ABSTRACT

ZHANG, FAN. Towards Development of a Novel Neural-machine Interface for Powered Artificial Legs. (Under the direction of Dr. He Huang).

Computerized, powered artificial legs hold great promise for improving the mobility and locomotive functions of lower limb amputees. However, current control strategy (i.e. manual mode switching) on commercialized devices has proved non-intuitive and unreliable, which may hinder the clinical application of powered artificial legs. The overall objective of this research is to develop a novel neural-machine interface for powered artificial legs, which could enable lower limb amputees to perform locomotive functions in an intuitive, reliable, and safe way. A neuromuscular-mechanical fusion based intent recognition algorithm has been developed in our group. This algorithm demonstrated promising results to accurately recognize prosthesis user’s movement intention and responsively predict locomotion task transitions. Despite the great potential of using fusion-based algorithm for neural control of powered artificial leg, several challenges still remain in making neural-machine interface clinically viable for prosthesis control. The research presented herein focus on addressing two major challenges in designing such an interface: (1) determining informative and optimal data sources of neural-machine interface is of great importance for practical implementation, which has not been done yet; (2) understanding the effects of errors in neural-machine interface on the operation of the prosthesis and user’s task performance is critical, however still unknown. The targeted patient population of this research is transfemoral amputees.
The usefulness and importance of different data sources which have been commonly suggested for locomotion mode recognition were investigated in Chapter 2. The considered data sources included eight surface EMG signals from residual thigh muscles, ground reaction forces/moments from a prosthetic pylon, and kinematic measurements from residual thigh and prosthetic knee. We ranked the included data sources based on the usefulness for locomotion mode recognition and selected a reduced number of data sources that ensured accurate locomotion recognition by using three source selection algorithms. The results showed that not all of the studied data sources carried important information and input redundancy do exist in the initial design of fusion-based interface. Importantly, the results suggested that EMG signals and ground reaction forces/moments were more informative than prosthesis kinematics. The selected data sources generated consistent performance across different experimental days, indicating the potential robustness of the selected data sources. In addition, we suggested a protocol for determining the informative data sources and sensor configurations for future powered artificial leg design.

In Chapter 3, we investigated the effects of neural-machine interface errors on the control of powered prosthesis and user’s task performance. Five able-bodied subjects and two transfemoral amputees were tested when they wore a prototype of powered knee prosthesis. Different types of locomotion mode recognition errors with varied duration and at different gait phases were purposely applied to the prosthesis control when the subjects performed tasks. The subjects’ gait stabilities were subjectively and objectively quantified. Interestingly, it was found that not all of the mode recognition errors disturb the subjects’ gait stability. The
effects of errors on the user's balance depended on (1) the gait phase when the errors happened and (2) the amount of mechanical work change applied on the powered knee caused by the errors. We successfully identified and characterized the “critical errors”, and suggested the use of "critical errors" as a new index to evaluate the performance of neural-machine interface for powered artificial legs. It is expected that the outcomes of this research could aid the further development of neurally controlled powered artificial legs to enhance the mobility of lower limb amputees.
Towards Development of a Novel Neural-machine Interface for Powered Artificial Legs

by
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DEDICATION

I would like to dedicate my dissertation work to my family, with a special feeling of gratitude to my loving parent, Heping Zhang and Jinfeng Wang. Thank you so much for all your support, encouragement, and endless love throughout my life. I love you!

This work is also dedicated to my advisor, Dr. He Huang. Thank you for your constructive suggestions, insightful criticism, and encouragement throughout my graduate studies.

Finally, I would like to dedicate this work to my girlfriend, Changhua Weng. I will always appreciate your love, patience, and support. I am so lucky to have you in my life.
BIOGRAPHY

Fan Zhang was born in Taiyuan, Shanxi, China in November 1981 and graduated from high school in the summer of 2001. Fan received his Bachelors of Science in Biomedical Engineering from Tianjin Medical University, China, in the summer of 2006, and Masters of Science in Biomedical Engineering from Tianjin University, China, in the summer of 2008. During his two-year graduate study, he was involved in research about design and optimization of rehabilitation walker system in the NeuroEngineering and Rehabilitation Laboratory at Tianjin University. Through this research opportunity, he gained solid knowledge and great interests in biomedical and rehabilitation engineering field.

After receiving his MS degree, Fan decided to pursue his Ph.D. degree in the Neuromuscular Rehabilitation Engineering Laboratory (NREL), which is directed by Dr. He Huang. Within almost 6 years at NREL, he has participated in research towards the development of neurally controlled artificial legs, funded by multiple federal and state funding agencies. His research interests focus on biomedical signal processing, machine learning, and the design of neural-machine interface for the robotic assistive device control. As November of 2014, he has co-authored 10 journal articles and 16 peer-reviewed conference papers. In addition, Fan has been invited by multiple journals to serve as a manuscript reviewer.
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CHAPTER 1:

General Introduction

1.1 Motivation

Limb amputation is a devastating event that has physical, psychological, and social impact on people’s daily life. There were nearly 1.6 million people living with limb loss in the United States in 2005 [1], with lower limb amputations occurring much more frequently than upper limb amputations. Due to the aging of the population and increasing rates of dysvascular disease related to diabetes and obesity, there are approximately 185,000 new limb amputees in the United States each year [2]. It was estimated that the total number will be more than doubled by the year 2050 to 3.6 million [1]. Therefore, there is a pressing need to restore as much function as possible to the large and increasing population of limb amputees. The targeted patient population of this research is transfemoral (TF) amputees (or above-knee amputees). It is not only because they have the second largest amputee population, but also they are a more challenging group in which case they lost both their knee and ankle joints, which makes restoration of mobility and function even more difficult.

Lower limb prosthetics are artificial devices designed to replace the missing lower limbs and restore the locomotive function as much as possible. Focusing on transfemoral knee prostheses, most of the current commercialized prosthetic knees are energetically passive devices, i.e. mechanically passive and microprocessor-controlled passive devices. The control of mechanically passive prosthetic legs purely relies on the mechanical design (e.g.
sliding joints or hydraulic valves) and the body movement of user’s trunk, pelvis, and residual limb. Microprocessor controlled prostheses (e.g. Ossur Rheo Knee, Otto Bock C-Leg, and the Freedom Innovations Plié knee, as shown in Figure 1) incorporate mechanical sensors and a microcontroller, and modulate the joint damping throughout the gait cycle by controlling either hydraulic [3] or magnetic rheological fluid [4]. These passive devices do provide lower limb amputees with increased mobility; however, they still have limited capability to assist lower limb amputees to negotiate uneven terrains (i.e. stairs and ramps) in a natural and efficient way, due to the lack of active net power on prostheses joints. In addition, it has been shown that transfemoral amputees with passive prosthetics expend up to 60% more metabolic energy [5] and exert three times of hip power and torque [6] during level-ground walking, compared to able-bodied persons.

Figure 1. Examples of commercially available microprocessor knees. Ossur Rheo Knee (left), Otto Bock C-Leg (middle), and Freedom Innovations Plié Knee (right).
1.2 Powered Artificial Legs and Control Strategy

Recent advancements in microcomputer-controlled, powered artificial legs have greatly increased the number of locomotive functions that lower limb amputees can perform [7-10]. One commercially available powered knee (i.e. Ossur Power Knne) and two representative research prototypes are shown in Figure 2. With powered prosthetics driven by active actuators, lower limb amputees can more easily and efficiently perform a variety of activities, such as stair climbing and slope walking, which are difficult or even impossible when they wear traditional passive devices. Powered artificial legs usually employ a finite-state machine

Figure 2. Examples of commercialized and research prototypical powered knees. Ossur Power Knee (left), powered lower limb prosthesis from Vanderbilt University (middle), and powered knee from MIT (right).
(FSM) based intrinsic control mechanism to adjust the joint impedance or joint position during ambulation [10, 11]. In addition, the control is mode-based [9, 10], which means prosthesis needs to switch control modes according to user’s different performing tasks, such as level-ground walking and stair ascent. Therefore, to seamlessly transition from one task to another, the user must “tell” the prosthesis his/her movement intention before performing the transitions so that the controller of the prosthesis can switch to correct mode in time. Conventional manual mode switching approach, such as pressing a remote key fob [3] or performing extra body motions [7], is functionally viable; however, the manual approaches are non-intuitive and cumbersome, sometimes unreliable and unsafe.

Alternatively, several smarter approaches, which automatically recognize prostheses users’ movement intention, have been explored to allow more intuitive control. One approach is called “echo control” [12, 13]. The concept is to control powered lower limb prostheses by tracking the motion of the sound side. Therefore, it requires amputees to use the sound leg to initiate task transitions every time. This approach has been used to allow for smooth gait initiations and terminations. This method assumes that the motions of two legs are symmetry during locomotion, which is however not always valid. For example, the motions of lower limbs are different in the transition from level-ground walking to stepping over an obstacle. In addition, this method requires the user to don and doff an instrumented orthotic on the unimpaired leg and cannot be used by bilateral leg amputees. Another approach is user intent recognition based on mechanical sensing measured from prostheses [14]. Ground reaction forces and kinematics of a powered artificial leg were used as system inputs to identify user’s
intention. Task transitions among level walking, sitting, and standing were investigated and tested on one patient with transfemoral (TF) amputation. The study reported 100% accuracy in recognizing the mode transitions and only 6 misclassifications during a 570s testing period. In addition, over 500ms system delay was reported, which may be inadequate for smooth control of prosthetic legs during transitions between dynamic locomotion modes.

Surface electromyographic (EMG) signals recorded from limb muscles contain important neural control information and have been used as a control sources for upper limb prosthetic control for several decades [15-18]. Due to the advent of powered artificial legs and the need for intuitive neural control of powered prostheses, the idea of design of a neural-machine interface based on EMG signals has gained increasing attention. Researchers have attempted to use EMG measured from lower limb muscles to interpret user's intended joint motion in lower limbs [19, 20] and identify locomotion modes for prosthetic leg control [9, 21-23]. For example, two previous studies [19, 20] demonstrated accurate decoding of the intended motion of the missing knee and ankle based on EMG signals recorded from residual muscles on TF amputees in a seated position. Au et al. [9] reported using EMG signals from residual shank muscles to identify two locomotion modes (i.e. level-ground walking and stair descent) on one transtibial amputee. More recently, Huang et al. [23] proposed a phase-dependent EMG pattern recognition strategy to identify locomotion modes. This approach was evaluated on eight able-bodied subjects and two TF amputees. Approximately 90% accuracy rate in recognizing seven daily encountered locomotion modes was reported.
1.3 Overview of User Intent Recognition Algorithm based on Neuromuscular-Mechanical Fusion

Although the results reported in [23] were promising, an increase in classification accuracy is desired to ensure the safety and reliability of powered artificial leg control. Inspired by the previous studies, our group proposed a novel locomotion mode recognition algorithm based on neuromuscular-mechanical fusion [24]. The idea was to combine the surface EMG signals recorded from residual thigh muscles and the mechanical sensing measurements from prosthetic legs to further improve the user intent recognition accuracy. The architecture of the fusion-based algorithm is demonstrated in Figure 3 [24].

Figure 3. Architecture of the neuromuscular-mechanical fusion based locomotion mode recognition algorithm.
The multichannel surface EMG signals and mechanical measurements from prosthesis were simultaneously sent into the system and then segmented into continuous, overlapped analysis windows (W1, W2, and W3 in Figure 4). In each analysis window, EMG signals and mechanical measurements were first pre-preprocessed. Then, the features that represented the characteristics of the signals were extracted from each EMG channel and each individual mechanical sensor. For EMG signals, four commonly used time-domain features were extracted, including (1) the mean absolute value, (2) number of zero crossings, (3) number of slope sign changes, and (4) waveform length as described in [25]; for mechanical sensors, the mean, minimum, and maximum values in each analysis window were extracted as the features. Both the EMG and mechanical features were concatenated into one feature vector. The fused feature vector was sent into a phase-dependent classifier. The phase-dependent classifier consists of multiple sub-classifiers, each one of which was established based on the

![Figure 4. Data windowing scheme and definition of gait phases in one stride cycle.](image-url)
data in one defined gait phase. The corresponding classifier was switched on based on the output of the designed gait phase detector. Four clinical gait phases (i.e. initial double stance, single limb stance, terminal double stance, and swing phase) are defined and detected by using mechanical sensor readings from prosthesis, as shown in Figure 4. In design of the pattern classifier, a linear classification method, i.e. linear discriminant analysis (LDA) [15, 16, 26] and a non-linear classification algorithm, i.e. support vector machine (SVM) [27, 28] were applied and compared. A post-processing algorithm, i.e. majority vote scheme, was applied to the decision stream to produce smoothed decision continuously.

