viable lower limb intent recognition system for a powered knee-ankle prosthesis.

5 Online Adaptation of Neural Control in a Powered Lower Limb Prosthesis

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5.1 Abstract

Previous research studies have shown that including electromyographic (EMG) signals can benefit pattern recognition algorithms used to control powered lower limb prostheses. However, these EMG-based algorithms have not been implemented clinically because the signal quality of EMG degrades over time, and the algorithm is static and cannot track these signal changes. To address this problem, we have developed an adaptive pattern recognition algorithm that can track changes in the EMG signals, allowing for their long-term use. In this study, we present a description of the proposed algorithm and the equipment needed to implement it in a powered lower limb prosthesis. We also evaluated the adaptive algorithm in online experiments performed across multiple days – transfemoral amputees used a powered lower limb prosthesis to ambulate while the adaptive algorithm tracked changes in EMG signals. We demonstrate that the algorithm, which began with a model of EMG data acquired from an initial experimental session, could update the model with data from a second experimental session. This resulted in consistent algorithm performance over long-term use. Finally, we measured the necessary computation time needed to execute the tasks of the algorithm to prove that that it can run in real-time during ambulation.

5.2 Introduction

Myoelectric control interfaces have been clinically implemented for decades for powered upper limb prostheses, but their use in controlling lower limb prostheses has not reached clinical implementation. This is primarily because most commercially available lower limb prostheses are passive, and do not require advanced control systems. Powered prosthetic legs are a new generation of prostheses that can produce different mechanical responses depending on the mode of locomotion (e.g., walking on level ground, inclines, or stairs), and therefore require advanced control [5], [6], [8]. Myoelectric interfaces could be used to address a current limitation in the control of these powered lower limb devices: the inability to automatically transition between the programmed modes of locomotion. Specifically, electromyography (EMG) signals recorded from residual limb muscles have been used as inputs to a pattern recognition algorithm that seamlessly transitions the prosthesis between locomotion modes (a process we will refer to as forward prediction in this study). This application of EMG has been promising; both offline and online studies have demonstrated that EMG signals significantly decrease the error rates of forward prediction algorithms when combined with the kinetic and kinematic information acquired from embedded mechanical sensors [10], [14]. The obstacle that is preventing full clinical implementation of these EMG-based algorithms is that previously studied decoders are fixed and cannot track changes in EMG signals that can occur during daily prosthesis use (e.g., electrode shifts relative to the muscles of interest that occur during donning and doffing [15], loss of skin-electrode contact [53], or variations in electrode/skin impedance [16]). These changes cause the performance of the forward predictor to deteriorate, limiting the clinical viability of the approach. Thus, what is missing is an adaptive forward prediction algorithm that can track these changes and maintain the benefits of EMG over long-term use. The objective of this study is to develop and evaluate such an adaptive forward prediction algorithm.

An effective adaptive forward prediction algorithm must be able to detect and compensate for EMG signal changes. We previously demonstrated that it is possible to prevent errors caused by changes in the EMG signals (e.g., electrode liftoff, electrode shifts between donning) by reverting to predictions that consider only mechanical sensors when large EMG changes are detected [53]. After detection, the algorithm must be retrained with the changed EMG signals in order to update the model of EMG data used to make mode predictions. Because our algorithm featured supervised learning, this required a method to automatically label new patterns of data with a label representing the user’s intent. We previously accomplished this through backwards estimation, wherein we categorized the kinetic and kinematic gait profile after each stride of the prosthesis and labeled the new data pattern used for adaptation with the correct class label [52]. The advantage of using backwards estimation was the ability to correctly label patterns that the forward predictor misclassified (either because the prediction was difficult, or because signal changes can cause errors, etc.). Our offline analyses have shown these techniques were an effective means of applying adaptation. What remains to be completed is an online implementation of the proposed adaptive algorithm. Such an online analysis was completed in this study with transfemoral amputee subjects walking on a powered lower limb prosthesis.

In this online analysis, we must also consider that the control system for the powered prosthesis has changed since our previous studies with EMG. Our group has implemented modifications in an effort to improve control, ease of use, and pattern recognition performance.

First, the powered prosthesis used in this study was equipped with more mechanical sensors than in previous experiments [14], [19], and the additional sensor information was used as an input to our forward prediction algorithm [61]. Second, various studies have investigated defining a critical timing window for mode transitions, and found that delaying the timing of theses transitions by a small window lowered the error rates of the forward prediction algorithm [63]–[65]. This delay was implemented for the online experiments described in this study. Third, we have implemented a mode specific classifier architecture, which has been shown to improve classification accuracy in lower extremity applications [18]. As a result, the current control system for the powered prosthesis in this study is one that is very different from those used in previous studies involving EMG-based pattern recognition. It is unclear how an online pattern recognition algorithm that uses EMG will perform given these modifications. Thus, this study will also investigate how these modifications impact the performance of an adaptive algorithm that is learning to reincorporate EMG into its predictions.

In this study, we present a fully integrated adaptive forward prediction system that can operate in real time during ambulation. We demonstrate that our algorithm can 1) detect EMG signal changes, 2) automatically label new patterns of data, and 3) update algorithm parameters while the user is ambulating. This online system was tested with six transfemoral amputees. To investigate if our algorithm could track changes in EMG signals over time, we evaluated our algorithm with EMG data collected from amputee subjects across multiple days, where we would expect changes in the quality of the EMG signals. To further explain our findings, we also investigated how changes to the control system of the prosthesis affect the performance of our adaptive algorithm.

Chapter 5 presents a powered leg prosthesis system that combines the techniques explored in the offline studies presented in Chapters 2, 3, and 4, and evaluates the full adaptive algorithm in an online setting with experiments with transfemoral amputee subjects. The experiment presented in this chapter is a significant contribution to the field of lower limb prosthetics because it is the first online implementation of an adaptive pattern recognition algorithm. It is also the first online implementation of the control system presented in Chapter 4.

5.3 Methods

5.3.1 Experimental Protocol

Six subjects with unilateral transfemoral amputations completed the experiment, which was approved by the Northwestern University Institutional Review Board. Subjects' ages ranged from 26 to 67 years, heights between 1.63 and 1.93 m, and weights between 61.68 and 86.18 kg. Written and verbal consent was obtained from each subject involved.

Each subject was fitted with a socket that was custom-made at the Rehabilitation Institute of Chicago. The type of socket, and method for collecting the surface EMG from the residual limbs of the subjects was selected based on the subject's definitive prosthesis. Three subjects wore a liner with embedded stainless steel electrodes (Figure 5.1A). Two subjects used a skin-fit suction socket with embedded stainless steel electrodes (Figure 5.1B). One subject used adhesive electrodes underneath a liner. Eight channels of EMG were acquired from the subjects; four pairs of electrodes were placed directly over the muscles (rectus femoris [RF], tensor fasciae latae [TFL], semitendinosus [ST], and adductor magnus [AM]), and the other four channels were cross-pairings between the proximal (prox) and distal (dist) electrodes over the direct muscle sites (TFLprox x STdist, STprox x AMdist, AMprox x RFdist, and RFprox x TFLdist). A

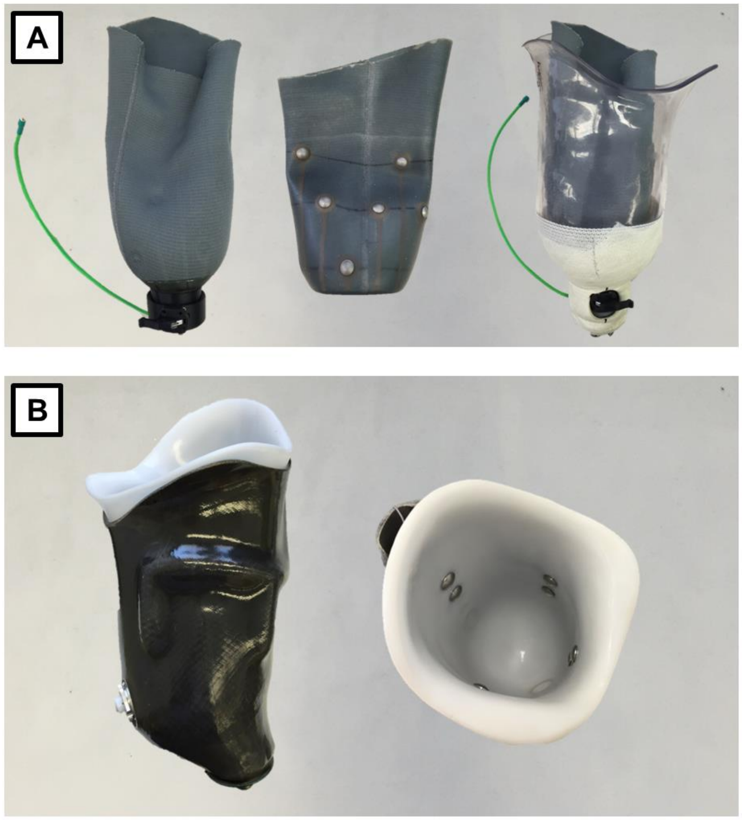

Figure 5.1: Experimental liners and sockets used to acquire EMG signals from the residual limb. Three subjects used a liner (A, left) that went over the residual limb of the amputee, and had stainless steel electrodes embedded into the fabric (A, middle). The amputee subject then donned the rigid socket over the liner (A, right), and connected to the electronics within the prosthesis. Two subjects wore just the rigid socket (B, left), that had stainless steel electrodes embedded into the socket (B, right).

certified prosthetist fitted and aligned a powered knee-ankle prosthesis that was designed by the Center for Intelligent Mechatronics at Vanderbilt University (Figure 5.2) [19]. Prior to this study, the powered prosthesis was configured for each subject for six different modes (standing, level ground walking, stair ascent/descent, ramp ascent/descent) [6], [44], [51]. All subjects had previous experience using the powered prosthesis prior to completing the experimental protocol.

Subjects participated in two experimental sessions. The first session was conducted to collect data from the subjects when completing the relevant mode transitions and to train the adaptive forward predictor algorithm. Subjects used the powered prosthesis within a laboratory environment to complete ambulation activities including walking on level ground, walking up and down a 10 degree inclined surface, and stair ascent and descent on both a 4-step staircase or a 3-step staircase. During this ‘offline session’, the experimenter used a key fob to transition the prosthesis between modes at critical points within the gait cycle [66]. Transitions between modes were programmed to occur 90ms after a gait event (i.e., 90ms after heel contact, toe-off, mid-swing, or mid-stance). Collecting the additional data after the gait event has been shown to improve pattern recognition performance in offline studies [64], [65], and transitioning between modes at this time point did not hinder the subjects’ ability to use the prosthesis.

