INTUITIVE NEURAL CONTROL OF POWERED LEG PROSTHESES

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- 4 Interrelated labs
- >50 people
- Focused translation research
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Lower Limb Amputations

We need to provide better options the help restore mobility to patients

623,000 Major Lower Limb Amputees

41,000 Major Upper Limb Amputees
State of lower-limb prostheses

Active prototypes
- Mechanically-active
- Mechanically-passive

Commercially-available
Lower Limb Prosthesis Control
Neural Control of Lower Limb Prostheses

- Independent control during non-weight-bearing activities
  - Repositioning the prosthesis for comfort
  - Prepare for difficult transfers

- Weight-bearing activities and weight transfers
  - Ambulation modes (walk, stairs, etc)
  - Sit-to-stand

- Provide *natural* transitions between activities
Powered Lower Limb Prostheses
We have tested approximately 20 different users (2 Veterans) and logged over 1500 hours of patient use.

- Ages: 19 – 65 Years
- Time from Amputation: 2 – 44 Years
- Amputation: Short transfemoral to knee disarticulation
- Weight: 93 – 246 lbs
What information remains?

Myoelectric control sites

Embedded electrodes

Knee Extension

Rectus Femoris

Vastus Lateralis

Biceps Femoris

Semitendinosus

Tensor Fasciae Latae

Adductor Magnus

Knee Flexion
Knee Extension
Ankle Plantarflexion
Knee Flexion
Ankle Dorsiflexion
Rest

Pattern Recognition

EMG Signals → Data Windowing → Feature Extraction → Classification → Intent
Targeted Muscle Reinnervation

1. **NEURAL SIGNALS STILL EXIST**

2. **AVAILABLE MUSCLE SITES**
   (Biological Amplifiers)

3. **INTUITIVE CONTROL**
Tested 2 patients after TMR surgery

- Allows access to neural control of the ankle

Knee Flex

Ankle Dorsiflex

Ankle Plantarflex
- Requires significant amount of power generation at the hip and knee
- Difficult activity for transfemoral amputees

Burger et al. 2005
- OSSUR Power Knee – a commercially available powered knee prosthesis
- Limited research shows small improvements in lower limb symmetry

Highsmith et al. 2011

(positive asymmetry values represented greater force through the intact side)
Powered Knee and Ankle Control

- Flexibility to tune the prosthesis and provide power generation/dissipation in different modes
More symmetric weight distribution using the Powered Knee and Ankle Prosthesis to stand up.

(positive asymmetry values represented greater force through the intact side)
Sit-to-Stand
**Walking Controller**

- Stance Stiffness/Damping
- Swing Stiffness/Damping

**Stated Based Control**
- Straightforward to control the stiffness or damping of the device based ‘mechanical sensors like load cells.'
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- The ‘impedance’ changes for each type of ambulation activity.
Stated Based Control

- Straightforward to control the stiffness or damping of the device based ‘mechanical’ sensors like load cells.
- The ‘impedances’ change for each type of ambulation activity.
- It is not straightforward to use mechanical sensors to naturally transition between activities.
Approaches used to Select Ambulation Activities

- Use key-fob (remote controls) to select the activity
- Make the user perform an unintuitive movement (i.e. rock back and forth)
- Make the user wear an orthotic on the sound side
- Use pattern recognition to learn patterns created by the sensors
Mechanical Sensor Patterns

A.

B.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Vertical Load (N)</th>
<th>Knee Angle (degrees)</th>
<th>Knee Velocity (deg/s)</th>
<th>Knee Motor Torque (Nm)</th>
<th>Ankle Angle (deg)</th>
<th>Ankle Velocity (deg/s)</th>
<th>Ankle Motor Torque (Nm)</th>
</tr>
</thead>
</table>
EMG Signal Patterns

A. 

B. 

Vertical Load (N)

Walk  Ramp Ascent  Ramp Descent  Stair Ascent  Stair Descent

Biceps Femoris (a.u.)

Semitendinosus

Sartorius

Rectus Femoris

Vastus Lateralis

Vastus Medialis

Adductor Magnus

Gracilis

Tensor Fasciae Latae
Non-Weight-Bearing Task
“Knee Flexion”

Ambulation Task:
“Walking”

- ‘Constant’ amplitude within a task
- Suitable for pattern recognition

- Time-varying and quasi-cyclic within one task
- Signals are very ‘noisy’
Phase Based Classification

EMG Signals → Filtering → Windowing → EMG feature extraction → Feature Concatenation

Mechanical Sensors → Windowing → Mechanical feature extraction → Feature Concatenation

Gait Phase Detection

Classification
- Stance Phase Classifier
- Swing Phase Classifier

Output Activity Mode

Helen Huang
NC State
Classification Method with Time History Information

**Bayes Law**

\[
P(\text{Mode} | \text{Sensors}) = n * P(\text{Sensors} | \text{Mode}) * P(\text{Mode})
\]

**Propagation of Time History**

13 Mechanical Sensors

**Prior = Posterior**

* Transitional Probability Matrix

Time History Information

Current Sensor Information

Locomotion Mode Prediction

Fusion of current Classifier

9 EMG Sensors

Current time point
‘Steady-State’ Error
Experience tuning powered knee and ankle prosthesis for:
  - Level ground walking
  - Ramp ascent and descent
  - Stair ascent and descent
  - Sit-to-stand and Stand-to-sit

85% reduction in tuning parameters
  - Developed impedance parameter functions scalable to body weight, ambulation speed, and specific user preferences between modes

Drastic reduction in initial accommodation period
  - Novice users can comfortably perform all modes in 2-4 hours
**Clinical Calibration Considerations**

- **Clinical tuning interface**
  - Developed relationship between clinical gait improvements and impedance parameter changes
Remaining Challenges

- Improved hardware (smaller, lighter, quieter)
- Electrode/socket interface
- Clinical interface and initial configuration setup
- Intent recognition system
  - Further reduce error rates
  - User-independent classifier
  - Adaptive classifier
- Fall detection and recovery
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