This algorithm was tested using the experimental data collected from five unilateral TF amputees. The monitored surface EMG sites included two gluteal muscles on the amputated side and the thigh muscles of the residual limbs. The locations for electrode placements were approximate and guided by palpation and EMG recordings when the subjects were instructed to perform hip flexion/extension and hip adduction/abduction and imagine and execute knee flexion/extension. The EMG electrodes were embedded in customized gel liners for both comfort and reliable electrode-skin contact. Ground reaction forces and moments measured by a 6-degree of freedom load cell mounted the prosthetic pylon were used as mechanical sensing information. Gait phase information was obtained by using insole pressure sensing system under both feet. During the experiment, the TF amputees wore a hydraulic passive knee prosthesis and were instructed to walk on an obstacle course built in a laboratory environment. The tested locomotion modes included level-ground walking, stepping over an obstacle, stair ascent, stair descent, ramp ascent, and ramp descent. In addition, transitions
between different locomotion tasks were captured. The data collected during the experiment was then used for offline evaluation of the proposed algorithm.

Due to difficulty in defining a moment that can clearly separate two task modes during dynamic task transitions, the performance of the algorithm was quantified in static states and transitional period separately. Static states were the states when subjects continuously performed the same task. In static states, the accuracy of locomotion mode identification was calculated as a quantification index. A transitional period was defined as the period when subjects switched locomotion modes, which included a full gait cycle and two stance phases of the amputated leg. The transitional period started at initial prosthetic foot contact before stepping on the upcoming terrain and terminated at the end of single stance phase after the transition. During transitional periods, the ability of the algorithm to accurately recognize stable transitions and the timing of predicting transitions were evaluated.

The offline results in [24] demonstrated that the developed neuromuscular-mechanical fusion based algorithm could accurately identify different locomotion modes and responsively predict task transitions performed by patients with TF amputation. The algorithm based on fusion strategy and SVM classifier produced best performance, with over 99% accuracy in the stance phase and 95% accuracy in the swing phase for recognizing locomotion modes during static states, as shown in Figure 5. In addition, this fusion-based SVM algorithm correctly predicted all the tested task transitions during transitional period with sufficient transition prediction time, as shown in Table 1 and Table 2. One important finding was that the neuromuscular-mechanical fusion based algorithm outperformed
methods that used only EMG signals or mechanical information. For example, as demonstrated in Figure 5, fusion-based method (indicated in black bar) always generated highest recognition accuracy in static states, compared to those using EMG or mechanical signals only. The advantage of fusion-based algorithm was more obvious in task transitional period. Table 1 and Table 2 demonstrated that the fusion-based method correctly predicted all the tested task transitions without any missed case and yielded earlier prediction time over other methods. More importantly, the fusion-based algorithm generated more stable locomotion recognition decisions than others using single data sources, as shown in Figure 6. This is of great importance for powered artificial leg control because accurate and stable intent recognition decisions can allow for smooth and seamless task transitions.
Figure 5. Classification accuracy in the static state averaged over five TF amputees.

The classification accuracies derived from EMG signals only (white bars), ground reaction forces/moments only (gray bars), and fusion of both data sources (black bars) using the SVM classifier and LDA classifier are shown for individual gait phases.

* indicates a statistically significant difference (one-way ANOVA, $P<0.05$).
Table 1.
The Number of Missed Transitions among All Tested Mode Transitions

<table>
<thead>
<tr>
<th>No. of Missed Transitions</th>
<th>TF01</th>
<th>TF02</th>
<th>TF03</th>
<th>TF04</th>
<th>TF05</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM Fusion</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SVM EMG</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>LDA Fusion</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

Note: The total number of tested task transitions was 75 for each subject.

Table 2.
The Prediction Time of Mode Transitions before the Critical Event

<table>
<thead>
<tr>
<th>Unit: (ms)</th>
<th>W→SA</th>
<th>W→RA</th>
<th>SD→W</th>
<th>RD→W</th>
<th>W→O</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM Fusion</td>
<td>420±175</td>
<td>390±140</td>
<td>652±143</td>
<td>355±231</td>
<td>301±156</td>
</tr>
<tr>
<td>SVM EMG</td>
<td>254±132</td>
<td>221±96</td>
<td>415±162</td>
<td>209±177</td>
<td>150±146</td>
</tr>
<tr>
<td>LDA Fusion</td>
<td>226±116</td>
<td>254±121</td>
<td>432±179</td>
<td>252±154</td>
<td>256±105</td>
</tr>
</tbody>
</table>

Note: W, SA, RA, SD, RD, and O denote level-walking, stair ascent, ramp ascent, stair descent, ramp descent, and stepping over an obstacle, respectively.
Figure 6. Example of continuous mode identification decisions from a representative trial that recorded a transition from level-ground walking and stair ascent. Red vertical line indicates the critical timing.
1.4 Objective and Summary of Research

Design of an effective and robust intent recognition algorithm, which can accurately and reliably recognize the prosthesis user’s intended locomotion tasks and predict the task transitions, is one of the essential cores in developing a neural-machine interface for artificial leg control. To make the interface clinically viable for safe and reliable prosthesis operation, there are still several challenges need to be addressed.

The overall objective of this research was to develop a novel neural-machine interface for powered artificial legs, which could enable lower limb amputees to perform locomotive tasks in an intuitive, reliable, and safe way. Specifically, this research aimed to address two major challenges in designing such an interface: (1) determining the informative and optimal data sources for user intent recognition is important for practical implementation of neural-machine interface on prosthesis control, which has not been done yet; (2) understanding the effects of intent recognition errors in neural-machine interface on the operation of the prosthesis and user's task performance is critical, however still unknown. In Chapter 2, we attempted to answer an important and practical question in designing a neural-machine interface: what are the most informative and necessary data sources for accurate and reliable locomotion mode recognition? To do so, we investigated the usefulness and importance of different types of data sources commonly suggested for locomotion mode recognition. Based on the analysis results, we were able to determine an informative set of data sources for neural control of artificial legs. The neuromuscular-mechanical fusion based algorithm demonstrated promising performance to accurately and reliably identify locomotion modes;
however, occasional errors were still inevitable. When these misrecognized locomotion modes are used for prosthesis control, the effects of the errors on the operation of the prosthesis and user's task performance is unknown. Therefore in Chapter 3, we (1) systematically investigated the effects of locomotion mode recognition errors on control of powered prosthetic legs and the user's gait stability, and (2) identified the critical mode recognition errors that impact safe and confident use of powered artificial legs in transfemoral amputees. In addition, we characterized these critical errors and suggested it as a new index to evaluate the performance of neural-machine interface for future development. It is expected that the outcomes and observations of this research could benefit the future development of neurally controlled artificial legs and eventually enhance the mobility and quality of life of individuals with lower limb amputations.
REFERENCES


CHAPTER 2: 

Source Selection for Real-time User Intent Recognition towards Volitional Control of Artificial Legs

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2.1 Abstract

Various types of data sources have been used to recognize user intent for volitional control of powered artificial legs. However, there is still a debate on what exact data sources are necessary for accurately and responsively recognizing the user’s intended tasks. Motivated by this widely interested question, in this study we aimed to (1) investigate the usefulness of different data sources commonly suggested for user intent recognition and (2) determine an informative set of data sources for volitional control of prosthetic legs. The studied data sources included eight surface electromyography (EMG) signals from the residual thigh muscles of transfemoral (TF) amputees, ground reaction forces/moments from a prosthetic pylon, and kinematic measurements from the residual thigh and prosthetic knee. We then ranked included data sources based on the usefulness for user intent recognition and selected a reduced number of data sources that ensured accurate recognition of the user’s intended task by using three source selection algorithms. The results showed that EMG signals and ground reaction forces/moments were more informative than prosthesis kinematics. Nine to eleven of all the initial data sources were sufficient to maintain 95% accuracy for recognizing the studied seven tasks without missing additional task transitions.
in real time. The selected data sources produced consistent system performance across two experimental days for four recruited TF amputee subjects, indicating the potential robustness of the selected data sources. Finally, based on the study results, we suggested a protocol for determining the informative data sources and sensor configurations for future development of volitional control of powered artificial legs.

2.2 Introduction

Limb loss is a physically and emotionally devastating event that renders people less mobile and at risk for loss of independence. It has been estimated that 664,000 persons have been living with major limb loss in the U.S. in 2005 [1], with lower limb amputations occurring much more frequently than upper limb amputations. With the increasing incidence of dysvascular amputations, the number of lower limb amputations in the U.S. is expected to increase to 58,000 per year by 2030 [2, 3]. Therefore, there is a pressing need to restore as much function as possible to the large and increasing population of lower limb amputees.

Recent advances in powered artificial legs [4-6] have allowed lower limb amputees to efficiently perform activities that are difficult or impossible when wearing passive devices (e.g. climbing a staircase). However, smoothly switching tasks (e.g. from level-ground walking to stair ascent) has been difficult for patients wearing powered prostheses. This is due to the lack of a user interface that can identify the user’s intent. Because the control parameters in current powered artificial legs are modulated by the user’s performing tasks [4], an intent-recognition interface is essential for natural and easy use.
Several approaches to intent recognition for powered artificial legs have been explored. These include manual approaches, such as use of a remote key fob [7] or performance of extra body motions [8]; or more automated approaches, such as echo control [9], intent recognition based on intrinsic mechanical feedback [10], or intent recognition based on EMG signals recorded from the residual limb [5, 11-13]. To date, manual approaches have proven cumbersome and sometimes unreliable. As for more automated approaches, echo control [9, 14] has been adopted to allow for smooth gait initiations and terminations. This approach requires the user to don and doff an instrumented orthosis on the unimpaired leg. A preliminary intent-recognition system based on mechanical feedback from a powered prosthesis [10] has been shown to identify gait initiations, terminations, and transitions between sitting and standing of one TF amputee. The study reported 100% accuracy in recognizing task transitions with 500ms delay and 6 false identifications in a 570s trial period. Two recent studies [11, 12] of intent-recognition systems based on EMG signals recorded from residual muscles demonstrated accurate decoding of the intended motion of the missing knee and ankle based on EMG signals recorded from TF amputees in a seated position. However, the performance of these designs during locomotion has not been reported. Au et al. [5] used EMG signals from residual shank muscles to identify locomotion modes of one transtibial amputee; however, their approach can only separate two locomotion modes. Huang et al. developed a phase-dependent EMG pattern recognition strategy [13] that can identify seven locomotion modes with approximately 90% accuracy as demonstrated with two transfemoral (TF) amputees. Motivated by previous approaches, our group further improved the interface design by fusing both EMG and mechanical information [15]. This
approach, we have termed neuromuscular-mechanical fusion, outperformed the approaches based on only EMG signals or mechanical measurements.

Various types of data sources including EMG signals recorded from residual limbs and ground reaction forces/moments measured from prosthetic pylon have been fused together to recognize user intent for volitional control of powered artificial legs. However, there is still a debate on what exact data sources are necessary for accurately and responsively recognizing the user’s intended tasks. Although the fusion of multiple data sources have demonstrated performance improvement over the approaches using single data sources, the use of a large number of data inputs would complicate the design of the instrumented prostheses, the intent-recognition algorithm, and the hardware necessary for its real-time application on powered artificial legs. Therefore, further investigation is needed to identify the informative data sources, reduce the number of system inputs, and create a more efficient real-time intent-recognition interface for artificial legs.