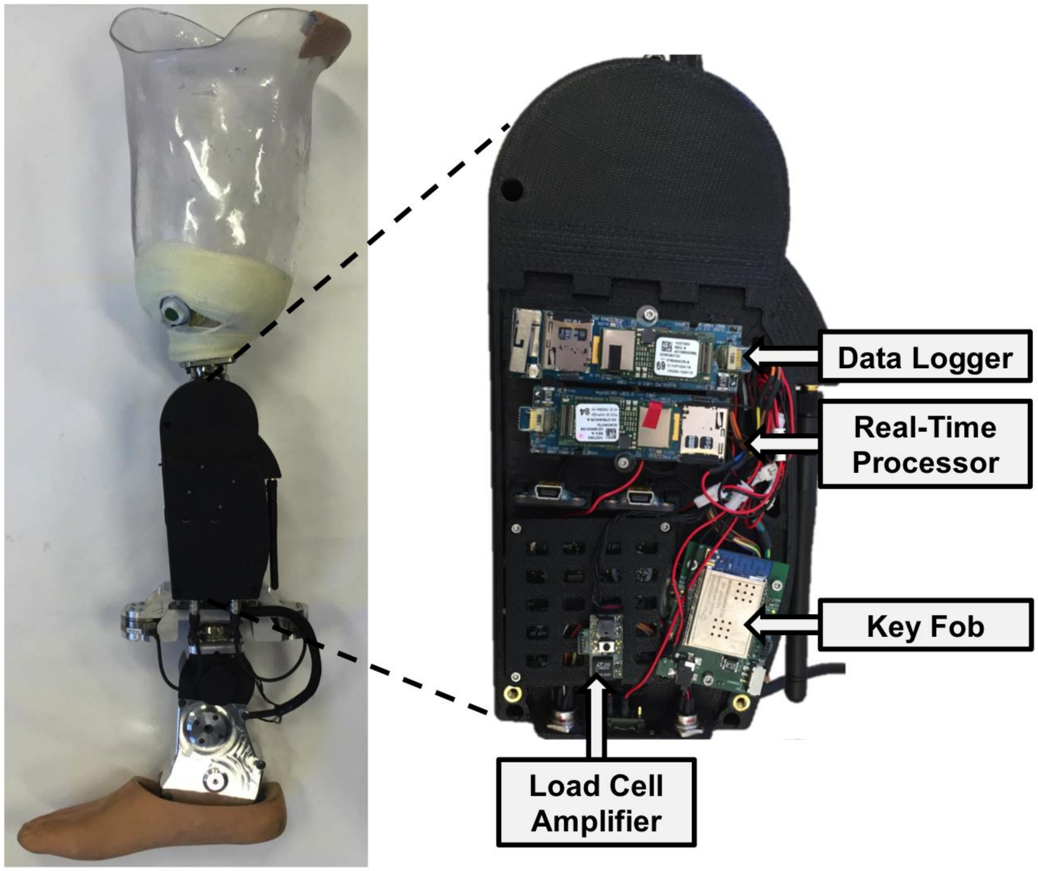

Figure 5.2: Powered prosthesis and embedded electronic hardware. Subject ambulated with a powered knee-ankle prosthesis (left). The figure shows the socket attached to the prosthesis, the housing for the electronics, and the 6 DOF load used in the experiment. Various electronics were housed in the case, including a diagnostic data logger, a real-time processor, a wireless key fob receiver, and the load cell amplifier.

The objective of the second experimental session was to determine whether the adaptive algorithm could automatically update the parameters of the EMG model (i.e., class means and covariances, explained below) used by the forward predictor, all while the subject ambulated with prosthesis. For most subjects, this session occurred several weeks after the offline session. In this 'online session', the subject completed the same ambulation tasks as the offline session. All mode transitions were controlled by the online adaptive forward prediction algorithm trained with data collected in the first session.

5.3.2 Signal Processing and Control System Architecture

Kinetic, kinematic, and inertial signals from 22 embedded mechanical sensors were recorded at 500 Hz. Mechanical sensors information included knee and ankle joint kinematics, motor currents, calculated thigh and shank inclination angles, and 6-Degree Of Freedom (DOF) forces and moments. Eight channels of EMG were also recorded at 1000 Hz using a TI ADS 1299. These channels of information were used to complete the tasks of the adaptive algorithm: state machine control, forward prediction, backwards estimation, and adaptation. These tasks have been presented before separately, but have not been tested together in an online system, as they were in this study. Here we present brief descriptions of each task:

5.3.2.1 State Machine Control

The joint torques of the prosthesis, τ_i, were determined according to an impedance-based model used in multiple powered lower limb prosthetic applications [19], [49]:

$$\tau_i = -k_i(\theta_i - \theta_{ei}) - b\dot{\theta}_i, \tag{5.1}$$

where i denotes the knee or ankle joint, θ is the joint angle, and $\dot{\theta}$ is the joint angular velocity. A finite state machine [14], [44], [47], [49] modified the impedance parameters of the prosthesis, k (stiffness), θ_e (equilibrium angle), and, b (damping coefficient) at different points in the gait cycle (i.e., the different states) and within different modes. The impedance parameters of each state were controlled according to previously defined control strategies [51]. Mechanical sensor data were used to transition the prosthesis between the different states of each mode. The selected torques were translated into motor command outputs that actuated the joint motors.

5.3.2.2 Forward Prediction

During the online session, a forward prediction algorithm transitioned the prosthesis between the different modes. Forward prediction was accomplished by classifying EMG and mechanical sensor patterns acquired before the user's stride so that appropriate impedance parameters could be set for the prosthesis (Figure 5.3A). The forward predictor was comprised of eight dynamic Bayesian network (DBN) [24] classifiers within a mode-specific classifier architecture [18]. Each classifier acted at a different part of the gait cycle (heel contact, mid-stance, toe off, and mid-swing) and within different modes. They were trained to predict six locomotion modes: standing, level-walking, stair ascent/descent, and ramp descent. This architecture was chosen because it has been shown to improve pattern recognition performance in lower limb applications; detailed description of the control system can be found in [18]. Level-walking and ramp ascent were trained as a single class because the impedance parameter settings for these two modes were similar. For forward prediction, data were segmented into 300ms windows. Since our control system used delayed mode transitions, the windows started 210 ms before the gait event and ended 90 ms after the gait event (Figure 5.4A, B). The features extracted from the mechanical sensors included the mean, standard deviation, maximum, minimum, initial and final values of the window for each mechanical sensor channel [9]. Features extracted from the EMG channels included the mean absolute value, waveform length, zero crossing, slope sign changes [68], and the six autoregressive coefficients of sixth-order autoregressive model extracted from each window for each EMG channel [48]. EMG and mechanical sensor feature sets were treated as statistically independent to facilitate adaptation of only EMG data, and to prevent overfitting. Both EMG and mechanical sensor feature sets were reduced from 80 and 132 features, respectively, to 50 features using Principal Component Analysis [67].

Each classifier within the forward predictor used a threshold based on the log-likelihood of the EMG feature vector to determine whether it was suitable to use EMG to make its predictions [53]. New EMG patterns were compared to a model of all EMG patterns in a training dataset modeled as a Gaussian distribution (Figure 5.4C, D). If the new EMG pattern had a log-likelihood that was more than three standard deviations from the average log-likelihood of the feature vectors in the training set, then it was concluded that the new pattern was unsuitable for forward prediction. In this circumstance, the forward predictor only used mechanical sensor data to make predictions. This technique was implemented to prevent errors caused by disturbances in the EMG signals that occurred across experimental sessions [53]. We expected that our adaptive algorithm would initially disregard most of the novel EMG signals in the online session, but gradually reincorporate EMG into its predictions as the new model of EMG data was updated.

5.3.2.3 Backwards Estimation

The backwards estimator acted *after the user completed a stride with the prosthesis* and provided a label for prediction patterns used for adaptation (Figure 5.3B). The backward estimator used a linear discriminant analysis (LDA) classifier and classified the mechanical sensor data acquired from the entire stride. Mechanical sensor data were segmented into windows between heel contacts, making the length of the window of data variable (Figure 5.4A, B). Most windows were approximately 1.5s and windows longer than 3s were not classified (and consequently not used for adaptation). The features extracted from these windows were the same as the mechanical sensor features used by the forward predictor. The dimensionality of this feature set was reduced from 132 features down to 13 using uncorrelated linear discriminant analysis (ULDA) [69]. This method resulted in a dimensionally reduced combination of mechanical sensor features. The backwards estimator classified the mechanical sensor data as one of the following classes: standing, level ground walking, ramp descent, stair ascent/descent, and various classes where the user was ambulating in the incorrect mode (e.g., walking down a ramp in level walking mode).

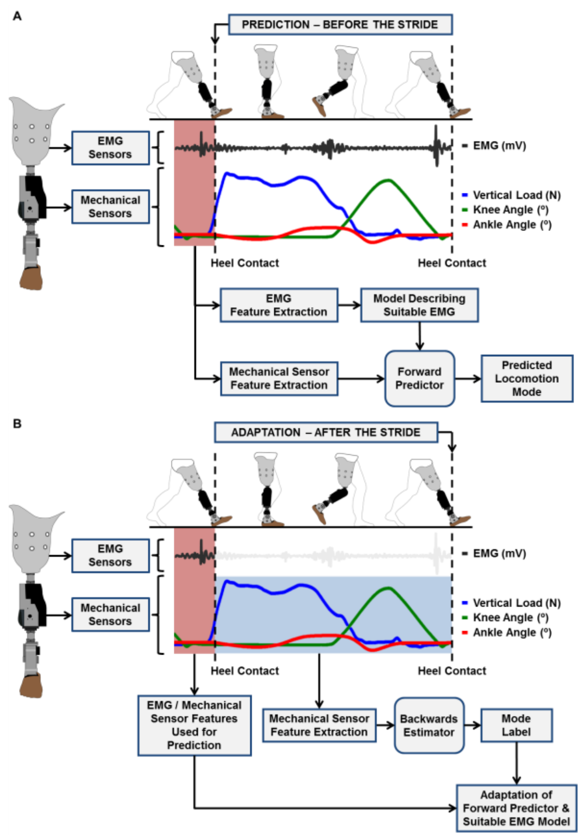

Figure 5.3: Overview of the adaptive algorithm. The components of the adaptive algorithm include: forward prediction (A), and backwards estimation (B). In forward prediction, features are extracted from EMG data and mechanical sensor data acquired before the stride (red window) and classified by the forward predictor, which then transitions the prosthesis into the predicted mode. The forward predictor determines whether to use EMG in making its prediction by comparing the EMG feature vector to a model describing suitable EMG data. In backwards estimation, we wait until after the user completes their stride with the prosthesis and then classify the acquired mechanical sensor data (blue window) as one of the modes of the prosthesis. This provides a label for the pattern of data used for prediction, which is then used to adapt the parameters of the forward predictor and the model describing suitable EMG.

