MYOELECTRIC CONTROL OF A POWERED TRANSFEMORAL PROSTHESIS DURING NON-WEIGHT-BEARING ACTIVITIES

Levi Hargrove$^{1,2}$, Ann M. Simon$^1$, Suzanne B. Finucane$^1$, Robert D. Lipschutz$^{1,2}$

$^1$Center for Bionic Medicine, Rehabilitation Institution of Chicago, Chicago IL, USA
$^2$Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL, USA

ABSTRACT

Lower limb prostheses have traditionally been mechanically passive devices without electronic control systems. Microprocessor-controlled passive and powered devices have recently received much interest from the clinical and research communities. The control systems for these devices rely on mechanical sensors placed on the prosthesis. Few studies have investigated control systems that rely on information extracted from myoelectric signals to help control lower limb prostheses. In this paper we show that sagittal plane motions of the knee and ankle can be accurately (>90%) recognized using only myoelectric signals (MESs) measured from residual thigh muscles. The control system for a powered transfemoral prosthesis was modified to accept myoelectric control information and subjects demonstrated real-time control of the knee and ankle for non weight bearing motions. This research is the first step in our long-term goal of implementing myoelectric control of lower limb prostheses during both weight-bearing and non-weight-bearing activities for individuals with transfemoral amputation.

INTRODUCTION

Lower limb amputation is a major cause of disability for millions worldwide. A variety of mechanically passive prostheses have traditionally been used to restore mobility to these individuals. Microprocessor-controlled variable damping knees have recently gained popularity due to their ability to enhance knee stability and adapt to different ambulation speeds [1]. However, these prostheses still only dissipate mechanical power—they cannot generate the power required for many activities, such as standing from a chair or ascending stairs. Microprocessor-controlled powered prosthetic legs have recently become commercially available, and several prototypes are in various stages of development. High-level state-based controllers interpret signals recorded from mechanical sensors embedded in the prosthesis or from an orthotic placed on the sound limb. These signals provide control information to lower-level position, force, torque, or impedance controllers.

Myoelectric control for lower limb prostheses is a developing field of research. Recent studies demonstrate that myoelectric signals (MESs) from the residual thigh of a transfemoral amputee can be used to estimate the subject’s ambulation mode activity during weight-bearing situations [2]. Using pattern recognition techniques, residual thigh muscle activity can also provide information to control a prosthetic knee [3] or a combined knee and ankle [4]. Subjects in these previous studies were not wearing prostheses during testing; the prostheses were either attached to a laboratory benchtop or the experiments were completed within a virtual environment. In this study we expand the number of subjects tested in [4] and report results for subjects fitted with a motorized transfemoral prosthesis.

METHODOLOGY

Two experiments were completed between September 2009 and May 2011 at the Rehabilitation Institute of Chicago. The Northwestern University Institutional Review Board approved the studies, and written informed consent was obtained from all study subjects.

Experiment 1: Real-Time Non-Weight-Bearing Control within a Virtual Environment

Eight subjects with transfemoral amputations (5 males, 3 female, mean (SD) age 49 years, mean number of years post amputation 19 years) participated in this study. Subjects were seated and the following nine muscles were identified based on anatomical location and palpation: semitendinosus, sartorius, tensor fasciae latae, adductor magnus, gracilis, vastus medialis, rectus femoris, vastus lateralis, and long head of the biceps femoris. Nine adhesive, gelled silver–silver chloride electrode pairs were placed over the muscles of interest with an interelectrode spacing of approximately 3 cm. All data were amplified by a factor of approximately 1000, digitized using a 16-bit analog to digital converter, and transferred over a controller area network (CAN) bus using the Prosthesis Device Control Protocol [5].

Custom software—Control Algorithms for Prosthetic Systems (CAPS)—instructed the subjects to perform the following movement: knee flexion, knee extension, ankle plantar flexion, ankle dorsiflexion, and no motion. The order that the trials were collected in was not randomized and eight repetitions of 3 s each were collected for each motion. Data from repetitions 1–4 were used to train a pattern recognition system, and data from repetitions 5–8 were used to compute classification accuracy. The pattern recognition system was based on time-domain features extracted from...
250 ms overlapped analysis windows and classified by a linear discriminant analysis classifier. This system has been well-documented [6] and shown to provide good classification performance for upper limb amputees [7].