The goals of this study were to (1) investigate the usefulness of different data sources commonly suggested for user intent recognition, and (2) determine an informative set of data sources for volitional control of prosthetic legs. In this study, we first implemented our previously designed neuromuscular-mechanical-fusion interface in real time. We then ranked included data source based on the usefulness for user intent recognition and selected a reduced number of data sources that ensured accurate recognition of the user’s intended task by using three source selection algorithms. The online performance of the intent-recognition algorithm was tested on four patients with TF amputations and compared with and without
the source selection. Finally, this study suggested a protocol for determining the informative data sources and sensor configurations for future development of volitional control of powered artificial legs.

2.3 Methods

2.3.1 Participants and Experimental Measurements

This study was conducted with Institutional Review Board (IRB) approval and the written, informed consent of all the recruited subjects. Two male and two female patients with unilateral TF amputations (TF01–04) were recruited (see Table 1). All subjects were regular prostheses users.

All available data sources were used for initial testing of the intent recognition interface. These measurements included EMG signals recorded from the residual thigh of TF amputees, mechanical loads on the prosthetic pylon, and the kinematics of the prosthesis. Eight active bipolar surface EMG electrodes were placed on the residual thigh. The targeted muscles included the *rectus femoris* (RF), *vastus lateralis* (VL), *vastus medialis* (VM), *tensor fasciae latae* (TFL), *biceps femoris long head* (BFL), *semitendinosus* (SEM), *biceps femoris short head* (BFS), and *adductor magnus* (ADM). The exact locations of electrode placement for each individual subject were determined by EMG recordings and muscle palpation. A ground electrode was placed on the bony area near the anterior iliac spine. It is noteworthy that it is not always possible to measure the activity of all muscles due to lower limb amputation and scar or fatty tissues on the residual limb. If fewer than eight muscles were identified,
additional EMG sites were selected where strong signals could be recorded when the subject
performed hip flexion/extension, hip adduction/abduction, or executed knee
flexion/extension. When executing knee flexion/extension, the subjects were asked to attempt
to flex/extend their amputated knee joints. The electrodes contained a preamplifier that band-
pass filtered the EMG signals between 10 and 2000 Hz with a pass-band gain of 20. The
EMG electrodes were embedded in customized gel liners (Ohio Willow Wood, US) for both
the users’ comfort and reliable electrode-skin contact. A 16-channel EMG system (MA 300,
Motion Lab System, US) was used to collect EMG signals. The cut-off frequency of the anti-
aliasing filter for EMG channels was 450 Hz. Mechanical ground reaction forces ($F_x$, $F_y$, $F_z$)
and moments ($M_x$, $M_y$, $M_z$) were measured by a six-degree-of-freedom (DOF) load cell
(PY6, Bertec Corporation, OH, US) mounted on the prosthetic pylon, with the $x$, $y$, and $z$
axes aligned with the mediolateral, superoinferior, and anteroposterior axes of the subject,
respectively. Both analog EMG signals and mechanical load values were sampled at 1000 Hz
by a data acquisition board (DATAQ DI-720, DATAQ Instruments, Inc., Ohio, US). In
addition, two inertial measurement units (IMUs) (Xsens Technologies B.V., Enschede,
Netherlands) were used to measure the kinematics of the prosthesis. Both IMUs were tightly
affixed to the lateral side of the prosthetic socket and pylon. The IMUs’ coordinate systems
were aligned with the coordinate system of the load cell in the standing position. A total of
12 kinematic data were derived from the IMU measurements, including three-DOF linear
accelerations of the thigh segment ($TAcc_x$, $TAcc_y$, $TAcc_z$), angular velocity ($TAV_x$,
$TAV_y$, $TAV_z$) and acceleration ($TAA_x$, $TAA_y$, $TAA_z$) of the thigh segment, knee angle
($KA$), knee angular velocity ($KAV$), and knee angular acceleration ($KAA$). The kinematics of
the residual thigh segment and prosthetic knee were specifically monitored because (1) motion of the residual thigh is still controlled by a transfemoral amputee and therefore represents the user’s voluntary control, (2) the selected kinematic parameters of the prosthetic socket and knee have been used to demonstrate the movement state of prosthesis [16] and classify user intent [10], and (3) all of these data sources can be measured by sensors mounted on the prosthesis. The kinematic measurements were sampled at 100 Hz and were synchronized with EMG and mechanical load measurements. All sampled data were streamed into a desktop computer (Dell OptiPlex 380 with 2.93 GHz Core 2 Duo E7500 CPU and 2 GB RAM) for real-time intent recognition.
Table 1.
Demographic Information of Four Subjects with Transfemoral Amputations (TF01-TF04)

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Weight (kg)</th>
<th>Height (cm)</th>
<th>Gender</th>
<th>Years post-amputation</th>
<th>Residual limb length ratio*</th>
<th>Prosthesis for daily use</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF01</td>
<td>40</td>
<td>65.7</td>
<td>162.6</td>
<td>F</td>
<td>31</td>
<td>68%</td>
<td>RHEO Knee</td>
</tr>
<tr>
<td>TF02</td>
<td>49</td>
<td>71.2</td>
<td>170.1</td>
<td>M</td>
<td>12</td>
<td>93%</td>
<td>C-Leg</td>
</tr>
<tr>
<td>TF03</td>
<td>54</td>
<td>64.0</td>
<td>164.0</td>
<td>F</td>
<td>33</td>
<td>84%</td>
<td>RHEO Knee</td>
</tr>
<tr>
<td>TF04</td>
<td>59</td>
<td>75.8</td>
<td>175.3</td>
<td>M</td>
<td>23</td>
<td>51%</td>
<td>RHEO Knee</td>
</tr>
</tbody>
</table>

Note: * Residual limb length ratio: the ratio between the length of the residual limb (measured from the ischial tuberosity to the distal end of the residual limb) to the length of the non-impaired side (measured from the ischial tuberosity to the femoral epicondyle). “RHEO” stands for a microprocessor-controlled prosthetic knee designed by Ossur.
Figure 1. Experimental setup on one transfemoral amputee subject (TF01).
2.3.2 Real-time User Intent Recognition

The architecture of our neuromuscular-mechanical-fusion interface has been previously reported [15]. The multichannel data are preprocessed and segmented into analysis windows. Features believed to capture the signal patterns are extracted and fused into one feature vector. The feature vector is then fed to a phase-dependent pattern classifier, composed of a gait-phase detector and multiple sub-classifiers corresponding to individually defined gait phases for mode recognition. The classification decisions are further post-processed to improve system accuracy. There are two procedures involved in real-world application of the intent-recognition interface: (1) offline training and (2) real-time testing. In this study, both procedure were implemented and tested using MATLAB (The Mathworks, Massachusetts, US).

1) Interface Training Strategy and Offline Training Algorithm: Training data were collected while lower limb amputees performed the assigned locomotion modes. In this study, the considered modes included level-ground walking, stair ascent, stair descent, ramp ascent, ramp descent, sitting, and standing. The latter two modes were included because they were important for gait initiation and termination and were difficult for leg amputees. For the task of level-ground walking, we instructed subjects to start from standing, walk along a straight walkway, and stop and stand. For sitting and standing tasks, subjects were asked to transition between sitting and standing. When in standing positions, subjects were allowed to make small steps and shift their weight; during sitting, subjects were allowed to move the prosthetic limb. During collection of training data for stair ascent/descent or ramp
ascent/descent, subjects switched from level-ground walking to stair ascent/descent or ramp ascent/descent and then switched back to level-ground walking. Stair ascent/descent and ramp ascent/descent were negotiated with a 5-step stair and a 10-foot ramp with 10 degrees of inclination, respectively. At least 30 seconds of data were collected in each mode and five repetitions of each task transition were captured.

Training data were preprocessed and segmented into overlapped analysis windows with a window length of 150ms and a window increment of 50ms. EMG signals were band-pass filtered by a 20–450 Hz sixth-order Butterworth digital band-pass filter. The mechanical forces/moments were filtered by a low-pass filter with a 45 Hz cut-off frequency. The linear accelerations and angular velocities of the thigh segment and knee angle were low-pass filtered with a 20 Hz cut-off frequency before the derivation of other kinematic data. Each window was labeled with a gait phase index and task index. The gait phase index was determined automatically by the gait phase detection algorithm based on the vertical GRF measured from the six-DOF load cell [17]. The labeling of tasks required manual indication of mode transitions from an experimenter. Four commonly used EMG time-domain (TD) features [18] (mean absolute value, number of slope sign changes, waveform length, and number of zero crossings) were extracted from each EMG signal in each analysis window. The mean, maximum, and minimum values of mechanical loads and motion parameters were extracted as features from each of these data sources. The features extracted from EMG signals (4 features×8 channels), mechanical loads (3 features×6DOF), and kinematic measurements (3 features×12 sources), were then concatenated into one feature vector.
The fused feature vectors for the same gait phase index were used to train the sub-classifier corresponding to that phase. A nonlinear support vector machine (SVM) classifier based on the “one-against-one” (OAO) scheme [19] and C-Support Vectors Classification (C-SVC) [20], was used to design the classifier. Finally, the parameters of each sub-classifier were calculated and stored for real-time testing.

2) Real-time Implementation of User Intent Recognition: In real-time testing, the classifier parameters calculated in the training session were reloaded into the memory of the computer. The time sequence of the real-time algorithm is shown in Fig. 2. Each analysis window (e.g. W1, W2, and W3 in Fig. 2) had the same window length (t_w = 150ms). The window increment (∆t = 50ms) determined the time delay for each decision. The processing time τ, consisted of the time required for preprocessing the data and extracting the features from each analysis window (B1), formulating and normalizing the feature vector (B2), detecting the gait phase and activating the corresponding classifier (B3), and classifying the user intent (B4). In order to make use of all of the streamed data for continuous decision making, the window increment (∆t) was required to be greater than or equal to the processing time (τ) [21]. At time t_0, the EMG, mechanical, and kinematic signals were simultaneously streamed into the computer. These acquired data were stored in a first-in first-out (FIFO) buffer. At time t_1, when the data for the first analysis window, W1, were available, the data were transferred from the FIFO buffer to system memory and execution of the real-time algorithm began. At the same time, new incoming data were stored in the buffer. At time t_2, the computation for W1 completed. The first decision, D1, was made to recognize the user intent.
for window W1. At $t_3$, the data for the second window, W2, were available for processing. Similarly, new incoming data continued to be stored in the FIFO buffer. At time $t_4$, the decision, D2, for window W2 was made. In addition, a five-point majority vote scheme was applied to eliminate erroneous decisions.
Figure 2. Continuous windowing scheme and time sequence for real-time implementation of user-intent-recognition interface.
2.3.3 Evaluation of the Intent-recognition Interface

2.3.3a Experimental Protocol

Each TF subject participated in two experimental days. On each day, the experiment took around three hours. In the first experimental day, all of the previously discussed measurements (EMG, kinematics, and pylon forces/moments) were used for real-time intent recognition. All subjects wore a hydraulic passive knee (Total Knee, ÖSSUR, Germany) and performed the instructed tasks in multiple trials. During the real-time testing session, the subjects were asked to transition among seven task modes in a fixed sequence: sitting, standing, level-ground walking, stair ascent, level-ground walking, ramp descent, level-ground walking, ramp ascent, level-ground walking, stair descent, level-ground walking, standing, and sitting. Each trial lasted approximately 1 minute. A total of 15 real-time testing trials were conducted. For the subjects’ safety, they were allowed to use a hand rail when walking on the staircase or ramp if necessary. Rest periods were allowed between trials to avoid fatigue. All of the data and real-time decisions collected during the experiment were saved for system evaluation and source selection analysis. In addition, a pressure-measuring mat was attached to the gluteal region of the subject to indicate the states of sitting and standing. The experiment was also videotaped for evaluation purposes.

The second experiment was conducted after the informative set of data sources (those that carried the majority of information for accurate intent recognition) was determined via an offline analysis of the data collected in the first experimental day. The experimental protocol was the same as the first experimental, except that only a subset of data sources was
used for interface training and real-time testing. The time between the two experimental days was 3 weeks, 2 weeks, 1 month, and 3 weeks for TF01-04, respectively.