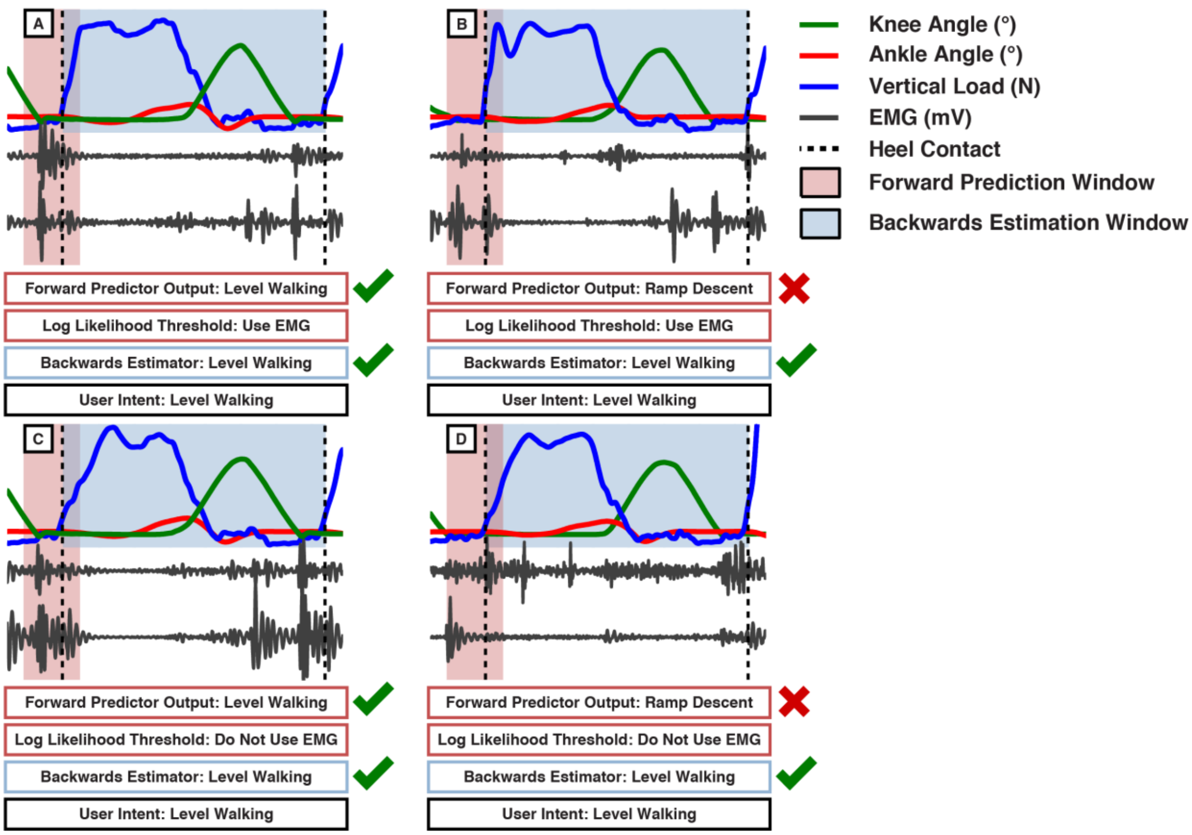

Figure 5.4: Illustrated examples of forward prediction, backwards estimation, and the log-likelihood threshold with real data. The figure displays representative data acquired from a single subject. Forward prediction used a 300ms window (the red shaded window) of data that began before a gait event (heel contact in this figure) and ended 90ms after that gait event. If the log likelihood threshold, which used the same window as forward prediction, determined that it was appropriate to use EMG, then both EMG data and mechanical sensor da¬ta were used to make forward prediction (A, B); otherwise, only mechanical sensors were used (C, D). The backward estimator used the entire window of mechanical sensor data between heel contacts (the blue shaded window). This data was classified to provide a label for a pattern used to update the forward predictor. This figure shows an example where the output of both the forward predictor and the backwards estimator matched the true intent of the user (A, C), as well as a circumstance where the forward predictor was incorrect, but the backwards estimator still correctly labeled the data (B, D). Green checkmarks mean that the output of the forward predictor and/or the backwards estimator matched the user intent; the red cross means that the output of the forward predictor did not match the user intent.

5.3.2.4 Adaptation of EMG

After a pattern was labeled by the backwards estimator, it was used to adapt the EMG model of the forward predictor and the model describing the log likelihood threshold of EMG data. The parameters of these models were the class means, μ_c, and covariances, Σ_c, of each classifier; *c* corresponds to the specific class. As the subject ambulated, the class means and covariances were updated with sequential estimation [70]. Equations 5.2 and 5.3 describe sequential estimation of a class mean, μ_c, and class covariance, Σ_c, based on *N* observations and given the contribution of the newest pattern, x_N.

$$\mu_{c,N} = \mu_{c,N-1} + \frac{1}{N}\left(x_{c,N} - \mu_{c,N-1}\right) \tag{5.2}$$

$$\Sigma_{c,N} = \Sigma_{c,N-1} + \frac{1}{N}\left(x_N {x_N}^T - \Sigma_{c,N-1}\right) - \mu_{c,N}{\mu_{c,N}}^T \tag{5.3}$$

These class means and covariances were then used to create updated classifiers. Class covariances were pooled (Σ) and used with the updated means to calculate the new weights, $\boldsymbol{W_c}$, and biases, w_c, of the classes of the DBN classifiers (Equations 5.4 and 5.5).

$$\boldsymbol{W_c} = \Sigma^{-1}\mu_c \tag{5.4}$$

$$w_c = -\frac{1}{2}\mu_c^t \Sigma^{-1}\mu_c \tag{5.5}$$

Adaptation of EMG was completed on an embedded microcontroller (a Texas Instruments DM3730 processor running at 600 MHz) running a Linux operating system, allowing for execution of multithreaded processes. Specific tasks could be set to high or low priority depending on their computational intensity and real-time processing requirements. Tracking means and covariances was not computationally intensive; labeling each pattern and updating the class means and covariances was set to a high priority thread and completed after every heel contact. Updating the weights and biases of the classifiers was more computationally intensive because of the inversion of the pooled covariance matrix. Consequently, this process was set to a low priority thread, and was completed when additional processing time was available. As a result, classifiers were updated periodically and less frequently than once per step.

5.3.3 System Evaluation

5.3.3.1 Online Analyses: Performance of the Online Adaptive Algorithm

In this study, we observed how much EMG was incorporated into the forward predictor's decisions throughout the online session. We also investigated whether the reincorporation of EMG would translate to a change in the error rate of the forward predictor. To evaluate the performance of the backwards estimator, we determined its error rate in the online session. We also investigated the algorithm's ability to run in real-time; we benchmarked the different components of the algorithm to determine the relative computational load of each task.

The patterns classified by the forward predictor and the backwards estimator were organized as steps (from heel contact to heel contact) completed with the prosthesis. Typically, a step contained a heel contact pattern and a toe-off pattern. A step was marked as an error if any of the patterns in that step were misclassified by the forward predictor. Similarly, if the forward predictor used EMG with any of the patterns in a step, then the whole step was marked as having used EMG.

To evaluate if the forward predictor used EMG over the course of the online session, all of the steps of the forward predictor were compiled and the total number of steps were divided into quarters. Within each quarter, the percentage of steps where EMG was incorporated into the forward prediction was determined. A one-way analysis of variance (ANOVA) was completed with quarter of the experiment as a factor, subject as a random factor, and the response was the percentage of patterns where EMG was used to make a forward prediction. To evaluate if the reincorporation of EMG affected the performance of the forward predictor, we calculated the error rate of the forward predictor within every quarter. Error rates are reported as the pooled misclassification rates of the eight classifiers of the forward predictor. Also shown are steps taken within each mode for each quarter. A one-way analysis of variance (ANOVA) was completed with quarter of the experiment as a factor, subject as a random factor, and the response was the online error rate of the forward predictor. Post-hoc tests were conducted on statistically significant variables of interest using Tukey's test.

To evaluate the automatic labeling strategy, backwards estimation, we report its online error rate. We chose this labeling strategy for its ability to outperform other strategies, specifically using the output of the forward predictor as a label for new data used for adaptation [53]. A one-sided paired t-test was completed comparing the online error rate of the backwards estimator to the online error rate of the forward predictor.

We present the computational processing time for the real-time execution of the adaptive algorithm. We timed the different components of our adaptive algorithm on our embedded system: a Texas Instruments DM3730 processor running at 600 MHz. The following activities were timed: baseline processing, feature extraction, forward prediction, backward estimation, and tracking of class means and covariances, Baseline processing represents the computation required for the prosthesis to function without the adaptive algorithm, and includes data acquisition, state machine execution, and motor outputs. Based on our previous work we required that our online system make forward predictions within a 30ms frame increment [14]. We also report the average number of times the classifiers were updated within a 10 minute period.

5.3.3.2 Offline Analyses: Benefit of EMG with the Current Control System

To determine the impact of the aforementioned control system modifications on algorithm performance, we compared the performance of our algorithm with the current control system (i.e., with modifications) to that of one with an older configuration used in previous studies. The older configuration (which we will term the null configuration) used a previous generation of the prosthesis with fewer mechanical sensors, did not incorporate the aforementioned 90ms delay in its mode transitions (i.e. a ‘non-delayed system’), and used a different classifier architecture. This null configuration was simulated with our current dataset in an offline analysis.

The combined data from the offline and online experimental sessions were used to conduct this analysis. To simulate results with fewer mechanical sensors, we removed the mechanical sensor channels that were not used in the previous generation of the prosthesis as inputs to the forward predictor. These included five degrees of freedom from the load cell and the calculated thigh and shank angles. Because all data were collected with a 90ms delay for mode transitions, a non-delayed system could be simulated and evaluated with the same dataset. To stimulate non-delayed mode transitions, data were segmented into 300ms windows immediately preceding gait events (e.g., from 300ms before heel contact to heel contact). Lastly, our older control system did not use a mode-specific classifier architecture where each mode had its own classifier. Instead, all transitions were handled by a single classifier regardless of which mode the prosthesis was in, and we assumed that EMG features and mechanical sensor features were not independent from one another (as was done in previous studies). This older pattern recognition architecture was used in this analysis.

We calculated forward prediction performance without any system modifications, and then added each modification (expanded mechanical sensors, delayed mode transitions, and the mode specific classifier architecture) to this null configuration one at a time to determine the individual effect of the modification. We also calculated forward prediction performance with all the different combinations of control system modifications, including when all modifications were used. For each condition, we calculated the performance of a forward predictor that only used mechanical sensors, and one that used the combination of mechanical sensors and EMG. Performance is reported in terms of forward prediction error rate. Error rate was further separated into steady-state and transitional errors. Steady-state errors are those that occur when the prosthesis did not switch to a different mode, and transitional errors are those that occur when the prosthesis was switching between modes. We made the distinction between these two types of errors for this analysis because previous studies (which used a control system similar to the null configuration) also differentiated between these two types of errors, and thus it was beneficial in understanding the differences between the older and newer control systems. A repeated measures ANOVA was performed for both steady-state and transitional error with classification error as the response and type of control system (Null vs. with all modifications) and type of forward predictor (mechanical sensors vs. mechanical sensors and EMG) as fixed within-subject variables with interaction terms.