After the pattern recognition system was trained, subjects completed a motion test within a real-time virtual environment [7]. The motion test required subjects to replicate motions displayed on a computer screen while real-time position feedback was provided by a virtual avatar. Each motion test consisted of nine trials of each of the four movements (the no motion class was not tested) presented in random order. A trial was completed successfully when the subject moved the virtual limb through its complete range of motion for the tested class. Trials could be completed in a minimum of 1 s and were terminated after 15 s. Performance metrics included classification accuracy, motion completion time, and motion completion percentage [4]. Motion completion time is the elapsed time from movement onset until the virtual limb is moved through the complete range of motion. Motion completion percentage is the number of successfully completed motions divided by the total number of trials.

Experiment 2: Real-time Non-Weight Bearing Control with a Powered Knee Prosthesis.

Two of the eight participants returned to complete a second experiment to evaluate their performance when controlling a powered knee prosthesis. MES control site locations were marked on a custom fabricated socket at the end of experiment 1 and stainless steel dome electrodes were embedded into the socket wall. MES data were amplified by a factor of 1000, sampled by a 16 bit analog-to-digital converter and streamed across a CAN bus to CAPS software.

The powered knee prosthesis used in this experiment was designed and fabricated at Vanderbilt University and is similar to the prosthesis described in previous work [3, 8] except that the ankle actuation unit was removed (Figure 1).

The powered knee was modified to implement the Prosthesis Device Control Protocol [5] so that it could send sensor data to and be controlled by CAPS software.

A volitional impedance controller was created within CAPS (Figure 2) and was very similar to architecture described previously by the Vanderbilt Group [3]. The pattern recognition system described in experiment 1 provided the two mutually exclusive outputs $\omega_k$ and $\omega_a$, corresponding to knee and ankle velocities, respectively. These velocities were integrated to provide an estimate of the desired knee and ankle positions. A joint torque command was generated according to the following equation:

$$\tau_i = k_i(\theta_i - \theta_{i\text{emg}}) + b_i \dot{\theta}_{i\text{emg}},$$  \hspace{1cm} (1)

where $i$ was an index corresponding to the knee or ankle, $k_i$ was an empirically determined virtual stiffness, $\theta_i$ was the position measured from the prosthesis, $\theta_{i\text{emg}}$ was an estimate of the desired joint position, $b_i$ was an empirically determined virtual damping term, and $\dot{\theta}_{i\text{emg}}$ was the joint velocity measured from the prosthesis.

When the prosthesis was initially powered on, the tuning parameters ($k_i$ and $b_i$) were set to 0 such that a joint torque command of 0 Nm was sent to the device while training and testing data were collected. The data were collected using the same procedure as used in experiment 1. The pattern recognition system was trained to recognize knee flexion, knee extension, ankle plantar flexion, and no motion. Next, the myoelectric impedance control parameters were tuned empirically. The values of $k_i$ and $b_i$ were slowly adjusted until the subject could move the knee through the full range of motion at a comfortable speed with a smooth kinematic profile. Since the prosthesis did not contain an ankle actuation unit, the ankle tuning parameters, $k_a$ and $b_a$, were left at 0. These parameters would also need to be adjusted in order to control an ankle actuation unit. Subjects practiced

![Figure 1: Subject wearing the powered knee prosthesis](image1.jpg)

![Figure 2: Architecture of the impedance controller used to generate the torque command provided to the powered knee prosthesis](image2.png)
controlling the knee for several minutes prior to completing motion tests with the physical prosthesis.

The motion tests were very similar to those described in experiment 1 except that the order of motions was not randomized; knee flexion and extension were tested first. Subjects were cued by the experimenter to perform the appropriate motion and move the knee joint through the full range of motion. Ankle motion tests were completed with the prosthetic knee positioned at 90 degrees of knee flexion (i.e. neutral position when sitting) and at 45 degrees of knee flexion. Testing in the two different positions allowed us to determine if the pattern recognition system could still recognize ankle motions when the knee was repositioned. Feedback was provided to the subject by both the virtual environment and the physical prosthesis: the output of the pattern recognition classifier was displayed on a computer monitor and if the pattern recognition system erroneously decoded a knee command, then the prosthesis would move. The performance metrics of the motion tests were motion completion percentage and motion completion time.