2.3.3b Evaluation Parameters

Three parameters were used to evaluate the real-time performance of the intent-recognition interface: (1) recognition accuracy in static states (RA), (2) the number of missed task transitions, and (3) transition prediction time. Static states were defined as states when subjects continuously performed the same task. More details about the definition of these evaluation parameters can be found in previous study [15].

2.3.4 Source Selection Analysis

2.3.4a Overview of Source Selection Methods

Data source or feature selection is commonly used in the field of machine learning to reduce the dimensionality of inputs and create an efficient classification model. If the considered unit for input selection is individual features, it is called feature selection; if the selected input is data source (consisting of multiple features), it is called source selection. Exhaustive searching method, which enumerates all the possible combinations of subsets, is generally used to find the globally optimal subset. However, due to computational complexity, this approach is not practical for real application. Instead in this study, we considered more efficient and commonly used searching methods to find the sub-optimal subset of data sources. The source/feature selection methods can be divided into two broad classes: wrapper methods and filter methods [22]. Wrapper methods require one
predetermined classification algorithm and use the classifier as a black box to select the subset of sources based on the discriminatory power [22]. The most commonly used wrapper methods are sequential forward selection (SFS) and sequential backward selection (SBS). Filter methods select the sources based on discriminating criteria, which are relatively independent from the classifier. Examples of such criteria are correlation coefficients [23], mutual information [24], and statistical tests (t-test and F-test) [25]. Recent studies [24, 26] used a minimum-redundancy-maximum-relevance (mRMR) criterion. This method considered the relevant and redundant features simultaneously when selecting the sources/features; it expanded the representative power of useful data sources/features and improved the generalization of the source/feature selection algorithm. In this study, two wrapper methods (e.g. SFS and SBS) and a filter method (e.g. mRMR) were applied to the data collected in the first experimental day to select the informative data sources for intent recognition.

2.3.4b Sequential Forward and Backward Selection Algorithms

The SFS algorithm was applied as follows. The algorithm started with two data source sets: the selected set, $A$, was initially empty; and the remaining set, $B$, included all 26 data sources. In the first search iteration, the data from each individual source were used to train and test the intent-recognition system. The source that yielded the highest average classification accuracy across all modes in the static state was selected as the most important source for the system and was added to set $A$. In the following iterations, each of the sources in set $B$ was paired with the selected sources in set $A$ to train and test the classifier. The
source from set $B$ that produced the maximum recognition accuracy when combined with the selected sources from set $A$ was added to set $A$. Only one source was selected in each search step. The sequence in which sources were selected produced a rank of the sources in terms of their importance for accurate mode recognition.

The SBS method began with set $B$ empty and set $A$ containing all 26 sources. In each search iteration, the source from set $A$ that produced the lowest decrease in recognition accuracy when removed was moved to set $B$. Only one source was removed from set $A$ in each iteration. The first source removed was considered to contain the least information; while the last source remaining in set $A$ was considered to be the most informative.

2.3.4c mRMR Source Selection Algorithm

The $mRMR$ algorithm selects the feature $i_f$ to satisfy the criterion in (1) [24, 26]. This approach simultaneously maximizes the relevance between this feature and the classes (intended tasks) and minimizes the redundancy among the studied features.

$$
\max_{i_f \in \Omega_s} \left\{ F (f_i, K) \left/ \left[ \frac{1}{|S|} \sum_{i_j \in S} c(f_i, f_j) \right] \right\} \right.
$$

In (1), $f_i$ and $f_j$ are different features. $s$ and $\Omega_s$ represent the selected important feature set and the remaining unselected feature set, respectively. $|s|$ is the number of selected features in $s$. $F(f_i, K)$ denotes the F-statistic test value of feature $f_i$ in the $K$ studied classes ($K=7$ in this study), which is used to evaluate the relevance between the feature and classes [24, 26]. The F-statistic value was calculated by
\[ F(f_i, K) = \left[ \sum_k n_k (\bar{f}_k - \bar{f})/(K - 1) \right] \left[ \left( \sum_k (n_k - 1)\sigma_k^2 \right)/(N - K) \right] \]  \hspace{1cm} (2)

In (2), \( \bar{f} \) is the mean value of feature \( f_i \) across all observations; \( \bar{f}_k \) is the mean value of \( f_i \) within the \( k^{th} \) class; \( n_k \) is the size of the feature in the \( k^{th} \) class. \( \sigma_k \) is the variance of the feature in the \( k^{th} \) class and \( N \) denotes the total number of observations. The Pearson correlation coefficient \( c(f_i, f_j) \) in (1) measures the redundancy among the features [24], defined as

\[ c(f_i, f_j) = \frac{\sum_{m=1}^N (f_{i,m} - \bar{f}_i)(f_{j,m} - \bar{f}_j)}{(N - 1)s_{f_i}s_{f_j}} \]  \hspace{1cm} (3)

where \( f_{i,m} \) denotes the \( m^{th} \) observation of \( f_i \); \( \bar{f}_i \) and \( \bar{f}_j \) denote the mean value of \( f_i \) and \( f_j \), respectively; \( s_{f_i} \) and \( s_{f_j} \) are standard deviations of \( f_i \) and \( f_j \).

It is noteworthy that the \( mRMR \) algorithm is usually used on the feature level. Therefore, in order to search the sub-optimal data source, two steps were involved: (1) each feature from all sources was ranked in terms of their importance for accurate intent recognition based on the \( mRMR \) criteria in equation (1); (2) the data sources were ranked based on the highest rank of the features associated with it. For all source selection methods applied, the number of selected data sources was determined based on two criteria: (1) the recognition accuracy in static states had to be greater than 95%; and (2) no additional missed mode transitions could be induced by the reduction in data sources. The 95% threshold chosen for the first criterion in this study can be modified based on the specific requirements for system performance.
2.4 Results

2.4.1 Performance of Source Selection Algorithms

The data collected in the first experiment were used for offline source selection. The effect of increasing the number of selected data sources on the intent recognition accuracy in static states was similar among the three tested algorithms (SFS, SBS, and mRMR) (Figure 3): when the number of applied data sources increased, the classification accuracy increased dramatically and gradually plateaued. When 95% accuracy (indicated by a red dashed line in Figure 3) was chosen as the criterion to select the informative set of data source for all studied selection methods, the number of selected sources was 9, 11, 10, and 10 for TF01-TF04, respectively.

Table 2 listed the informative set of data sources selected by SFS, SBS, and mRMR for TF01-TF04. The sources were ranked in descending sequence in terms of the order they were selected or removed for the sequential forward/backward searching or based on the calculated relevance-redundancy value for mRMR selection method. The number of selected sources and the rank of the selected sources varied among the different subjects. However, the majority of the top ranked data sources selected by SFS, SBS, and mRMR overlapped for individual subject. The number of EMG signals in the selected set was larger than half of the total number of selected sources across all the subjects and selection algorithms. Of all the data sources, only the vertical ground reaction force was consistently selected across all the subjects and all selection methods. Except for the thigh segmental acceleration, no other kinematic measurements were selected as the important sources for intent recognition.
Figure 3. Accuracy of intent recognition in static states when the number of selected data sources increased. The applied source selection methods were (A) sequential forward selection (SFS), (B) sequential backward selection (SBS), and (C) minimum-redundancy–maximum-relevance (mRMR).
Table 2.
The Sources Selected for Four Recruited TF Subjects (TF01-TF04)

<table>
<thead>
<tr>
<th></th>
<th>TF01</th>
<th></th>
<th></th>
<th>TF02</th>
<th></th>
<th></th>
<th>TF03</th>
<th></th>
<th></th>
<th>TF04</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SFS</td>
<td>SBS</td>
<td>mRMR</td>
<td>SFS</td>
<td>SBS</td>
<td>mRMR</td>
<td>SFS</td>
<td>SBS</td>
<td>mRMR</td>
<td>SFS</td>
<td>SBS</td>
</tr>
<tr>
<td>Fz</td>
<td>My</td>
<td>BFL</td>
<td>TFL</td>
<td>My</td>
<td>BFL</td>
<td>TFL</td>
<td>My</td>
<td>BFL</td>
<td>TFL</td>
<td>My</td>
<td>BFL</td>
</tr>
<tr>
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<td>My</td>
<td>VM</td>
<td>TFL</td>
<td>Mx</td>
<td>Mx</td>
<td>RF</td>
<td>Mx</td>
<td>TFL</td>
<td>RF</td>
<td>Mx</td>
<td>TFL</td>
</tr>
<tr>
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<td>My</td>
<td>VM</td>
<td>Mx</td>
<td>Mx</td>
<td>RF</td>
<td>Mx</td>
<td>TFL</td>
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<td>Mx</td>
<td>TFL</td>
</tr>
<tr>
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<td>Fz</td>
<td>TFL</td>
<td>SEM</td>
<td>BFS</td>
<td>Mx</td>
<td>TFL</td>
<td>TAcc_y</td>
<td>E1*</td>
<td>TFL</td>
</tr>
<tr>
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<td>RF</td>
<td>BFL</td>
<td>BFL</td>
<td>BFS</td>
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<td>Fz</td>
<td>BFL</td>
<td>Fy</td>
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<td>Fz</td>
<td>VM</td>
</tr>
<tr>
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<td>BFL</td>
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<td>ADM</td>
<td>Fy</td>
<td>VM</td>
<td>ADM</td>
<td>SEM</td>
<td>SEM</td>
<td>Fz</td>
<td>VL</td>
<td>E1*</td>
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<tr>
<td>Mz</td>
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<td>RF</td>
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<td>TFL</td>
<td>Fy</td>
<td>VL</td>
</tr>
<tr>
<td>TAcc_y</td>
<td>TFL</td>
<td>Fy</td>
<td>TAcc_y</td>
<td>Fz</td>
<td>Fz</td>
<td>VM</td>
<td>Fz</td>
<td>Fz</td>
<td>SEM</td>
<td>SEM</td>
<td>SEM</td>
</tr>
<tr>
<td></td>
<td>SEM</td>
<td>TAcc_y</td>
<td>Mx</td>
<td>RF</td>
<td>TAcc_z</td>
<td>BFS</td>
<td>Mz</td>
<td>ADM</td>
<td>Mx</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * indicated the extra muscles which were not targeted. E1: a distal quadriceps muscle; E2: a distal hamstring muscle. Underlined data sources: the sources that were selected by all three selection algorithms.
Additionally, we compared the execution time of three different source selection algorithms. \textit{mRMR} required the shortest execution time (an average of 84 seconds over the four subjects), while \textit{SBS} was the most time-consuming algorithm (requiring an average of 1978 seconds). \textit{SFS} took approximately 383 seconds for data source selection. Since \textit{mRMR} was the most computationally efficient algorithm and yielded similar performance to the other two searching algorithms (Table 2 and Figure 3), the sources selected by \textit{mRMR} were used in the second experiment for real-time mode recognition in order to evaluate the robustness of the selected data sources across days.

2.4.2 Real-time Performance with and without Data Sources Selection

The performance of the intent-recognition interface in static states was compared with and without data source reduction (Figure 4). The accuracy decreased to approximately 95% when the data sources selected by \textit{mRMR} were used (gray and white bars in Figure 4), compared to around 98% accuracy derived from all data sources (the black bars in Figure 4). This was to be expected, as 95% accuracy was used as the threshold in one of the searching criteria. Importantly, the system produced stable performance in the static states by using the same data sources selected by \textit{mRMR} across days, which implied that the selected data sources robustly captured important information for accurate intent recognition.

When all data sources were used for online testing (in the first experimental day), the average processing time for one decision (i.e. the duration of B1–B4 in Fig. 2) was 45.2 ± 2.7ms. When the number of data sources was reduced by the \textit{mRMR} method (in the second
experiment), the online processing time ranged from 21.3ms to 28.8ms for the four subjects, which would result in more frequent decision-making.