5.4 Results

All subjects were able to transition between the required locomotion modes and complete the different activities using the online system. The percentage of forward predictions where EMG was incorporated per quarter is shown in Figure 5.5. In the first quarter of the online session, EMG was used in 68.85% [11.43%], mean [standard error] of forward predictions. The percentage of patterns where EMG was used increased in every following quarter, and by the end of the experiment the algorithm used EMG in 96.84% [1.17%] of forward predictions. The percentage of EMG used in the first quarter was statistically different from that in the following quarter ($p = 0.004$).

The overall error rate of the adaptive forward predictor was 3.97% [2.12%]. This level of performance was consistent across the experiment, with no statistical differences found between the online error rates between quarters ($p = 0.51$) (Figure 5.5). The backward estimator was able to label patterns used for adaptation with a low error rate. The online error rate of the backwards estimator was 1.69% [0.13%] (Figure 5.6), which was significantly lower than the online error rate of the forward predictor, 3.97% [2.12%] ($p = 0.049$).

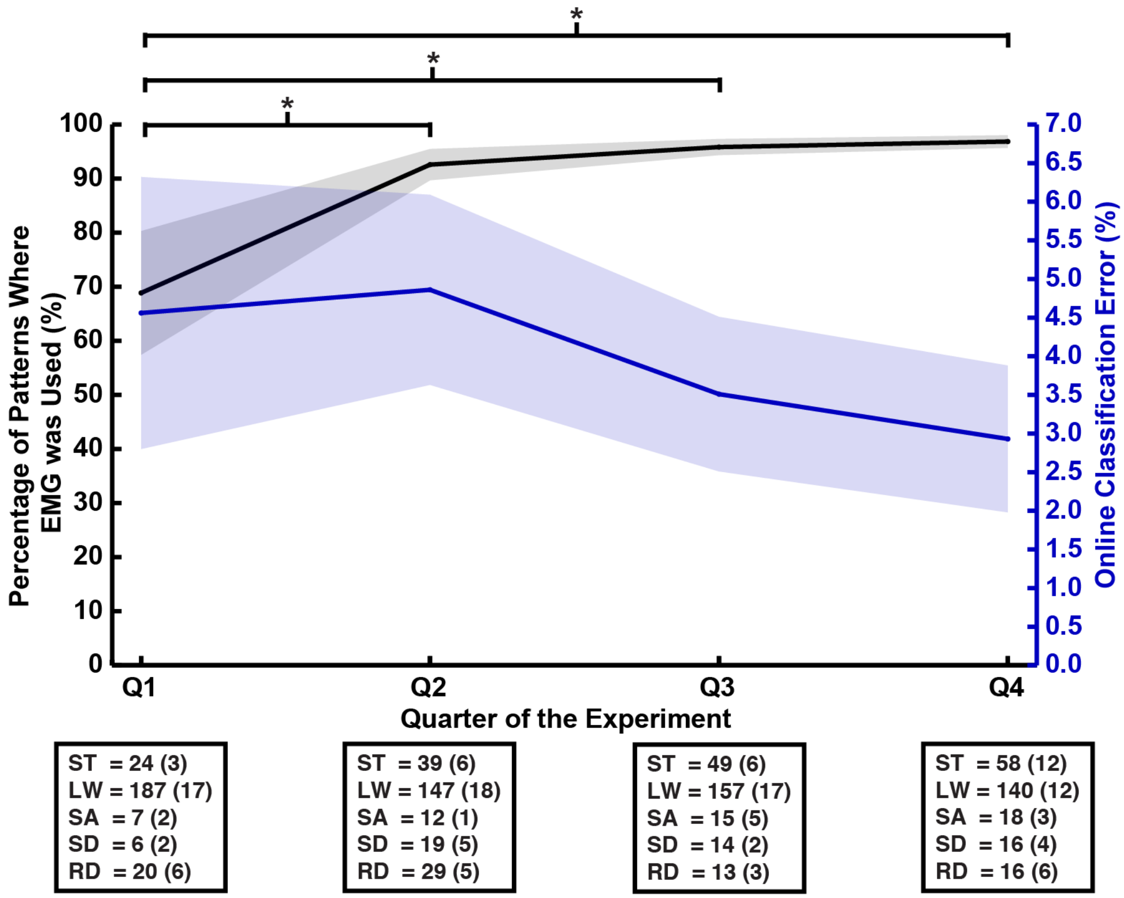

Figure 5.5: Online performance of adaptive forward predictor and percent of patterns where EMG was incorporated into the prediction throughout the experiment. The total amount of patterns classified by the adaptive forward predictor was divided into quarters (Q1 – Q4). The figure shows the online error rate of the predictor (blue line) and the progression of EMG use throughout the experiment (black line). For each pattern, the pattern recognition algorithm used the combination of EMG data and mechanical sensor data, or only mechanical sensor data. To illustrate the activities completed, the figure also shows the true class of the patterns in each quarter (ST = standing, LW = level walking, SA = stair ascent, SD = stair descent, RD = ramp descent). Data are averages of six subjects (+/- 1 SEM). * denotes statistically significant differences ($p < 0.05$).

The online computational time for the control system processes can be found in Table 5.1. Baseline processing, backwards estimation, and feature extraction were the most time-intensive processes. The average time to execute all the relevant processes of the prosthesis while running the adaptive algorithm was 22.9ms [2.5ms], well below our 30ms requirement. Within a ten minute period, the forward predictors were updated 125 times.

Performance was compared between forward predictors with no modifications (i.e., the null condition), with modifications individually, and in combination with each other (Figure 5.7). When using the null control system, the forward predictor that used both mechanical sensor signals and EMG signals had lower error rates than the forward predictor that only used mechanical sensors (a 0.44% decrease for steady-state error; a 1.55% decrease for transitional error). Adding modifications to the control system typically reduced the error rates of both types of forward predictors. The lowest error rates were obtained when applying all modifications. When all modifications were added, the forward predictor that used both mechanical sensor signals and EMG signals had higher error rates than the forward predictor that only used mechanical sensors (a 0.01% increase for steady-state error; a 0.10% increase for transitional error). The results of the ANOVA revealed that there was a significant effect due to the type of control system (null vs. with all modifications) for both steady-state error ($p < 0.001$) and transitional error ($p < 0.001$). All other factors were found to be non-significant ($p > 0.05$)

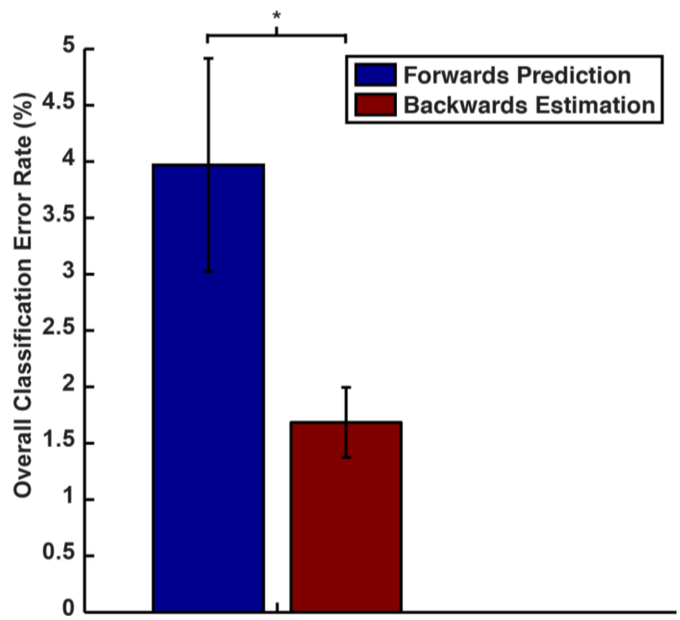

Figure 5.6: Performance of chosen labeling strategy. The adaptive algorithm used backwards estimation to label new patterns. The figure shows the performance of the backwards estimator (red) that was used during online assessment of the adaptive algorithm. This strategy is compared to using the output of the online forward predictor (blue). Data are averages of six subjects (+/- 1 SEM). * denotes statistically significant differences ($p < 0.05$)

TABLE 5.1: REAL-TIME COMPUTATION

Process	Average Time (ms)	Standard Deviation (ms)
Baseline Processing	15.1	2.4
Feature Extraction	2.4	0.02
Forward Prediction	0.3	0.04
Backward Estimation	4.6	0.2
Tracking of Means, Covariances	0.5	0.2
All Processes	22.9	2.5

5.5 Discussion

The purpose of this study was to develop an online adaptive intent recognition algorithm for a powered lower limb prosthesis, and to evaluate its performance during online experiments involving transfemoral amputees. First, our results show that the adaptive algorithm could appropriately select when to incorporate EMG into its forward predictions. Because EMG signals were likely different across experimental sessions as a result of donning and doffing the prosthesis, it was desirable that the algorithm initially did not incorporate all EMG into its