**RESULTS**

**Experiment 1: Real-Time Non-Weight-Bearing Control within a Virtual Environment**

Subjects achieved high classification accuracies and completion percentages for both knee and ankle motions (Table I, Figure 3). The classification accuracy from one of the subjects was excluded as an outlier; we determined that this subject only held the contraction briefly while training data were collected resulting in many ‘no motion’ class errors. Nonetheless, this subject could still control the prosthesis during the real-time tests.

<table>
<thead>
<tr>
<th>Classification Accuracy (SD), %</th>
<th>Completion Time (SD), s</th>
<th>Completion Percentage (SD), %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>92.1 (3.7)</td>
<td>2.40 (0.82)</td>
</tr>
<tr>
<td>Knee</td>
<td>92.1 (2.8)</td>
<td>2.03 (0.84)</td>
</tr>
<tr>
<td>Ankle</td>
<td>88.1 (9.2)</td>
<td>2.79 (1.23)</td>
</tr>
<tr>
<td>No Motion</td>
<td>99.9 (0.4)</td>
<td>n/a</td>
</tr>
</tbody>
</table>

**Table I. Virtual prosthesis performance metrics (n = 8)**

**Experiment 2: Real-time Non-Weight Bearing Control with a Powered Knee Prosthesis**

The tuned impedance parameters were \( k = 0.8, b = 0.05 \) for subject 1 and \( k = 0.6, b = 0.08 \) for subject 2.

Subjects performed slightly better with the physical prosthesis in comparison to using only the virtual environment (Table II, Figure 4). Importantly, the pattern recognition system could still reliably decode ankle motions when the knee joint was repositioned at a 45 degree ankle (Table II).

**DISCUSSION**

Accurate classification of knee motions was expected because the MESs were recorded from physiologically appropriate residual limb muscles that had previously been used to control the knee. Accurate classification of ankle motions was unexpected; the muscles that control the ankle are located below the knee and were lost as a result of the amputation. Nonetheless, subjects were generating distinct and repeatable co-activity patterns that were properly

![Figure 3: The cumulative motion completion percentage for eight subjects.](image1)

![Figure 4: Cumulative motion completion percentage comparing performance between the physical prosthesis and the virtual prosthesis for two subjects, TF02 and TF10.](image2)
interpreted by the pattern recognition system. This is analogous to recognizing subtle differences in hand grasp patterns using only the extrinsic forearm muscles of transradial amputees [9].

To the authors’ knowledge, this is the first demonstration of myoelectric control of a powered transfemoral prosthesis. Although the results are preliminary, they are promising. Both subjects were able to reliably to control the knee in real time. Furthermore, the pattern recognition system properly interpreted ankle commands when the prosthesis was repositioned to a 45 degree angle, suspending freely in space from the socket. This suggests that MES changes resulting from dynamic loading on the socket do not degrade pattern recognition performance. Further testing with additional amputees is required to see if this result can be generalized across subjects. It also should be noted that only changes in the knee angle were tested and not changes in the position of the residual limb.

Proportional control estimates of knee velocity were not incorporated into the control system, and the parameters of the myoelectric impedance controller were adjusted empirically by the experimenter. Proportional control signals may be added by taking a simple average of MES amplitudes [10] or by using a weighted average of MES amplitudes determined by principle component analysis [3]. Smoother kinematic profiles may be obtained by optimizing the selection of the impedance parameters—the objective of ongoing research.

**FUTURE WORK**

Non-weight-bearing control is only one portion of the overall control system for a powered lower limb prosthesis. Non-weight-bearing control may be considered an activity mode in a state machine constructed to control the prosthesis during both weight and non-weight-bearing situations (Figure 5).

![Figure 5: Conceptual block diagram of the overall control system for a powered prosthesis.](image)

Existing powered lower limb prostheses use mid-level ‘intrinsic controllers,’ depicted conceptually inside the square boxes in Figure 5, to generate appropriate joint torques that are sent to the prosthesis [11]. Current intrinsic controllers rely on mechanical sensor data to transition between phases. Mechanical sensor data is also currently used to transition between activity modes. MES data has been shown to provide information that helps discriminate between activity modes [2]. Future work will quantify the benefits of adding MESs to improve activity mode recognition rates and reduce latencies between activity mode transitions.

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**REFERENCES**