The real-time system performance during transitions derived from the informative data sources in the second experiment was similar to that derived from all data sources in the first experiment. For both days, 3 out of the 720 transitions (12 transitions* 15 trials* 4 TF subjects) tested in all four subjects were missed. These missed transitions included the transitions from level-ground walking to ramp ascent and ramp descent to level-ground walking. The prediction times for the 12 transitions were averaged across all the testing trials and all the subjects, excluding the missed task transitions. Similar prediction times were observed when using all data sources and when using selected sources (Table 3).
Figure 4. Intent recognition accuracy in static states. The *black bars* were derived from the real-time decisions in the first experiment when all the data sources were used. The *gray bars* were computed offline based on the data in the first experiment, but with a reduced number of data sources selected by *mRMR*. The *white bars* denote the real-time results derived from the second experiment when the same data sources as used for *gray bars* were applied.
Table 3.
Average Task Transition Prediction Time across Subjects in the First and Second Real-time Experiments

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>All Sources (Real-time results in the experiment 1)</td>
<td>120.8</td>
<td>114.5</td>
<td>127.1</td>
<td>115.4</td>
<td>107.7</td>
<td>104.4</td>
<td>105.9</td>
<td>116.5</td>
<td>86.2</td>
<td>118.4</td>
<td>88.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Selected Sources (Real-time results in the experiment 2)</td>
<td>119.3</td>
<td>112.4</td>
<td>115.9</td>
<td>111.9</td>
<td>118.3</td>
<td>113.4</td>
<td>102.4</td>
<td>134.7</td>
<td>96.4</td>
<td>124.7</td>
<td>94.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: W: level-ground walking; SA: stair ascent; SD: stair descent; RA: ramp ascent; RD: ramp descent; ST: standing; S: sitting.
2.5 Discussion

In this study we aimed to investigate the usefulness of each data source used for user intent recognition, and determine an informative set of data sources for efficient real-time intent-recognition for the control of artificial legs. The offline source-selection analysis showed that when the number of data sources was reduced from 26 to approximately 10, the interface was still able to accurately recognize the subject’s intents (above 95% accuracy in static states) without missing additional mode transitions. These results indicate that not all of the studied data sources carried important information for intent recognition and input redundancy existed in the initial design of fusion-based interface. Therefore, reduction of system redundancy is necessary to improve the efficiency of the design for its eventual clinical use for artificial legs. At the hardware level, removing sources that capture less important or redundant information can simplify the design of the instrumented prosthetic leg, I/O circuits, wiring, and embedded system. At the software level, reducing the number of data sources decreases the computational complexity of the intent-recognition algorithm. For example, in this study we showed that the computational speed for recognizing intents with a reduced number of data sources was almost 1.9 times faster than that when using all data sources.

By ranking the data sources based on the usefulness for user intent recognition, a reduced number of data sources that ensured accurate recognition of the user’s intended task was selected by using three source selection algorithms for individual subject. Although there was a variation in types and ranks of data sources selected across the different selection methods
and subjects, some consistency was still observed. First, more than half of the selected sources for all subjects were EMG signals, which implied that neuromuscular information measured from the residual limbs may be the essential data source for accurate and responsive intent recognition. However, it was difficult to unify which muscles were necessary for intent recognition across different subjects, which may be due in part to the variations in the level of amputation, cause of amputation, surgical approach, and locomotion pattern among the TF amputees. Therefore, the optimization of EMG signal inputs should be customized for each individual in the future clinical application for artificial legs. Second, with the exception of thigh acceleration, no kinematic information was selected by the algorithms, implying that the kinematics of the prosthetic knee is not important for differentiating user intent and predicting the studied task transitions. Additionally, the vertical ground reaction force was selected as an important source by all searching methods for all tested subjects. This indicates different patterns of GRF on the prostheses even before the users switched locomotion modes. Since the GRF was also used as the input for gait phase detection in the current system design and is usually available for intrinsic control of lower limb prostheses, it is necessary to include it as one of the informative data sources. At the sensor level, based on the results from this study, we suggested that the sub-optimal sensor configuration for future design of intent-recognition interface for powered artificial legs should include at least four surface EMG sensors (two targeting quadriceps and two targeting hamstring muscles), a 6-DOF load cell mounted on prosthetic pylon, and one accelerometer instrumented on prosthetic socket.
The results of this study showed that all three methods selected similar data sources when at least 95% accuracy for recognizing user intent was required. However, the mRMR method is suggested for future clinical application because (1) it was much more computationally efficient than the other two searching methods; (2) the mRMR algorithm can be used regardless of the type and structure of the classifier; while SFS and SBS involve the direct goal of maximizing the classification accuracy of one particular classifier. Furthermore, the data sources selected by mRMR were robust over time. Similar performance was observed across experimental days when the mRMR-selected sources were used to classify task modes.

Another important contribution of this study was the real-time PC implementation of our previously designed intent-recognition interface. Unlike previous design, in which we used offline cross validation to evaluate the interface [15], this study included a system-training protocol for quick calibration and real-time algorithm for online system testing. The real-time interface could make a decision every 50ms and produced high accuracy for intent recognition and task transition prediction, similar to the results of the offline analysis [15]. These results imply the soundness of our designed training protocol and real-time intent-recognition algorithm; these designs can be used for the future embedded implementation of an intent recognition interface for artificial legs.

In summary, this study suggested a protocol for determining the informative data sources and sensor configurations for future development of volitional control of powered artificial legs. Software based on the mRMR algorithm can be developed for prosthetists to allow them to customize the sub-optimal sensor placement for each TF amputee. The prosthetists may
simply choose the optimization criteria and run the program for quick sensor placement
guidance. In addition, our real-time mode-recognition algorithm can be directly implemented
in the embedded control units in prosthetic knees. Nevertheless, several study limitations
were also identified. First, the evaluation of the system was done in the laboratory, due to the
limitations of our experimental setup. It will be important to further test our system in more
realistic environments. In addition, the reported execution speed for locomotion mode
recognition was not the true online processing speed for CPU implementation. This is
because we did not ignore background programs in the PC, and MATLAB does not allow
multi-threaded programs. The execution speed should be faster when a powerful digital
signal processor is used. Furthermore, this study fixed the optimization criteria to 95%
classification accuracy. Further studies are needed to justify whether or not this criterion is
sufficient for safe prosthesis control. Finally, it was noteworthy that the suggestion of sub-
optimal sensor configuration for volitional control of power artificial legs was made only
based on the results from the recruited subjects. Customization of sensor configuration for
each individual user is desired in the future clinical application.

2.6 Conclusion

In this study, we analyzed the usefulness of different data sources for user intent
recognition and identified an informative set of data sources for volitional control of
prosthetic legs. First, our previously designed interface based on neuromuscular-mechanical
fusion was implemented in real time. We then ranked data sources based on the usefulness
for user intent recognition and selected a reduced number of data sources that ensured
accurate recognition of the user’s intended task by using three source selection algorithms. The real-time performance of the intent-recognition algorithm with and without source selection was evaluated and compared on four patients with TF amputations on different experimental days. Based on the study results, we suggested a protocol for determining the informative data sources and sensor configurations for future development of volitional control of powered artificial legs.

REFERENCES


CHAPTER 3:

Effects of Locomotion Mode Recognition Errors on Volitional Control of Powered Above-Knee Prostheses

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3.1 Abstract

Recent studies have reported various methods that recognize amputees' intent regarding locomotion modes, which is potentially useful for volitional control of powered artificial legs. However, occasional errors in locomotion mode recognition are inevitable. When these intent recognition decisions are used for volitional prosthesis control, the effects of the decision errors on the operation of the prosthesis and user's task performance is unknown. Hence, the goals of this study were to (1) systematically investigate the effects of locomotion mode recognition errors on volitional control of powered prosthetic legs and the user's gait stability, and (2) identify the critical mode recognition errors that impact safe and confident use of powered artificial legs in lower limb amputees. Five able-bodied subjects and two above-knee (AK) amputees were recruited and tested when wearing a powered AK prosthesis. Four types of locomotion mode recognition errors with different duration and at different gait phases were purposely applied to the prosthesis control. The subjects' gait stabilities were subjectively and objectively quantified. The results showed that not all of the mode recognition errors in volitional prosthesis control disturb the subjects’ gait stability. The effects of errors on the user's balance depended on (1) the gait phase when the errors
happened and (2) the amount of mechanical work change applied on the powered knee caused by the errors. Based on the study results, "critical errors" were defined and suggested as a new index to evaluate locomotion mode recognition algorithms for artificial legs. The outcome of this study might aid the future design of volitionally-controlled powered prosthetic legs that are reliable and safe for practice.

3.2 Introduction

Rapid advancement of powered artificial legs has attracted increasing attention in recent years [1-5]. The advantage of powered artificial legs over traditional passive devices is that they can enable lower limb amputees to more easily and efficiently perform a variety of activities, such as stair climbing. Powered artificial legs usually employ a finite-state machine (FSM) to control the joint impedance or joint position [3, 4]. In such a control scheme, the joint impedance or position varies across gait phases for cyclic locomotion tasks or movement state for non-cyclic tasks. The control of a powered prosthesis also depends on the user’s intent regarding locomotion modes. This is because the required dynamics and kinematics of prosthetic limbs are different among different locomotion modes (e.g. level-ground walking and stair ascent/descent). Therefore, in order to enable smooth locomotion mode transition in prosthesis users, it is essential to integrate locomotion mode recognition with FSM-based intrinsic control for volitional operation of powered lower limb prostheses.

Various approaches have been explored to recognize the user's locomotion mode for volitional control of powered lower limb prostheses. A recent study [6] used mechanical feedback from a powered prosthesis to identify the user's locomotion mode. The decisions
were used to modulate the impedance control of a powered AK prosthesis. The reported method can identify gait initiations, terminations, and transitions between sitting and standing of one AK amputee with 100% accuracy rate and 500ms system delay. Another approach is to interpret the user’s intent regarding locomotion mode by monitoring the neuromuscular control activity measured from the residual muscles or reinnervated muscles. Au et al. [5] used electromyography (EMG) signals from residual shank muscles to identify two locomotion modes (i.e. level ground walking and stair descent) of one below-knee amputee. All tested mode transitions were accurately identified to manipulate a powered foot-ankle prosthesis. Huang et al. [7] proposed a phase-dependent EMG pattern recognition strategy that can identify seven locomotion modes with approximately 90% accuracy rate as demonstrated with two above-knee (AK) amputees. To better improve the accuracy in recognizing the user's locomotion mode, our group made use of both EMG signals and mechanical feedback from the prosthesis to classify the user's locomotion mode [8]. Such a method based on neuromuscular-mechanical fusion was evaluated on above-knee amputees online [9] and showed improved performance compared to the locomotion mode recognition method based on EMG or mechanical signals only. A recent study [10] reported a successful case of using EMG signals from targeted reinnervated muscles and mechanical measurements from a prosthesis to interpret an amputee’s intent and control a powered above-knee prosthesis.

Despite the high accuracy rate for recognizing the user's locomotion mode, occasional recognition errors still occur. These errors, if used for volitional prosthesis control, may
trigger the erroneous operation of prostheses, disturb the user’s task performance, or even cause posture instability or the user's falls. These volitional control errors may significantly affect the confident and safe use of powered prostheses in lower limb amputees. Therefore, identification and elimination of the negative effects of these user intent recognition errors on the control of powered artificial legs is imperative. To the best of our knowledge, a very limited number of studies have reported the effects of locomotion mode recognition errors on volitional control of lower limb prostheses. Varol et al. [6] reported that a user intent recognition error that falsely classified the standing mode as level ground walking mode did not affect the prosthesis control and the user's performance. However, only one type of error was reported, and no systematic investigation was provided. In a recent study [10], intent recognition errors were observed to cause disturbance of the subject’s gait stability to varying degrees.

The objectives of this study were to (1) systematically investigate the effects of locomotion mode recognition errors on volitional control of powered prosthetic legs and the user's gait stability, and (2) identify the critical mode recognition errors that impact safe and confident use of powered artificial legs in lower limb amputees. To conduct this study, a locomotion mode recognition simulator was designed to artificially generate four different types of errors with different durations and at different phases that modulates FSM impedance control of a powered prosthesis. Five able-bodied (AB) subjects and two patients with AK amputations were recruited and tested when wearing our powered prosthesis. The effects of the errors on the powered prosthesis and the user's gait stability were evaluated.
The results of this study could completely change the way for evaluating locomotion mode recognition systems for powered AK prostheses and propel the future design of volitionally-controlled powered artificial legs that are functional and safe-to-use.