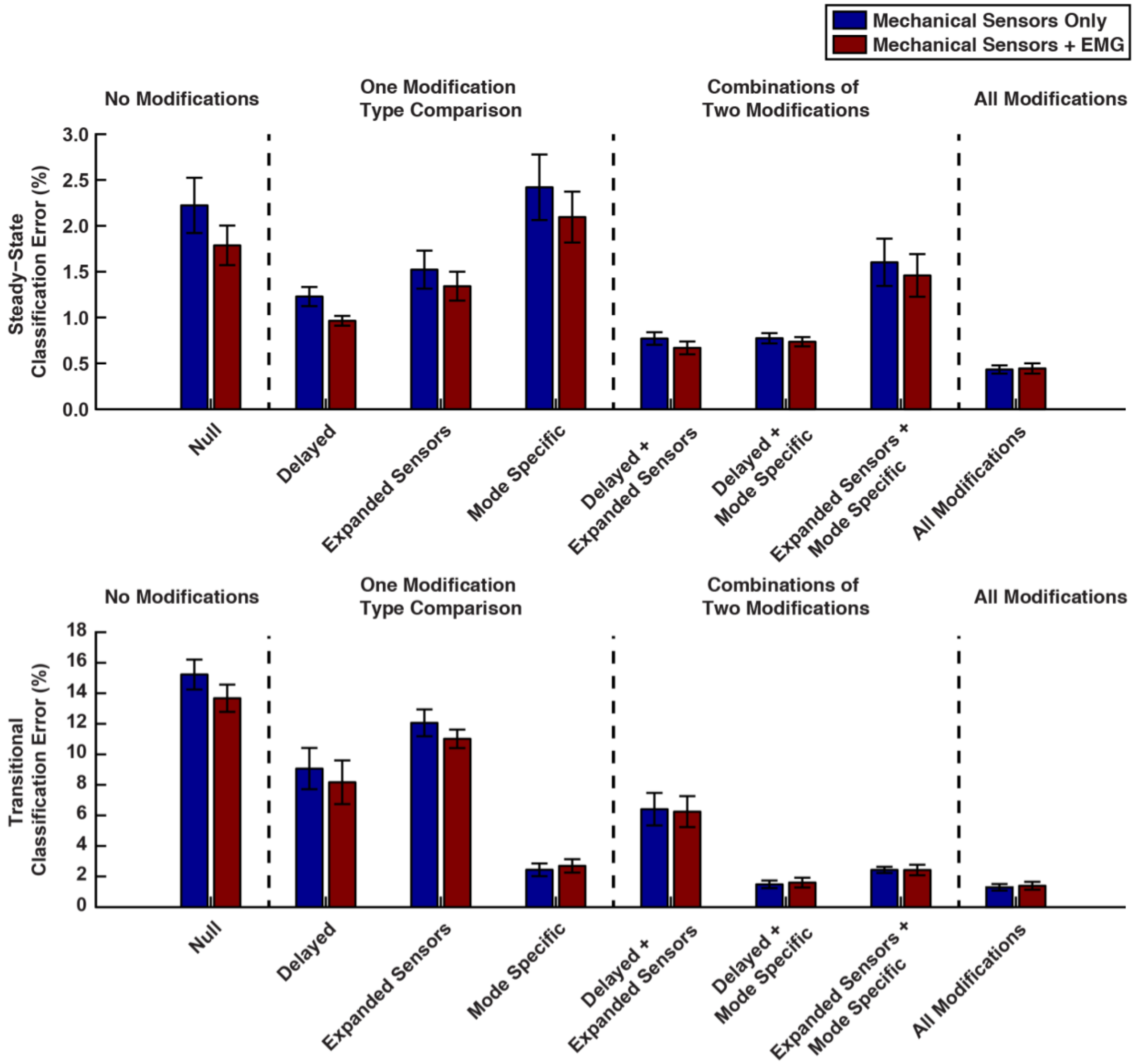

Figure 5.7: Effect of control system modification on forward prediction steady-state (top) and transitional (bottom) error rates. The effect of four different modifications to the prosthesis control system – delayed transitions, expanded mechanical sensors, and mode specific classifier architecture – on forward prediction were compared separately and in all possible combinations with each other. Two types of forward predictors were compared – one that used only mechanical sensor signals (blue bars), and one that used the combination of EMG signals and mechanical sensors (red bars). Data are averages of six subjects and error bars represent +/– 1 SEM.

forward predictions. In previous offline studies, we demonstrated that a log likelihood threshold can be used to determine whether to use both EMG and mechanical sensor signals to make a forward prediction, or to simply use mechanical sensors [53]. With this study, we verify that our proposed threshold performs as expected in real-time. This likely prevented forward prediction errors that would have occurred as a result of using EMG that contained disturbances, or were different across days; reverting to using only mechanical sensors was a safer alternative.

Our results also show that the adaptive algorithm learned to reincorporate EMG over time. As the subjects were ambulating, our algorithm gathered new patterns of EMG data, labeled them with a mode representing the user's intent, and updated the model of EMG training data. As a result, the model begins to describe EMG acquired from multiple experimental sessions and the log-likelihood threshold, which was also updated in the process, allowed more EMG to be used in the forward predictions. The percentage of EMG that was incorporated into the forward predictions in the online session increased as the subject ambulated. We expect that it would increase past what was recorded as users take more steps with the prosthesis. In summary, the combination of the log-likelihood threshold and adaptation results in a control system that prevents errors associated with changes in EMG, but also learns from these signal changes to create a robust model of EMG data over time.

The increase in the number of predictions that incorporated EMG did not significantly impact the online performance of the forward predictor. This was unexpected because previous studies have demonstrated that including EMG into forward predictions significantly decreased online error rates (previous studies reported an error rate of 14.1% when only mechanical sensors were used; including EMG decreased this error rate to 7.9%) [10], [14]. To further explain this finding, we conducted an offline analysis that investigated the effect of control system modifications on forward predictor performance. Our analysis showed that including these modifications decreased the error rate of the forward predictor, and that combining these modifications resulted in the lowest error rates. More importantly for this study, the analysis revealed that the benefit of including EMG signals, if any, is much less apparent when these control system modifications are included, as was done in our experiment. Thus, despite our adaptive algorithm learning to reincorporate EMG signals into its predictions, the benefit of including EMG was minimal given our current control system. This finding is important because it implies that EMG may not be necessary for intent recognition in powered lower limb devices, and that using other techniques (e.g., choice of classifier architecture, mechanical sensors, or the timing of mode transitions) could replace the benefits of EMG, which is cumbersome to implement in a lower limb prosthesis setup. Despite this, it should also be noted that EMG signals could have use beyond intent recognition and be used to accomplish other important tasks involving lower limb prostheses (e.g., detection of falls or stumbles, or volitional actuation of joints to reposition the prosthesis).

In interpreting this finding, one must also consider that other factors could be contributing to the lack of benefit of including EMG information. First, we had only a small number of subjects that participated in this experiment. It is possible that the benefit of adding EMG was small and we had insufficient power to detect changes. Second, implementing and acquiring EMG information in a lower limb prosthesis during the dynamic task of ambulation is challenging, and as a result, the EMG data that were acquired were likely not of the highest quality. Further efforts are needed to develop EMG acquisition systems that seamlessly integrate with lower limb prostheses, and can acquire high quality EMG data during ambulation. Third, it is possible that more data are required to build a representative model of EMG data; however, obtaining a large of amount data is challenging, and requires that the amputee user participate in long and burdensome experimental sessions. Fourth, the adaptive system used in this analysis did not include a forgetting factor and additional data were simply pooled with prior data. It is possible that a forgetting factor is necessary to track changes in EMG signals. Further efforts are needed to address these issues.

Similar to a previous offline study [52], the backward estimation labeling strategy was able to label new patterns in real-time with a very low error rate (1.69% [0.13%]). Thus, we were able to verify that this labeling strategy works in an online setting, where incorrect forward predictions alter the gait patterns of the user, and could impact the ability of the backwards estimator to label data. Backwards estimation is reliable because the modes of the prosthesis are preprogrammed and ambulation is cyclical; the resulting steps with the prosthesis can be accurately classified as specific ambulation modes. The main advantage of this strategy is that it can label patterns statistically more accurately than using the output of the forward predictor. It is also useful to use backwards estimation because of its ability to accurately classify steps when the forward predictor made an error (i.e., the prosthesis in the wrong mode). We pre-programmed the backward estimator to recognize when the prosthesis in the incorrect mode (e.g., when the user is ambulating down an incline but the prosthesis is still in level-ground walking mode). We can still infer the user's intent despite mistakes made by the forward predictor. We expect this method to be even more useful in across user applications, where higher forward predictor error rates may exist.

Our adaptive algorithm ran efficiently in real-time. All processes needed for the prosthesis to function appropriately were completed within the 30ms frame increment (though it should be noted that this chosen increment is somewhat arbitrary and maybe could be decreased without any detriment to the user). In addition, our algorithm updated the classifiers of the forward predictor frequently (125 times in 10 minutes), allowing for fast adaptation that incorporates the newest sensor data. Our online implementation is particularly important because it is critical to evaluate control algorithms while the user is in the loop. In our application, errors made by the online control system affect the ambulation of the user, making it more likely for the control system to make another error. Offline studies do not capture this human-machine interaction and the propagation of errors. Thus, we believe that we have presented the most accurate representation of algorithm performance in our online study.

In conclusion, this study improves the control of powered lower limb prostheses by allowing pattern recognition systems to adapt to changes in input signals. This study specifically addressed this limitation with EMG signals. We demonstrated that the adaptive algorithm could learn a new model of EMG data acquired across experimental sessions. We also investigated the impact of control system modifications on the benefit of using EMG signals for forward predictions, and determined that the modifications that we implemented for this experiment decreased the benefit that EMG information provided. Regardless, our adaptive algorithm moves pattern recognition control systems for lower limb prostheses towards clinical viability by addressing its main limitation: the inability to track signal changes. We expect our adaptive algorithm to be useful in other applications as well, specifically across user applications. Adaptation could be used to update the model of mechanical sensor information and create intent recognition systems for novel users during ambulation. This will be investigated in future studies.

6 Concluding Remarks

6.1 Summary of Findings

The overall objective of this work was to develop an adaptive pattern recognition algorithm for a powered lower limb prosthesis, and evaluate its performance in real-time experiments with transfemoral amputees. The studies enclosed in this dissertation:

- demonstrated that changes in EMG signals can be reliably detected with a log-likelihood threshold, and that mechanical sensors can be used as alternative means of making mode predictions in those circumstances (Chapter 2);
- demonstrated that backwards estimation can be used to accurately classify strides of mechanical sensor data acquired during ambulation with the prosthesis, and that this strategy can label patterns used to adapt the pattern recognition algorithm (Chapter 3);
- evaluated the adaptive algorithm in an online, multi-day experiment with transfemoral amputees ambulating with a powered lower limb prosthesis that uses EMG signals; in this study, the algorithm adapted EMG signals in real-time (Chapter 5);
- provided preliminary evidence that this adaptive algorithm can also be used to adapt mechanical sensors for novel users using the pattern recognition system (Appendix A)
- provided evidence that control system modifications lower prediction error rates, but also replace the benefits of including EMG as a control signal (Chapter 5)

6.2 Implications for Lower Limb Prostheses and Other Applications

Many lower limb amputees desire a prosthesis that automatically changes its behavior according the intent of the user. Pattern recognition algorithms can address this need by allowing for seamless transitions between locomotion modes that are transparent to the user. However, the limitations of these algorithms (i.e., that they are static and do not generalize well to other users) are obstacles towards clinical implementation. This dissertation demonstrates that the use of adaptation provides solutions to the limitations of pattern recognition algorithms, by allowing the algorithm to track changes in input signals and to generalize across users. These results are timely because powered prostheses have recently become commercially available [57], and pattern recognition algorithms could be implemented as a control strategy to provide the seamless transitions between ambulation tasks that able-bodied individuals complete regularly.

Specifically, this dissertation lays the groundwork for the development of EMG-based pattern recognition algorithms for powered lower limb prostheses. Previous studies demonstrated that adding EMG signals as an input to the pattern recognition algorithm significantly decreased algorithm error rates [10], [14], but these studies were completed in a single experimental session and do not address the limitations of using EMG long-term, i.e., that EMG signal quality degrades over time. This dissertation addresses these limitations and develops a clinically viable way to include EMG signals into the control of a lower limb prosthesis.