3.3 Methods

3.3.1 Design and Control of a Powered Above-Knee Prosthesis

A prototype of AK prosthesis with a powered knee joint and a passive ankle joint has been designed and fabricated by our group [11] (see Figure 1). The knee joint was constructed by utilizing a moment arm supported by an actuator on one side and an aluminum pylon on the other. The knee motion was driven by a DC motor (RE 40, Maxon, Switzerland) through a ball screw (THK 12mm×2mm). A potentiometer (RDC503013A, ALPS, Japan) was instrumented on the knee joint to measure the knee joint angle. An encoder (MR series, Maxon, Switzerland) was connected to the DC motor to estimate the knee angular velocity. In addition, a 6 degree-of-freedom (DOF) load cell (Mini58, ATI, NC) was mounted on the prosthetic pylon to measure the ground reaction force. The measurements from these mechanical sensors were used for intrinsic prosthesis control. All the sensor measurements were sampled at 100Hz by a multi-functional data acquisition (DAQ) card (PCI-6259, National Instruments, TX). A digital-to-analog converter on the DAQ sent analog control signal to drive the DC motor through a motor controller (ADS50/10, Maxon, Switzerland).

The architecture of our proposed powered prosthesis controller consisted of two levels: a
high-level controller for locomotion mode recognition and a low-level intrinsic controller, as demonstrated in Figure 1. In the high level controller, a locomotion mode recognition system was designed to interpret the user’s intended activities (e.g. level ground walking, ramp ascent, and ramp descent in this study). The system monitored the EMG signals measured from user’s residual limb muscles and mechanical measurements from the prosthetic pylon, recognized user’s intent, and then switched the control mode in the low-level controller. The low-level intrinsic control is based on the mechanical feedback measured from the prosthesis only. It consists of a finite-state machine (FSM) and impedance controller. Impedance control has been widely used for prosthetic legs [3, 6, 12] because it is believed that humans control the stiffness of leg muscles while walking [13, 14]. The goal of the intrinsic control is to ensure that the prosthetic knee acts as a passive spring-damper-system with predefined impedance (i.e. stiffness $k$, damping coefficient $c$, and equilibrium position $\theta_k$) that matches the biological knee impedance during walking [12]. To achieve this goal, five states were defined, each of which correspond to one gait phase. The defined five states were initial double support (IDS), single support (SS), terminal double support (TDS), swing flexion (SWF), and swing extension (SWE) (Figure 1). The state transitions are triggered by intrinsic measurements, such as ground reaction force ($F$), knee angle ($\theta$), and angular velocity ($\dot{\theta}$). Once a state $i$ was selected, the desired knee impedance $[k_i, c_i, \theta_k]$ corresponding to this state was then sent to the impedance controller. The output of impedance control was the torque needed to drive the powered knee. In this study, we adopted the same impedance control as that reported in previous studies [6].
Figure 1. The architecture of powered lowered limb prosthesis control
3.3.2 Investigated Locomotion Mode Recognition Errors

In this study, we selected several types of mode recognition errors which were often observed in our previously developed mode recognition system for artificial legs. Locomotion mode recognition based on neuromuscular-mechanical fusion has been designed and evaluated on AK amputee patients in real time in a previous study. Despite high accuracy rate for mode recognition reported, occasional errors were still observed. Table 1 listed the confusion matrix derived from our designed mode recognition algorithm tested online on four AK amputees [9]. The diagonal numbers represented the accuracy rate (in percent) for recognizing individual locomotion modes; the non-diagonal elements denoted the misclassification rate (in percent) between two modes. The interface was used to recognize five cyclic locomotion modes (e.g. level-ground walking, stair ascent/descent, and ramp ascent/descent) and two non-cyclic locomotion modes (sitting and standing). The table shows that most of the confusion errors happened among the tasks of level-ground walking, ramp ascent, and ramp descent (indicated by gray areas in Table 1). This observation was also consistent with the results from a recent study [15] in which an intent recognition system was evaluated on four AK amputees wearing a powered knee and ankle prosthesis. Their results also indicated that ambulating on ramps had a significantly (P<0.01) higher error rate than walking on staircases. Therefore, based on the knowledge from previous studies, four types of frequently occurring mode recognition errors were considered in this study: level-ground walking misclassified as ramp ascent (W→RA) or ramp descent (W→RD), ramp ascent misrecognized as level-ground walking (RA→W), and ramp descent misrecognized as level-
ground walking (RD→W). Since immediately transitions between ramp ascent and descent rarely happen, the errors for recognizing between these two modes (i.e. RA→RD and RD→RA) were not considered. Besides the types of errors, the error durations and occurred timing were also investigated. Based on the observation in our previous study, it has been found that the continuous error decisions generally lasted no more than 300ms. Therefore, in this study, four different types of errors (W→RA, W→RD, RA→W, and RD→W) with different durations (100, 200, or 300ms) at all defined phases (IDS, SS, TDS, SWF, or SWE) were investigated.

To systematically investigate the effects of selected mode recognition errors, a mode recognition simulator was used to replace the high-level control shown in Figure 1. The simulator directly sent the user’s locomotion mode to low-level intrinsic control; no mode recognition algorithm was employed here. Using this simulator, experimenters can easily program an investigated error with a specified duration in any selected gait cycle and gait phase.
Table 1.
Confusion Matrix for Locomotion Mode Recognition Derived Based on Neuromuscular-mechanical Fusion Strategy

<table>
<thead>
<tr>
<th>(%)</th>
<th>Targeted Modes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
</tr>
<tr>
<td>Estimated Modes</td>
<td></td>
</tr>
<tr>
<td>W</td>
<td>96.11</td>
</tr>
<tr>
<td>SA</td>
<td>0.12</td>
</tr>
<tr>
<td>SD</td>
<td>0.19</td>
</tr>
<tr>
<td>RA</td>
<td>1.68</td>
</tr>
<tr>
<td>RD</td>
<td>1.76</td>
</tr>
<tr>
<td>ST</td>
<td>0.14</td>
</tr>
<tr>
<td>S</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: (1) W: level-ground walking; SA: stair ascent; SD: stair descent; RA: ramp ascent; RD: ramp descent; ST: standing; S: sitting. (2) The results were derived from the testing on four AK amputees in our previous study [9].
3.3.3 Participants and Measurements

This study was conducted with the approval of Institutional Review Board (IRB) and with informed consent of all the subjects. Five able-bodied subjects (AB01-05) and two patients with unilateral above-knee amputations (AK01-02) were recruited in this study. The recruited AB subjects were all male and free from orthopedic or neurological pathologies. The average age of the AB subjects was 28.6 (±5.3) years. The average height was 181.6 (±4.8) cm. The average weight was 82.3 (±11.7) kg. AK01 (age: 60 years; height: 175.3 cm; weight: 75.8 kg) was a male amputee with 33-year post-amputation; AK02 (age: 41 years; height: 162.2 cm; weight: 65.7 kg) was a female amputee with 32-year post-amputation. They both were regular passive prostheses users. During the experiments, the AK subjects wore suction prosthetic sockets. For AB subjects, a special designed bent-knee adaptor was used so that they can walk with the powered prosthesis.

The experimental setup was demonstrated in Figure 2. The measurements of intrinsic mechanical sensors on the prosthesis were used for both intrinsic control and an evaluation purpose. In addition, an inertial 3D motion capture system (Xsens Technologies B.V., Enschede, Netherlands) was used to capture the full-body motion of the subjects. Kinematic measurements were used to quantify the user’s gait stability (refer to Section 4.3.5). All the measurements were sampled at 100Hz and synchronized. The experiment sessions were also video-recorded.
Figure 2. Experimental Setup on one AK amputee subject (AK01).
3.3.4 Experimental Protocol

Before the experiments, all the subjects were trained to walk with the designed powered prosthesis. Each subject received at least 10-hour gait and balance training sessions, led by a physical therapist. This training was necessary because the powered device redefined the gait dynamics in the recruited subjects. Amputees must re-adapt to the powered device. The prosthesis alignment and desired joint impedance parameters for each studied locomotion mode (including level-ground walking, ramp ascent and descent) were calibrated for each individual subject by a prosthetist and an experienced experimenter. All the subjects were able to adapt to the powered prosthesis and generate stable and consistent gait patterns when performing each assigned locomotion mode.

Each experiment was composed of at least 120 trials. Only one type of error with a specific duration and at a specific gait phase was applied in each trial. The same type of error with the same duration and at the same gait phase was simulated at least twice. First, the mode recognition simulator sent the output locomotion mode, the same as the user’s performing mode, to the intrinsic controller. The subject was asked to perform this activity at a self-selected walking speed wearing the powered prosthesis. For level-ground walking, the subject was asked to walk on a straight walkway; for ramp ascent/descent, the subject walked on a 10-foot ramp with 8-degree inclination angle. Then, the simulator generated an erroneous mode at a targeted gait phase with a specified duration in randomly selected gait cycles. The sequence of trial orders was randomized. A fall-arrest harness system was used to protect subjects from falls. Rest periods were allowed between trials to avoid fatigue.
3.3.5 Evaluation of Gait Stability

The effects of mode recognition errors on the prosthesis user’s gait stability were evaluated both subjectively and objectively. A four-scale questionnaire (score 0-3) was designed to subjectively evaluate the gait stability of the subjects when the errors occurred. Table II listed the designed question and the descriptions for each scale of answer. After each trial, the subject was asked to report the score regarding the gait stability according to Table 2. For the same error, the subjective result was obtained by averaging the scores across multiple tests. If the averaged score was greater than 1, the error was considered to cause subjective feeling of gait instability.

The gait stability was also evaluated objectively by monitoring full-body angular momentum. Biomechanical investigations [16, 17] have demonstrated that the conservation of total angular momentum about the body’s center of mass (COM) is highly regulated during human’s ambulation. The full-body angular momentum has been used for the analysis of human walking stability [16, 18]. To calculate the subject’s whole-body COM and angular momentum [16], a simplified human model was constructed in this study. The simplified model consisted of 12 rigid body segments: head, trunk, and bilateral upper arms, forearms, thighs, shanks, and feet. The head was modeled as a sphere. The arms, forearms, trunk, thighs, and shanks segments were modeled as cylinders. The foot segment was modeled as a rectangular box. Anthropometric measurements were taken from each subject to accurately reconstruct the representative model. These measurements included body weight, height, radius of head, and segment lengths and base radii of arms, forearms, trunk, thighs, and
shanks. The mass of each segment was estimated by using the modified Hanavan model described in [19]. The position of whole-body’s COM was calculated as a sum of the products of each individual segment’s relative masses and COM locations [16]. The full-body angular momentum, \( \vec{L} \), was calculated as the sum of each individual segment’s angular momentum about the whole-body’s COM as (1).

\[
\vec{L} = \sum_{i=1}^{12} \left[ (\vec{p}_{COM}^i - \vec{p}_{COM}) \times m_i (\vec{v}_{COM}^i - \vec{v}_{COM}) + \vec{I}^i \vec{\omega}^i \right]
\]

\( \vec{p}_{COM}^i \) and \( \vec{v}_{COM}^i \) denote the \( i \)-th segment’s COM position and velocity. \( \vec{p}_{COM} \) and \( \vec{v}_{COM} \) are the whole-body COM’s position and velocity, respectively. \( m_i \) represents the mass of the \( i \)-th segment. The second term in the square bracket is the angular momentum of the \( i \)-th segment about its own COM positions. \( \vec{I}^i \) and \( \vec{\omega}^i \) denote the \( i \)-th segment’s inertia tensor (3×3) [16] and angular velocity (3×1) about the segment’s COM, respectively. In this study, the coordinate frame was determined based on the right-hand rule with the z-axis directed vertically up, the y-axis pointing in the walking direction (anterior–posterior direction), and the x-axis pointing to the right side of the subjects (medio-lateral direction). The full-body angular momentum (\( \vec{L}_x \)) in the sagittal plane (“+”: posterior and “-”: anterior) was used as a parameter to quantify the gait stability. If the observed angular momentum exceeded a defined range, the subject was considered to be unstable. In this study, the defined range for each subject was between the maximum angular momentum in the anterior direction and the maximum momentum in the posterior direction, measured when the subject performed the
investigated locomotion modes wearing the powered prosthesis without simulated control errors.

### 3.3.6 Characterization of Critical Errors

In this study, the change of mechanical work at the knee joint caused by errors was calculated to characterize the critical errors. It is because the error effects on the prosthesis joint depend not only on the erroneous torque applied to knee joint caused by the errors, but also on the current state of knee joint (i.e. knee joint angular velocity). Therefore, the change of mechanical work that takes into account both factors was used to characterize the critical errors. This parameter was calculated as the time integral of the knee joint torque multiplied by the joint angular velocity [20]. This value was then normalized by subject body weight. The amount of mechanical work change caused by a simulated error was defined as the difference of mechanical work generated over the error duration from the mechanical work derived over the same duration and at the same gait phase when no error was applied. The latter value was obtained by averaging the calculated mechanical work across multiple gait cycles before the errors were simulated.
Table 2.
Questionnaire for Subjective Evaluation of Gait Stability

<table>
<thead>
<tr>
<th>Score</th>
<th>How do you feel about the errors?</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>I did NOT perceive the error</td>
</tr>
<tr>
<td>1</td>
<td>I perceived the error but still felt stable</td>
</tr>
<tr>
<td>2</td>
<td>I felt unstable but I can recover</td>
</tr>
<tr>
<td>3</td>
<td>I felt unstable and would fall</td>
</tr>
</tbody>
</table>
3.4 Results

Table 3 lists the number of subjects who subjectively reported gait instability and the number of subjects whose quantified balance index showed gait instability when different types of errors with different durations were purposely applied at different gait phases. None of the errors with 100ms duration are shown in Table 3 because these errors neither caused the subjects to feel unstable nor obviously affected the gait stability in terms of whole-body angular momentum. The table shows that the effects of errors on the powered prosthesis control depended on not only the types of errors but also the error durations and phases when the errors happened. The distribution of the errors that caused gait instability varied across different types of locomotion mode errors. Errors with long duration were tending to cause instability in the testing subjects. Even for the same error type, the effects of errors were different across phases. Interestingly, the errors that occurred at PSW did not elicit any reported or quantified instability in this study. The results derived from AB subjects and those derived from AK amputees were basically consistent, although slight difference was observed. For example, when the W→RA errors with 300ms duration occurred in swing extension, none of the AK subjects subjectively or objectively showed unstable gait. However, the stabilities of two AB subjects were disturbed based on their subjective feedback in this case. All the errors that caused gait instability based on the objective measurement were also reported as unstable by the subjects. On the contrary, not all the errors that were subjectively reported as unstable cases caused the obvious angular momentum change. Therefore, in this study, any error that caused the subjective feeling of
unstable balance in any one of the subjects was defined as a critical error, which should be avoided in the locomotion mode recognition system for volitional control of artificial legs. This was because (1) subjective measurement was more sensitive in measuring user instability than objective balance index used in this study, and (2) subjectively reported errors might reduce the user's confidence in using the powered artificial legs even though they did not obviously influence the stability.

Figure 3 and 4 showed the change of mechanical work at the powered knee joint caused by investigated errors. These figures were derived from able-bodied subjects and amputees, respectively. The red asterisk indicates the defined critical errors, which affected the stability of the subjects based on the subjective feedback. Generally, these critical errors were observed to cause larger change of mechanical work generated at the powered knee joint than the errors that were not identified as the critical errors. Additionally, the amount of mechanical work change caused by the critical errors varied across different gait phases. For example, in SS phase (as shown in top-right corner of Figure 3 and 4), the errors that only generated 7×10⁻³ -9×10⁻³ J/Kg of mechanical work change can cause the subjective feeling of gait instability, while in TDS phase (as shown in middle-left of Figure 3 and 4), even the errors that caused 0.08 J/Kg of mechanical work change did not affect the gait stability. Finally, the amount of mechanical work change caused by the critical errors in each gait phase derived from able-bodied subjects (Figure 3) were generally close to those derived from AK amputees (Figure 4). In SWF and SWE phases, AB subjects showed a slightly lower threshold in sensing the error effects on gait stability.
Figure 5 demonstrated a representative trial from one AK amputee when level-ground walking was misrecognized as ramp ascent for 300ms in the IDS phase. When the error occurred around 3.5 seconds, the knee angle deviated from regular knee motion in level-ground walking. About 300ms after the end of the applied error, the full-body angular momentum of the subject in the sagittal plane also demonstrated obvious large change and exceeded the pre-defined stability threshold. The subject also reported feeling unstable, scored as a 2 on the scale.
Table 3.
The Number of AB and AK Subjects who Subjectively Reported Gait Instability (S) and the Number of AB and AK Subjects whose Quantified Balance Index Showed Gait Instability (O) when Different Type of Errors with Different Durations Were Applied at Different Gait Phase

<table>
<thead>
<tr>
<th>Error Phases</th>
<th>W→RA</th>
<th>W→RD</th>
<th>RA→W</th>
<th>RD→W</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Error Durations</strong></td>
<td><strong>IDS</strong></td>
<td><strong>SS</strong></td>
<td><strong>TDS</strong></td>
<td><strong>SWF</strong></td>
</tr>
<tr>
<td><strong>200 ms</strong></td>
<td>S</td>
<td>5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>O</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>300 ms</strong></td>
<td>S</td>
<td>5</td>
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Note: “S”: subjective feedback with gait instability; “O” denotes objectively identified gait instability. Gray area indicates the gait instability was reported.
Figure 3. Change of mechanical work at the knee joint caused by the locomotion mode recognition errors (AB). The results were averaged across 5 able-bodied subjects. Red asterisk indicates critical errors.
Figure 4. Change of mechanical work at the knee joint caused by the locomotion mode recognition errors (AK). The results were averaged across 2 AK subjects. Red asterisk indicates critical errors.
Figure 5. One representative trial from one AK amputee subject (AK01) when the level-ground walking was misrecognized as ramp ascent mode for 300ms in the IDS phase. Phase “1-5” represented IDS, SS, TDS, SWF, and SWE, respectively.
3.5 Discussion

To investigate the effects of different error types, durations, and occurred timing on the volitional control of powered AK prosthesis, the gait stability of the subjects wearing the powered prosthetic leg was evaluated. Interestingly, not all the studied errors caused balance instability (as shown in Table III) for both AB subjects and AK amputees. We observed that the effects of errors not only depended on the types of errors, but also were related to the phases where the errors occurred and the error durations. This observation implies that purely using locomotion mode recognition accuracy or error rate, which has been widely employed in previous studies, may be inadequate to truly evaluate the potential of locomotion mode recognition system for volitional control of powered artificial legs. Instead, we suggested in this study that the mode recognition system should be evaluated by identification of the "critical errors" that cause the instability of prosthesis users, which is more functionally related.

The effects of the locomotion mode recognition errors on the user's gait stability were evaluated both subjectively and objectively. It was noted that all the errors that caused the subjects' instability in terms of the quantified balance index used in this study were also subjectively reported to disturb the subjects’ gait stability. However, not all of the errors that caused subjective feeling of instability were observed to affect the quantified balance index significantly. This implied that the subjective feedback was more sensitive to measure user’s instability than the objective quantified balance index used in this study (i.e. whole-body's angular momentum). Although some errors may not obviously disturb the whole-body
angular momentum in the subjects, they elicited insecurity in the subjects regarding their balance stability and therefore lowered the subjects' confidence in using the powered device. Therefore, in this study, errors that elicited the subjective feeling of unstable balance were identified as the critical errors, which should be avoided in the locomotion mode recognition system for volitional prosthesis control. The results of this study could provide a new guidance for designing, evaluating, and optimizing locomotion mode recognition systems for artificial legs.

After we correlated the identified critical errors with their effects applied on the prosthetic knee, it has been found that the effects of errors essentially depended on (1) the phases when the error happened and (2) the amount of mechanical work change at the knee joint caused by the errors. The error effects are phase-dependent because people have different levels of demand for balance across different gait phases [21, 22]. The results in Fig. 3 and 4 implied that the SS phase was the most unstable phase because only $9 \times 10^{-3}$ J/Kg mechanical work change elicited the feeling of gait instability in both the AB and AK subjects. This conclusion was also reported in a previous study [22], which stated that the gait instability resulted from a single limb support phase (i.e. the SS phase in this study). Whereas, none of the AB and AK subjects felt unstable (Table III) even when the errors generated over 0.08 J/Kg mechanical work change at the knee joint (Fig. 3 and 4). This implied that TDS was relatively a stable phase. This observation is also consistent with the finding in [21], in which authors found that postural adjustment was absent if the gait perturbation occurred at the terminal double support phase.
In each individual phase, all identified critical errors were observed to generate relatively large mechanical work changes at the knee joint, which implied that the mechanical work change was one of the essential factors. It is because the error effects were determined by the knee joint torque change caused by the errors and the current states of knee joint, both of which were considered when calculating the mechanical work change. To alleviate the effects of critical errors, one potential solution is to first identify the tolerance range of mechanical work change at the knee joint caused by the errors in each gait phase and then carefully design the impedance parameters for each locomotion mode in each state so that when the errors happen, the resulted mechanical work change is still within the tolerable range.

This study suggests use of (1) the phases when the error happened and (2) the amount of mechanical work change at the knee joint caused by the errors as generalized criteria to define the critical errors. These criteria can be applicable to other type of AK prosthesis design and control. It should be noted that if the error types or error durations were used to define the “critical errors”, such critical errors may not be valid for other design or control of AK prostheses. For example in position control-based AK prostheses, even the errors with shorter durations (e.g. 100ms) may become critical errors because large mechanical work may be generated.

This study’s results showed that the amount of mechanical work change caused by the critical errors in each gait phase derived from the AB subjects were close to those derived from the AK amputees. The AB subjects were slightly more sensitive to error effects on gait
stability, maybe partly because the AB subjects require more gait and posture adjustments from their daily walking pattern when walking with powered prostheses. These observations suggested that the tolerable range of mechanical work change at the powered knee joint as discussed above may be defined based on the testing on AB subjects as well, which could reduce the experimental and system design cost. However, our results were derived from a limited number of recruited human subjects. Testing more subjects is required to guide the future design of volitionally controlled powered artificial legs.

All the errors were simulated in this study. One of the follow up questions is whether non-critical errors further affect the performance of intent recognition interface. To address this question, an additional experiment was conducted on one AB subject. Multichannel surface EMG signals from the subject’s thigh muscles and mechanical ground reaction forces/moments measured from the prosthetic pylon were collected as the data sources of the intent recognition interface. The tested intent recognition interface was the same as the one reported in our previous study [8]. During the experiment, the subject wore the prototypical powered prosthetic leg through a special designed bent-knee adaptor. Training data for the intent recognition interface was collected at the beginning of the experiment. The subject was asked to perform different tasks, including standing, level-ground-walking, ramp ascent, and ramp descent. Then, the subject went through the same experimental procedure described in Section II D. Four different types of errors (W→RA, W→RD, RA→W, and RD→W) with different durations (100, 200, or 300ms) at all defined phases (IDS, SS, TDS, SWF, or SWE) were simulated. The same type of error with the same duration and at the same gait phase
was simulated twice. All the errors were randomized. The EMG signals and ground reaction forces/moments were recorded during the whole experiment and used for offline intent recognition analysis. The user intent recognition decisions were carefully examined. If any misclassification in intent recognition interface was observed within 300ms after a simulated error, this error was considered as one error that further affected the intent recognition interface. The number of such errors was counted. As results, we did not observe obvious pattern changes in EMG signal and ground reaction force after applying non-critical errors identified in this study. Only 1 out of 104 non-critical errors caused the intent misclassifications. Additionally, it was unclear whether those misclassifications were caused by the simulated errors or were actually the inherent errors in the intent recognition interface because the misclassification rate derived here was lower than the inherent error rate of the intent recognition algorithm reported [9]. Therefore, based on these preliminary results, we anticipated that the non-critical errors reported in this study would not impact the performance of the intent recognition system. However, it should be noted that these results were obtained from limited number of subjects. More systematic experiments are needed to address this question.