First, the ability to detect changes in the EMG signal is a significant upgrade to EMG-based pattern recognition algorithms. By creating a probabilistic model of appropriate EMG signals, a wide range of disturbances can be detected. The log-likelihood threshold developed in this dissertation reliably detected disturbances in the EMG signals including electrode liftoff, short-circuiting, and, perhaps what is the most practical and relevant change, electrode shift due to donning and doffing the prosthesis. Granted, other studies have developed methods for detecting changes in EMG signals [46], [71], but the advantage of using the log-likelihood as a threshold is that it does not need be calibrated and only requires a model of training data that is easily created. This makes the log-likelihood threshold a powerful tool for detecting changes in EMG signals, but more importantly, enables the development of strategies to compensate for these changes. Any pattern recognition algorithm that uses EMG signals should have a method for detecting disturbances, as this would inform the algorithm when to ignore EMG information, and also provide information for what kind of compensation strategy should be used. This noise detection technique could also be used to strengthen applications where EMG is not a control signal, but rather a diagnostic measure in detecting or monitoring neuromuscular abnormalities.

By using a powered lower limb prosthesis with embedded mechanical sensors, there exists an alternative means of making locomotion mode predictions [9], [24]. The chosen compensation strategy in this dissertation was to revert to using only mechanical sensors to make predictions when EMG disturbances were detected. Mechanical sensor signals provide more stable performance across experimental sessions, and are not vulnerable to the same types of disturbances as EMG signals are [15], [52]. They are a signal source that can reliably make mode predictions if EMG signals are not available. This compensation strategy prevented many errors that would have otherwise occurred if EMG signals were used. Thus, this dissertation provides evidence that a pattern recognition algorithm for a lower limb prosthesis should be instrumented with sensors that can provide consistent outputs over long-term use. Furthermore, any algorithm that uses EMG signals (or any signals prone to excessive noise) over long periods of time should be paired with more consistent signal sources, such as those acquired from mechanical sensors. Otherwise, any benefits that EMG signals provide are mitigated and could not be implemented clinically.

This dissertation also details the backwards estimation labeling strategy, which categorizes strides taken by the amputee as one of the locomotion modes of the prosthesis to provide a label for new patterns. Classification of gait profiles has been used to distinguish the gait of able-bodies individuals from that of those with gait abnormalities [38]–[40], but categorizing the strides of a prosthesis using information from embedded mechanical sensors is a novel contribution to the literature. Perhaps the most useful aspect of this strategy is the ability to detect when the user took a step with the prosthesis in the incorrect mode. This is obviously valuable for labeling data used for adaptation, but also has considerable potential for detecting stumbles and/or falls made with the prosthesis. This method could also be used to identify gait pattern changes that are associated with falling in at-risk populations (e.g., geriatric patients or stroke survivors). Thus, with the rapid growth of wearable sensors, backwards estimation could emerge as a gait diagnostic tool, one that informs future measures needed to prevent falls and/or stumbles. Lastly, the cyclic nature of ambulation enables the use of backwards estimation as a labeling strategy, but there is some potential to extend this concept to upper limb applications, where the workspace of prosthesis movement is larger and is not cyclic. It may be possible to instrument an upper limb prosthesis with extra mechanical sensors, and use the sensor outputs to determine if the predicted movement was what the person actually intended.

Adaptation of EMG signals will no doubt be necessary if EMG-based pattern recognition is to be implemented for lower limb prosthesis control. The statistical properties of EMG are not likely to be stationary outside a controlled laboratory setting – EMG signal characteristics clearly change over time, especially during ambulation [52]. Adaptation can update algorithm parameters to include various examples of EMG data under different conditions (e.g., electrode displacement, sweat, fatigue, or changes in control strategies adopted by the user [15], [16]). The adaptive mechanism developed in this dissertation allows the algorithm to adapt to such changes, and thus, it is an imperative addition to EMG-based pattern recognition algorithms. Moreover, it updates algorithm parameters *during ambulation*. This is big improvement over other strategies used to update EMG-based pattern recognition algorithms, which have mostly relied on supervised retraining strategies [29]. The adaptive algorithm developed in this dissertation was able to update itself in a way that did not require that the user interrupt their ambulation activities – all adaptation was completed in a way that was transparent to the user. It is undesirable for the amputee to stop their current activities to recalibrate the control system for their prosthesis, and the ability of the proposed adaptive algorithm to complete all recalibrations without the patient noticing will hopefully encourage other groups to include similar functionality in their control systems. The work in this dissertation could also be potentially useful to other types of adaptive recalibration besides pattern recognition, such as automatic adaptive tuning of impedance parameters. Moreover, one could extend this work to study motor learning concepts such as co-adaptation. In the online adaptation experiments, the parameters of the pattern recognition algorithm were changing, but the behavior of the user may have also changed in response to the adaptation of the algorithm. An adaptive pattern recognition algorithm for a lower limb prosthesis could provide an opportunity to study the co-adaptivity between the user and the implemented control strategy [72].

In addition, the benefits of adaptation are clearly observed in user-independent applications. Beginning with an algorithm trained with data from many other users and incorporating subject-specific data during ambulation is a critical improvement to lower limb pattern recognition algorithms [18]. Current data collection protocols are lengthy, tiring, and are currently only completed within a research setting. Across user adaptation could potentially remove the need for a novel user to participate in the long and burdensome training sessions and instead provide a smaller amount of subject-specific data that be acquired outside a research setting. If pattern recognition algorithms become the standard for lower limb prosthesis control, creating a large collection of data acquired from amputees ambulating with a powered prosthesis could be used to create a "generic" pattern recognition user, while adaptation updates the algorithm the subject-specific data to generate an optimal set of parameters that are unique to the novel user.

Another important implication of this research is the role of EMG within lower limb prostheses. The results from Chapter 5 showed that an updated model of EMG data could be created with adaptation, but they also showed that modifications to the control system had an impact on how much benefit could be acquired from including EMG signals. Clearly, the benefits of including EMG signals can be replaced with other techniques related to the timing of transitions, classifier architectures, and the amount of mechanical sensors embedded within the prosthesis. This could eliminate the need to include EMG signals within lower limb pattern recognition systems, which are cumbersome and challenging to implement within a lower limb prosthesis system. The research in this dissertation will hopefully encourage more investigations to further clarify what the role of EMG is within lower limb prostheses. This includes the development of methods to acquire high quality EMG, advanced techniques to fuse its information with that of mechanical sensors, and the development of alternative, more clinically viable methods to acquire similar information.

6.3 Limitations and Future Directions

This dissertation lays a foundation for adaptive lower limb prosthesis control and raises questions regarding lower limb prostheses, adaptive machine learning, myoelectric control, and motor learning. Thus, this dissertation provides a starting point for a wide variety of future work.

The motivation for developing an adaptive EMG-based pattern recognition algorithm was to maintain the benefits of including EMG signals over long-term prosthesis use, and prevent the prediction errors due to EMG disturbances. The work in this dissertation accomplished these goals, but the techniques that were used were first steps and the methods behind them could become more sophisticated. For instance, the log-likelihood threshold was created from a model of appropriate EMG training data, but it is likely useful to also model the specific EMG disturbances that are encountered during daily prosthesis use (e.g., electrode liftoff, short-circuiting). The ability to detect not only that there is a disturbance, but also *what kind* of disturbance would be helpful in developing appropriate compensation techniques. It would be particularly helpful in choosing which data is used to adapt the forward prediction system. Some disturbances (e.g., electrode liftoff) contain no predictive information, and should not be used to adapt the forward predictor [46]. Other disturbances, such as those caused by electrode shift, still contain useful information that should be incorporated into the initial training dataset [15], [17]. The ability to differentiate between these two circumstances was not investigated in this dissertation, and thus all data, regardless of what kind of disturbance it contained, were added to the training dataset. This may have resulted in the forward predictor learning noise instead of useful information, though we took care to prevent this from happening during the online experiments. This limitation could be avoided by modeling different types of disturbances, though admittedly, acquiring the data to accomplish this would be very time consuming and challenging.

The compensation strategy used in this dissertation (i.e., reverting to using only mechanical sensors) was effective, but was fairly simple. There may be more elegant ways to fuse mechanical sensor data and EMG data, and these were relatively unexplored in this dissertation. Previous studies have investigated the development of multi-expert classification techniques [73], wherein the different types of signals are weighted differently in different circumstances. Future work should explore these techniques in order to maximize the benefit of including the different types of signals.

Moreover, the techniques used in this dissertation may not be the optimal way to implement adaptation of pattern recognition algorithms. These studies adapted algorithm parameters (i.e., class means and covariances) by labeling new patterns of data and sequentially updating the parameters [70]. That is, this method updates the model of training data by adding new exemplars of data, resulting in a large, robust model of data that contains all different types of ambulation. It may be beneficial to explore other types of adaptation such as domain adaptation [74] or sparse representation classifiers that instead determine a mapping between different models of ambulation (such as those acquired in different experimental sessions). This would potentially result in being able to use a single training session that could be applied to other collections of ambulation data without having to include examples from the latter. Finding mappings between multiple days' worth of EMG data or between different users in this manner could also accomplish the goals of this dissertation and address the limitations of using pattern recognition.

The use of a forgetting factor was not implemented in these studies. The pattern recognition algorithm did not "forget" any old data, but rather simply added new exemplars of data to the already existing model of data. It is unclear how this affected the results of this dissertation. On one hand, adding more exemplars creates a large, robust model that could benefit performance. For example, training a pattern recognition algorithm with multiple plausible EMG electrode displacements has demonstrated that this strategy is helpful [15]. On the other hand, it is possible that a pattern recognition algorithm may perform optimally when only the most recent dataset is used for training. Further investigation on this matter is required to determine whether a forgetting factor is needed for adaptation.

In addition, it will be of great importance to fully investigate the effect of control system modifications on the benefit of including EMG. While previous studies have demonstrated that including EMG significantly improves mode prediction performance, these studies used a very different control system from the one that was used in the online adaptation experiments. We demonstrated that the added modifications (i.e., expanded mechanical sensors [61], using a mode-specific classifier architecture [18], delaying mode transitions [65]) had a large impact on what was observed in the online experiments in Chapter 5. This will need to be further investigated in future work. The impact of this knowledge could produce easily implementable techniques that replace the benefits of including EMG, which is challenging and cumbersome to work with and implement (or, on the other hand, also produce methods that can still obtain benefits from including EMG despite these modifications). Granted, the quality of the EMG signals that were acquired during these experiments is probably of lower quality than other applications because of the difficulty of implementing EMG acquisition systems within a prosthetic socket. Greater emphasis should be placed on developing sophisticated techniques and devices that can acquire EMG data in such conditions. It is not unlikely that implanted intramuscular hardware is the key to acquiring high quality EMG data [75].

Another important aspect of this dissertation that needs to be further explored is the impact of forward prediction errors on user performance [63], [64]. Many of the amputee subjects were affected by the mistakes made by the forward predictor, especially in how confidently they ambulated after such an error. It has been shown in previous studies that errors made by the forward predictor propagate because of the altered gait of the user [14]. Thus, it is of great importance to explore and develop control strategies that allow the patient to recover if the forward predictor makes a mistake. The lack of these strategies is a major obstacle towards the implementation of pattern recognition systems for the control of lower limb devices. The impact of mistakes on patient safety is quite large, and will need to be addressed in future work if lower limb pattern recognition is to become clinically viable.

It is possible that the impact of these errors may be mitigated if the patient were given more control of the prosthesis. The use of pattern recognition allows for seamless transitions between modes, but the added autonomy of the prosthesis takes control away from the user. The result is that when the forward predictor makes a mistake, the user must usually “walk through” the perturbation (as with misclassifications into ramp descent or stair descent mode), which can result in a stumble or fall, and the user cannot modify the behavior of the prosthesis. The pattern recognition algorithm used in this dissertation was "phase-based," meaning that classification decisions only happen at specific, discrete time points within the gait cycle (e.g., heel contact or toe-off) [23], [24]. Therefore, the prosthesis cannot correct itself until the next gait event, and the user must experience a perturbation. Future work should investigate the development of continuous classifiers that will allow for corrections and recoveries to happen more frequently [10].

Another potential solution would be to provide more control back to the user, and only take it away when necessary. This concept of "shared control" has been explored with other assistive devices, such as powered wheelchairs, and is used to appropriately assign control commands between the human user and the autonomous robot [76], [77]. It may be possible to apply shared control methods to lower limb prosthesis control, and develop a method to revert control back to the user at the appropriate time (e.g., when there is a misclassification by the forward predictor). This would involve a careful assignment of which control mechanisms should be given by the user, which ones can be given to the autonomous device, and when these roles need to change.

Including sensory feedback would also likely improve the user's ability to compensate for pattern recognition errors. Pattern recognition addresses mobility restoration with lower limb prostheses by providing a means to transition between modes seamlessly, but the user lacks the sensory feedback to compensate for pattern recognition errors. Other studies have investigated providing sensory feedback to amputees, and have observed functional benefits such as increased ownership of the prosthesis and the ability to detect specific gait phases [78]–[82]. These benefits, when combined with lower limb pattern recognition, could inform the user about the decisions of the prosthesis, and potentially allow the user to develop compensation strategies that prevent stumbles or falls in the case of a misclassification. Sensory feedback could also provide information about foot placement, heel contact, and center of pressure, which would allow the user to take advantage of all the motor capabilities of powered prostheses.

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Appendix A. Preliminary Results for an Adaptive Pattern Recognition System for Novel Users Using a Powered Lower Limb Prosthesis

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A.1. Abstract

Powered prosthetic legs are capable of improving the gait of lower limb amputees. Pattern recognition systems for these devices allow amputees to transition between different locomotion modes in a way that is seamless and transparent to the user. However, the potential of these systems is diminished because they require large amounts of training data that is burdensome to collect. To reduce the effort required to acquire these data, we developed an adaptive pattern recognition system that automatically learns from subject-specific data as the user is ambulating. We tested our proposed system with two able-bodied subjects ambulating with a powered knee and ankle prosthesis. Each subject initially ambulated with a pattern recognition system that was not trained with any data from that subject (making each subject a novel user). Initially, the pattern recognition system made frequent errors. With the adaptive algorithm, the error rate decreased over time as more subject-specific data were incorporated. When compared to a non-adaptive system, the adaptive system reduced the number of errors by 32.9% [8.6%], mean [standard deviation]. This study demonstrates the potential improvements of an adaptive pattern recognition system over non-adaptive systems presented in prior research.

A.2. Introduction

Powered prosthetic knees and ankles provide joint power to lower limb amputees and assist them in completing a variety of ambulation tasks (e.g., walking on level ground, stairs, or inclines) [6], [8]. These devices are typically programmed with different locomotion modes that change the behavior of the device (e.g., provide or dissipate power) as the user is completing the different tasks [25], [50], [51]. Finding a robust method for seamlessly and automatically transitioning the device between the different modes remains a challenge. Pattern recognition algorithms have been proposed for automatically selecting the desired mode of the user. These algorithms can use kinetic and kinematic information from mechanical sensors embedded within the prosthesis to infer the user's intent and transition the prosthesis into the desired mode [14], [24], [25], [50], [61]. One disadvantage to using pattern recognition is that a large amount of data must be collected to train the algorithm to learn user-specific patterns and recognize how a particular user completes the different mode transitions. To acquire these data, the user must complete a long and burdensome protocol where he or she uses the prosthesis to complete the mode transitions. Developing a pattern recognition algorithm that does not require the subject's unique data to perform at a high level would eliminate the need for the demanding training protocol and improve the clinical viability of these devices.

A more robust pattern recognition algorithm could be developed by using training data collected from multiple users, obviating the need to collect training data from a novel user. However, previous studies have shown that these user-independent systems (i.e., those that are trained with data from multiple users but without the novel user's unique data) have increased error rates, suggesting that subject-specific data is required for optimal performance [18]. One could address this limitation and improve user-independent systems by designing one that is adaptive. Specifically, an adaptive user-independent system could gather unique training data from the novel user as they are using the prosthesis to ambulate outside a clinical setting. This strategy would decrease error rates over time as the system automatically learns from unique subject patterns during daily use. The use of an adaptive algorithm would particularly innovative because adaptation in lower limb prosthetics has mostly focused on tracking nonstationary signals such as electromyography (EMG). Its use in novel user applications is unexplored and could positively impact the clinical viability of powered lower limb prosthetics.

The objective of this study was to develop and evaluate an online adaptive pattern recognition system for a powered lower limb prosthesis, specifically for novel user applications. This analysis was completed with two able-bodied individuals using an adaptive system initially trained with data from a different user. The adaptive system was automatically updated with mechanical sensor data from the novel user as they were ambulating with the prosthesis in real-time. We hypothesized that users would experience fewer errors over time while using our adaptive system. Moreover, we highlight the benefits of using an adaptive system by comparing its performance to that of a system that was non-adaptive. This use of the adaptive algorithm for novel users demonstrates its ability to address problems in lower limb prosthetics beyond the tracking of non-stationary EMG signals (which was the focus of most of this dissertation). The ability of adaptive algorithm to learn from different types of input signals also pushes the research on novel users in lower limb pattern recognition systems, which is fairly unexplored.

A.3. Methods

A.3.1. Adaptation Algorithm

Our proposed adaptive algorithm used supervised learning, meaning that all data used for training had to be paired with the correct class (in this case, the desired mode of the user). Thus, our adaptive algorithm had to meet the following requirements: 1) predict the desired mode of the user before critical transition points (e.g., heel contact, toe-off), 2) automatically label new patterns used to update the system with a class that matched the user's intent, and 3) add the labeled pattern to the training dataset to update the system (i.e., updating parameters such as means, covariances, weights, etc.)

The first requirement of predicting the desired mode of the user is accomplished by classifying mechanical sensor information acquired before the user's next step with the prosthesis, a process we term forward prediction. To accomplish the second requirement of automatic labeling of new prediction patterns, we use a separate pattern recognition system to classify mechanical sensor information acquired from the user's entire completed stride. This process, which we term backwards estimation, classifies the executed gait pattern of the user. This has been shown to be an accurate strategy for labeling patterns that will be used to update the forward prediction system (Figure A.1) [52].

Consider an example where the user's desired mode is level walking. The forward prediction system classifies a pattern (P_{FP}) before the stride as level walking and the prosthesis is controlled in level walking mode. P_{FP} will also be used to update the forward prediction system, but requires a class label that should match the desired mode of the user. The backwards estimator classifies the gait pattern acquired from information from the entire completed stride (hopefully as level walking) and provides a class label for P_{FP}. The combination of P_{FP} and the class label can be used to update the appropriate parameters of the forward predictor.

Included in the design of the backwards estimator is the ability to provide a correct label for P_{FP} even when the forward prediction system misclassifies it (causing the user to take a stride in the incorrect mode). Consider again an example where the user's desired mode is level walking but now the forward predictor incorrectly classifies P_{FP} as ramp descent. In this case, the user takes a step on level ground while in ramp descent mode. The backwards estimator can recognize this executed gait pattern and still provide a class label of level walking for P_{FP}. Thus, the label is correct because it matches the user's desired mode.

A.3.2. Experimental Protocol

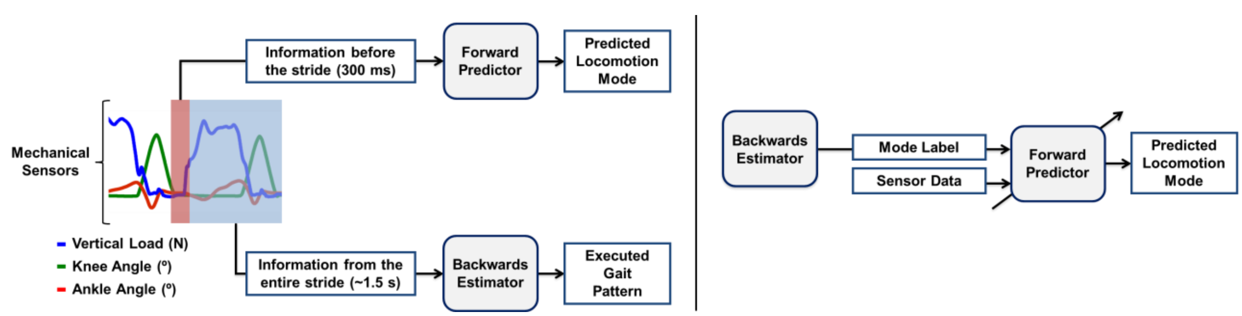

Figure A.1: Illustration of adaptive algorithm. A forward predictor (left) classifies mechanical sensor patterns from data before the stride and transitions the leg into the predicted mode. After mechanical sensor data from the entire stride is collected, a backwards estimator classifies this longer window of data and determines the executed gait pattern. The output of the backwards estimator then provides a mode label for the pattern of data acquired before the stride (right). The pattern of sensor data and its given label are used to update the parameters of the forward predictor.

Two abled-bodied subjects completed the experiment, which was approved by the Northwestern University Institutional Review Board. Written and verbal consent was obtained from each subject involved.

Subjects wore a bypass socket (Figure A.2) that allowed them to ambulate with a prosthesis despite being able-bodied. The Center for Intelligent Mechatronics at Vanderbilt University designed the prosthesis used for this study [8]. A certified prosthetist attached the powered knee and ankle prosthesis to the subjects' socket. Each subject had previous experience walking with the prosthesis and published strategies were used to tune the leg for each mode [44], [47], [51].

Each subject participated in a session to collect training data for a forward predictor and a backwards estimator. This first session was designed to capture all relevant transitions between modes. Each subject completed tasks including standing, walking on level ground, stair ascent and descent on a 4-step and 3-step staircase, and walking on ramps. The experimenter used a key

Figure A.2: Able-bodied subject with a bypass socket wearing the powered knee-ankle prosthesis.

fob to trigger all mode transitions at specific points within the gait cycle (heel contact, toe-off, mid-swing, and mid-stance). The subjects were also asked to complete various activities while ambulating in the incorrect mode (e.g. walking down a ramp while in level walking mode). This was completed to provide data for the backward estimator so that it could recognize the true intent of the user if the prosthesis transitioned to the incorrect mode. Data from these experimental sessions were then used to train a forward predictor and a backwards estimator unique to each subject. We will refer to this session as the 'offline session.'