Several limitations were still identified in this study. First, only the errors with 100-300ms durations were considered in this study. The selected error durations were based on the results of our previous study, in which lower limb amputees ambulated with a passive prosthesis. However, it is unknown whether similar error durations will be observed when lower limb amputees walk with a volitionally-controlled prosthetic leg. This is because user
intent recognition errors may change the kinematics or joint impedance of the prosthesis, which may alter the user’s interaction with the prosthesis, and in turn induce additional errors (errors with longer duration) in the intent recognition interface. Additionally, without closed-loop operation of intent recognition interface, it is unknown whether the user would have different feeling from that when the user directly interacts with the powered device. Hence, future study should involve testing of volitionally controlled powered lower limb prostheses with human-in-the-loop on more leg amputees. Second, intent recognition errors related with stair ambulation which rarely occurred, were not investigated in this study. However, it should be noted that even though this types of errors had a much lower error rate, once occurred, they may still cause critical impact on user’s gait stability according to a recent study [10]. Our future work will focus on involving users in the closed-loop control of powered artificial legs and evaluating the user’s gait performance when ambulating on terrains that are frequently encountered in daily life. Third, only the errors during static states when subjects continuously performed one activity were considered in this study. The errors that fail to recognize the activity transitions were not considered. It was because this type of errors was not observed in evaluation of our designed intent recognition system on above-knee amputees [8, 9]. Based on our previous observation and experiences, the timing when to switch the prosthesis control mode during the transition period is a more important issue and should be investigated in the future.

In a summary, “critical errors” were identified and characterized in this study. The results of this study could shift the paradigm for evaluation and optimization of intent recognition
systems and benefit the future design of volitionally-controlled powered AK prostheses. Our future work included (1) optimizing the locomotion mode recognition system by minimizing *critical errors* defined in this study rather than purely improving recognition accuracy that was traditionally suggested, (2) finding solutions to reduce the mechanical work change if the critical error happens, and (3) testing of powered lower limb prostheses with human-in-the-loop control on more leg amputees.

### 3.6 Conclusion

The effects of locomotion mode recognition errors on the volitional control of powered lower limb prostheses were investigated in this study. A prototypical AK prosthesis with a powered knee joint was used as a test bed. Five AB subjects and two AK amputees were recruited and tested when wearing our powered prosthesis. Four frequently-occurred mode recognition error types at different gait phases and with varied durations were purposely applied to modulate the intrinsic control of the prosthesis. The results showed that not all the mode recognition errors affected gait stability in the prosthesis users. The effects of errors depended on the phases when the errors happened and also the amount of mechanical work change applied to the knee caused by the errors. In addition, we defined and characterized the "*critical errors*", a new index to evaluate the potential of locomotion mode recognition systems for volitional control of powered artificial legs. The study results might shift the paradigm for evaluating and optimizing the performance of locomotion mode recognition system and aid the future design of volitionally-controlled powered artificial legs.
REFERENCES


CHAPTER 4:

General Conclusion and Future Work

4.1 General Conclusion

The research presented in this dissertation has developed a novel neural-machine interface for powered artificial legs, which demonstrated potential to enable lower limb amputees to perform various locomotive functions in a more intuitive, reliable, and safe way. The general concept is to decode lower limb amputees’ movement intention by using neural control information (i.e. surface EMG signals measured from lower limb residual muscles) and intrinsic mechanical measurements from prosthesis itself. The identified movement intention is then used to switch the control modes of the prosthesis for intuitive control. In our group, a novel locomotion mode recognition algorithm based on neuromuscular-mechanical fusion and phase-dependent pattern recognition paradigm has been developed previously. This algorithm demonstrated great ability to accurately recognize the user’s intended locomotion tasks and promptly predict the upcoming task transitions during dynamic ambulation.

Despite the promising performance of designed intent recognition algorithm, several challenges still remain in making the neural-machine interface clinically viable for neural control of powered artificial legs. One of the major challenges is to determine the informative and optimal data inputs for the neural-machine interface. Although in our previous study [1], we concluded that fusion of multiple data sources can improve the performance of intent recognition over the approaches using single data source, it is still unclear what exact data
sources are necessary for accurately and responsively recognizing the user’s intended tasks. Therefore, in Chapter 2, we investigated the usefulness of different data sources commonly suggested for user intent recognition and determined an informative set of data sources for volitional control of prosthetic legs. The results indicated that not all of the studied data sources carried important information for intent recognition and input redundancy do exist in the initial design of fusion-based interface. This also implied that reduction of system redundancy is necessary to improve the efficiency of the design for its clinical application on artificial legs. More importantly, we found that EMG signals and ground reaction forces/moments were more informative than prosthesis kinematics. In addition, this study suggested a protocol for determining the informative data sources and sensor configurations for future development of neural control of powered artificial legs. Another major contribution of the study presented in Chapter 2 was the real-time PC implementation of our previously designed user intent recognition algorithm. Unlike the offline cross validation of the algorithm reported in [1], this study proposed a system-training protocol for quick calibration and implemented the real-time algorithm for online system testing. The neural-machine interface with fusion-based algorithm was able to update intent recognition decisions in a real-time manner and produce high accuracy for intent recognition and task transition prediction, which was consistent with the offline results reported in [1]. These results implied the soundness of applying our designed interface for the future embedded implementation on powered artificial legs.
It is noteworthy that the framework of the neural-machine interface proposed in this work is not only useful for powered artificial leg control, but also applicable to other robotic assistive devices, such as powered lower extremity exoskeletons. Similar to powered artificial legs, powered lower extremity exoskeletons can also generate positive net power at the joints. To command exoskeletons to coordinate with users’ intended movement, an user-machine interface is necessary [2, 3]. It is expected that applying neural-machine interface to powered exoskeletons for intuitive control could greatly improve the locomotion functions of people with mobility dysfunctions. One good example is patients with multiple sclerosis (MS). Although MS is caused by damage to the myelin sheath, which slows or stops electrical signal conduction between nerve cells [4], clear modulation of muscle activity in MS patients’ lower extremities can still be observed during ambulation [5, 6]. This implied that neuromuscular control information is still represented in leg EMG signals, which can be potentially used for intent recognition. Furthermore, the neural-machine interface has been preliminarily evaluated on one MS patient in our group [5]. The interface demonstrated above 98% accuracy in recognizing the patient’s three tasks (sitting, standing, and level-ground walking) and sufficient prediction time (100-130ms) in predicting upcoming task transitions. However, the number of recruited MS patients was limited. Testing on more MS patients with different types of locomotion modes is required to further evaluate the feasibility of the designed neural-machine interface for lower extremity exoskeleton control.

Understanding and eliminating the effects of errors generated in neural-machine interface on the operation of the prosthesis and user's task performance is imperative to ensure safe
and reliable use of powered artificial legs. In doing so, we systematically investigated the effects of errors in neural-machine interface in Chapter 3. It was observed that not all of the studied errors disturbed the gait stability of the tested subjects. This observation implied that purely using locomotion mode recognition accuracy or error rate, which has been widely employed in previous studies, may be inadequate to truly evaluate the potential of neural-machine interface for volitional control of powered artificial legs. Instead, we suggested that system evaluation should focus on identification of the "critical errors" that cause the instability of prosthesis users, which is more functionally related. Furthermore, we found that the effects of errors on the user's balance depended on two factors: (1) the gait phase when the errors happened and (2) the amount of mechanical work change applied on the powered knee caused by the errors. These important findings may shift the paradigm for evaluating and optimizing the performance of neural-machine interface and aid the future design of neurally controlled powered artificial legs.

4.2 Future Work

The neural-machine interface designed in this study was mainly evaluated based on offline analysis using the experimental data collected from transfemoral amputees and online testing without connecting with powered artificial legs for real-time neural control. The performance of the interface when integrating with powered prostheses for human-in-the-loop real-time control is more clinically relevant, however, still unknown. Two recent studies [7, 8] has reported preliminary evaluation of the designed interface for real-time powered artificial leg control. With this interface, the tested transfemoral amputees were reported to
seamlessly transition between different locomotion tasks, such as level-ground walking, slope walking, and stair climbing. But, a very limited number of lower limb amputees were tested and there is still a lack of strong evidence to demonstrate the true benefits of neurally controlled powered artificial legs over conventional passive devices and manually controlled powered devices. Therefore, our future work will focus on the outcome measures in neurally controlled powered artificial legs and systematic comparison with other devices. The evaluation metrics could include biomechanical parameters (e.g. joint angles, joint torques, ground reaction forces, etc.), gait performance evaluation indexes (e.g. stride length, walking speed, gait symmetry, gait stability, etc.), energy expenditure, cognitive load, and subjective feedback about safe and confident use of lower limb prostheses. The outcomes of the planned study are expected to significantly propel the neural control of powered artificial legs into clinical application.

In this study, we investigated and identified the effects of neural-machine interface errors on the gait performance of prosthesis users and the control of powered lower limb prosthesis. Our next step will seek to eliminate the critical effects of these errors in order to ensure the safety and reliability of neural control. One potential solution is to design a fault tolerant control mechanism within current control system. The fault tolerant control is mainly composed of two components: fault detection module and control reconfiguration mechanism. The fault detection module is used to responsively detect the errors once they happen. The role of control reconfiguration is to actively re-adjust the prosthesis controller parameters to eliminate or minimize the error effects. In Chapter 3 we observed that when the
error duration was 100ms, the error did not cause any effects in the users; when the duration reached 200ms or 300ms, some error became disruptive. These results implied that fault tolerant control is potentially feasible to eliminate the disruptive effects of neural-machine interface errors before the users perceive them. It is our hope that this future study could enhance the safety and reliability of neurally controlled artificial legs.

It should be noted that, besides the challenges addressed in this research, additional engineering efforts are still needed to make the neural-machine interface clinically viable for powered artificial leg control. First, improving the robustness of neural-machine interface over time is necessary. Surface EMG signals, as an important data source for neural-machine interface, are susceptible to signal disturbances, such as motion artifacts, environmental noise, electrode conductivity changes, electrode location shifts or loss of contact. Since the intent recognition algorithm in neural-machine interface involves learning the muscle activity patterns and does not accommodate changes in EMG signals, these disturbances may threaten the interface robustness and therefore challenges the clinical values of neural-machine interface. Potential solutions include design of a robust EMG sensing interface [9] and implementation of adaptive EMG pattern recognition algorithms [10]. Second, seamless integration of surface EMG sensors with prosthetic socket is of particular importance. Relative movements between the residual limb and the prosthetic socket not only introduce motion artifacts in EMG signals, but also cause regions of high pressure and friction against the residual limb which may lead to discomfort during ambulation and poor gait patterns. Therefore, design of a sensor-socket interface that provides high-quality surface EMG signal
recordings and maximizes high level of patient comfort holds great values for application of neural-machine interface on prosthesis control [11]. Third, enabling lower limb amputees to successfully recover from stumbles can significantly enhance the safety of powered artificial legs. Falling is a common problem in lower limb amputees, which can cause serious injuries and lower balance confidence. Powered robotic legs have presented capabilities to allow lower limb amputees to actively recover from stumbles in a natural way; but, control mechanism of stumbling corrective reaction is still demanded. A stumble detection system which can accurately and promptly identify stumbling events has been developed in our lab [12]. Improving the detection performance and resolving the challenges that remain in implementing the stumble detector on powered artificial legs will be our future work. Finally, implementing the neural-machine interface on an embedded computing system is essential to make neurally controlled artificial legs practical and available to lower limb amputees. Online streaming and storing multi-channel sensor data, running complex user intent recognition algorithm, and real-time monitoring sensor and prosthesis status at the same time require an embedded system with high processing speed and computation power. To meet these requirements, a powerful and efficient embedded computing system prototype has been designed in our group [13-15]. Our future work will focus on designing a user-friendly calibration/training interface and miniaturizing embedded system for implementation on self-contained and lightweight powered artificial legs.
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