In a second experimental session, the subjects completed a similar but shortened protocol to that of the offline session. In this session, an online forward prediction system trained *with only the other subject's data* controlled the prosthesis. Therefore, each subject was a novel user because they were ambulating with a forward prediction system that was trained with data other than their own. It is important to note that the forward predictor sometimes made errors and transitioned the leg into the incorrect mode during this 'online session'. As each subject was ambulating, the backwards estimator (also trained with the other subject's data) labeled patterns used by forward predictor, and these patterns were then used to update the parameters of the forward predictor. In this case, class means and covariances were sequentially updated after every step with the prosthesis. The experimenter updated and saved the weights of the predictor periodically throughout the session. It should be noted that subject 2 completed five sets of a four-step staircase with a key fob instead of with an online predictor in the beginning of the online session. This was done to facilitate stair descent and to update the adaptive system with correctly-classified patterns. The backwards estimator still labeled the patterns from this offline set.

A.3.3. Signal Processing and Classifier Architecture

Kinetic and kinematic information from twenty-two embedded mechanical sensors were recorded at 500 Hz. These included joint angles, joint velocities, motor currents, and load applied through the prosthesis.

For forward prediction, data were segmented into windows of 300 ms *before* the aforementioned transition points. The mean, standard deviation, maximum, minimum, initial and final values of each mechanical sensor were calculated as features from each window [50]. The dimensionality of this feature set was reduced from 132 features down to 50 using principal component analysis [67]. The forward predictor was a dynamic Bayesian network, which incorporates the time history of the mechanical sensors into its predictions [24]. We used a mode specific classifier architecture for forward prediction. Thus, each mode had its own classifier that predicted transitions between modes. We used this architecture because it has been shown to improve performance for novel users [18]. The forward prediction system used in this study predicted transitions between the following modes: level ground walking, standing, stair ascent/descent, and ramp descent.

For backwards estimation, mechanical sensor data were segmented by strides (i.e., from one heel contact to the next heel contact). For each mechanical sensor, the same set of features as those used for forward prediction were also extracted from this stride window [52]. The dimensionality of this feature set was reduced from 132 features down to 13 using uncorrelated linear discriminant analysis (ULDA) [69]. The backward estimator used linear discriminant analysis (LDA) classifier to classify the executed locomotion mode at every heel contact. The classes of the backwards estimator included standing, level ground walking, ramp descent, stair ascent/descent, and various classes where the user was ambulating in the incorrect mode (e.g., walking down a ramp in level walking mode, completing stair descent one step at a time instead of step-over-step stair descent).

A.3.4. System Evaluation

To evaluate the performance of the adaptive system, we calculated the number of errors made by the forward predictor in the online session for each subject. We also calculated the number of mistakes the forward predictor would have made if the system were not adapted throughout the online session. Comparing the number of errors of both systems revealed the benefits of adaptation. It is worth noting that the non-adaptive system was not tested in real-time and that its response was determined offline.

We also determined the performance of the forward predictor before and after adaptation by testing the initial and final set of weights on the subject-specific data collected in the offline session. Error rates for this analysis are the pooled misclassification rates at the critical transition points of the prosthesis. Misclassifications were categorized as either steady-state or transitional misclassifications, where steady-state misclassifications occur when the prosthesis should not switch modes, and transitional errors occur when the prosthesis should switch modes.

A.4. Results

Both subjects initially had difficulty using the prosthesis to transition modes and completing the different ambulation tasks. For instance, subject 1 had difficulty initiating and completing step-over-step stair ascent/descent. The forward predictor of subject 2 would frequently miss transitions from level walking mode to ramp descent mode.

Fortunately, the backwards estimator correctly classified many of these steps and added these new patterns to the subjects' training sets with the correct label. The result is that fewer mistakes were made over time (Figure A.3). If subject 1 had used a non-adaptive system, their predictor would have made 67 misclassifications. Instead, the adapted predictor made 49 misclassifications (a 25% reduction). The non-adaptive predictor of subject 2 would have made 41 misclassifications; their adapted predictor made 25 (a 39% reduction).

The benefits of using the adaptive system were also observed when each subject's final system (after all adaptation was finished) was tested on their unique dataset that was collected in the offline session (Figure A.4). For transitional steps (when the leg should switch modes), the adapted predictor had a transitional error rate of 10.18% [3.80%], mean [standard deviation], whereas the initial predictor before any adaptation had a 22.92% [12.82%] transitional error rate. For steady-state steps, (when the leg should not switch modes) the adapted predictor had an error rate of 3.26% [2.39%], mean [standard deviation], whereas the initial predictor before any adaptation had an error rate of 3.19% [2.68%].

A.5. Discussion

This preliminary study demonstrates how an adaptive pattern recognition system that

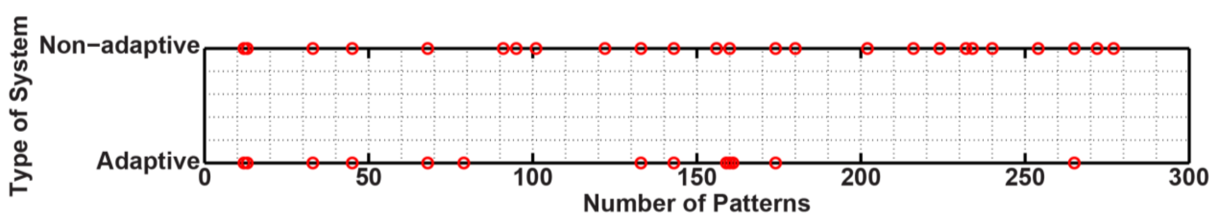

Figure A.3: Example of number of misclassifications made by one adaptive and non-adaptive classifier for one subject in the online session. The figure shows the number of misclassifications (marked with red circles) made by the heel contact classifier acting in level walking mode throughout the course of the online session. No red mark means that no misclassification occurred for that particular pattern. The top line of patterns shows the decisions that the non-adaptive classifier would have made, and the bottom line of patterns shows the decisions made in real-time by the online adaptive system.

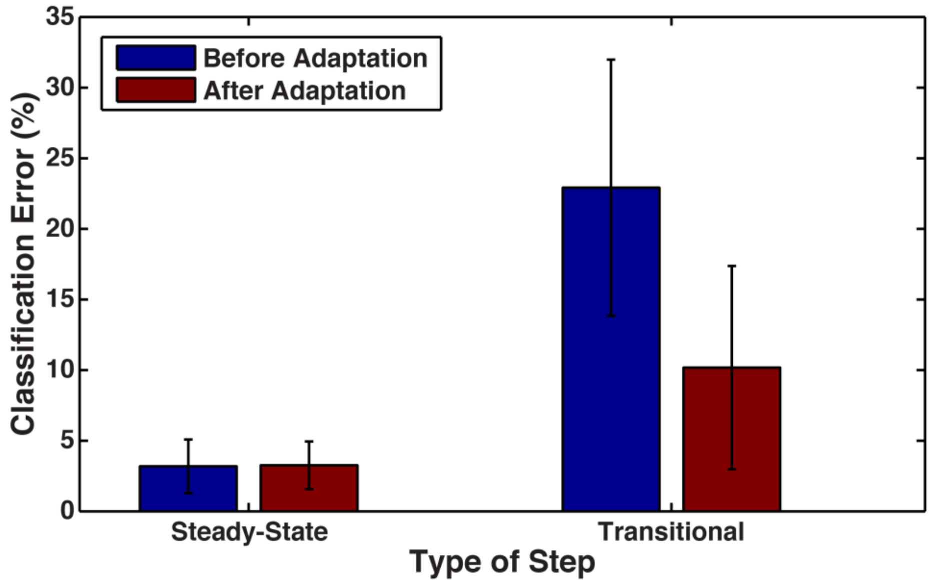

Figure A.4: Steady-state and transitional error rates of the forward predictor before and after adaptation. Data are averages of two subjects and error bars represent +/- 1 SEM.

learns subject-specific data can prevent errors that would have normally been made by a system that did not use adaptation. In this study, two able-bodied individuals walked on a powered knee-ankle prosthesis with an online adaptive pattern recognition system. The system was originally trained with data from the other subject, making each subject a novel user. Both subjects initially experienced frequent errors made by the forward predictor. Over time, the adaptive system learned to incorporate new subject-specific data from the user to retrain the algorithm during ambulation. As a result, the forward predictor made fewer errors over time, and made fewer errors than the non-adaptive system would have made.

The backwards estimator was able to correctly classify gait patterns when the prosthesis was in the correct mode and also in the incorrect mode. For instance, subject 2's initial forward predictor would frequently misclassify the mode transition from level walking to ramp descent. This resulted in subject 2 taking their first step on the ramp in level walking mode. This step generated a unique gait pattern which the backwards estimator then correctly classified as a step where the prosthesis should have been in ramp descent mode. The adaptive system then took the pattern that was originally misclassified by the forward predictor, and applied a corrected label of ramp descent to update the predictor. Often, only one or two examples of a specific transition were required to teach the forward predictor how to correctly initiate the transition.

The performance of the adaptive system was also observed when the final predictor was tested on the datasets acquired in the offline session. The final adaptive system reduced error rates for transition steps by 12.74% [9.02%]. It is notable that this decrease in error rate was achieved even though both subjects took fewer steps in the online session than they did in the offline session. We would expect error rates to continue to decrease as more data from the current user are added to the training set.

This study has several limitations. First, the subjects in this study were able-bodied, Future experiments will investigate whether similar results can be found with lower limb amputees. Moreover, the forward predictors were particularly limited because they only had data from one individual. Clinical implementations of this system would likely start with a training set composed of data from many other individuals. Also, the current adaptive system did not 'forget' data from the other subject; instead, new data from the user was simply added to the training set, resulting in a dataset comprised of two individuals. Future implementations of the adaptive system will likely include a forgetting factor.

Another limitation is that we compared the performance of an *online* adaptive algorithm to the *offline* performance of the non-adaptive algorithm. This is not an entirely fair comparison because the performance of the non-adaptive algorithm would not capture the effect of human-in-the-loop interaction between the user and the prosthesis. It is possible that the non-adaptive algorithm would have behaved differently had we tested it in an online experiment. However, our comparison is not entirely uninformative. We believe that the adaptive algorithm would still have outperformed the non-adaptive algorithm if the latter were tested online. This because errors made by the non-adaptive forward predictor would affect later steps with the prosthesis, and likely cause more errors than were captured in this offline analysis. The fact that our adaptive algorithm still outperformed the non-adaptive algorithm without these added errors is telling, but an online test of the non-adaptive algorithm is still needed to fully verify this.

Lastly, although system parameters such as class means and covariances were sequentially estimated as the subjects were ambulating, our system did require that the experimenter manually and periodically update the weights of the forward predictor. This is because calculating the weights is computationally intensive and caused the leg to misbehave if done during ambulation. Future studies should investigate how often the system should be updated, and after which activities.