INTUITIVE NEURAL CONTROL OF POWERED LEG PROSTHESES

Rehabilitation Institute of Chicago

Levi J. Hargrove, PhD, P.Eng.
Center for Bionic Medicine

Center for Bionic Medicine

- 4 Interrelated labs
- >50 people
- Focused translation research

Center for Bionic Medicine

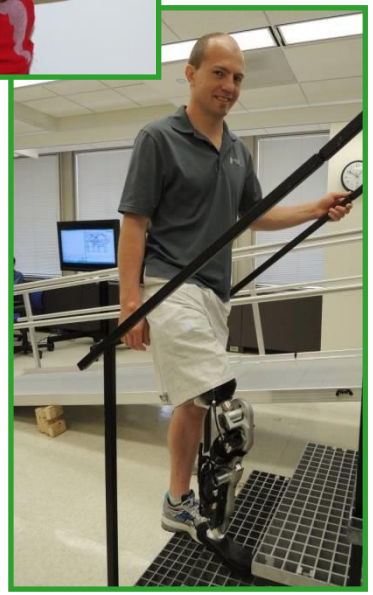
- Center for Bionic Medicine
  Todd Kuiken

  - Neural Engineering for Prosthetics & Orthotics Lab
    Levi Hargrove

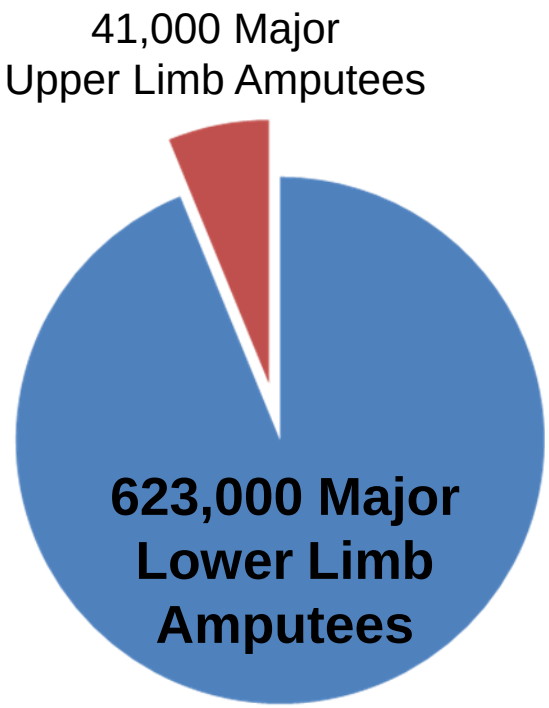
  - Rehabilitation Technologies & Outcomes Lab
    Arun Jayaraman

  - Prosthesis Design & Control Lab
    Elliott Rouse


BOOT
CAMP



Lower Limb Amputations



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

State of lower-limb prostheses

Commercially-available

Active prototypes

Mechanically-active

Mechanically-passive

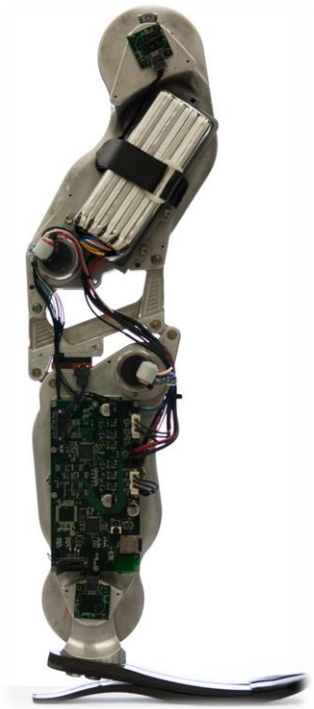
Lower Limb Prosthesis Control

The Need for Power

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

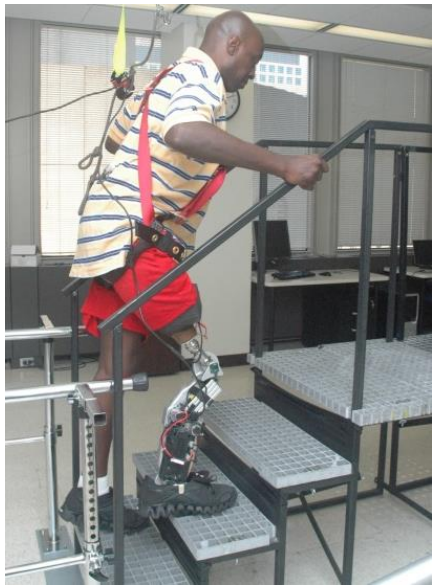


VANDERBILT UNIVERSITY

Massachusetts Institute of Technology

Variety of Users

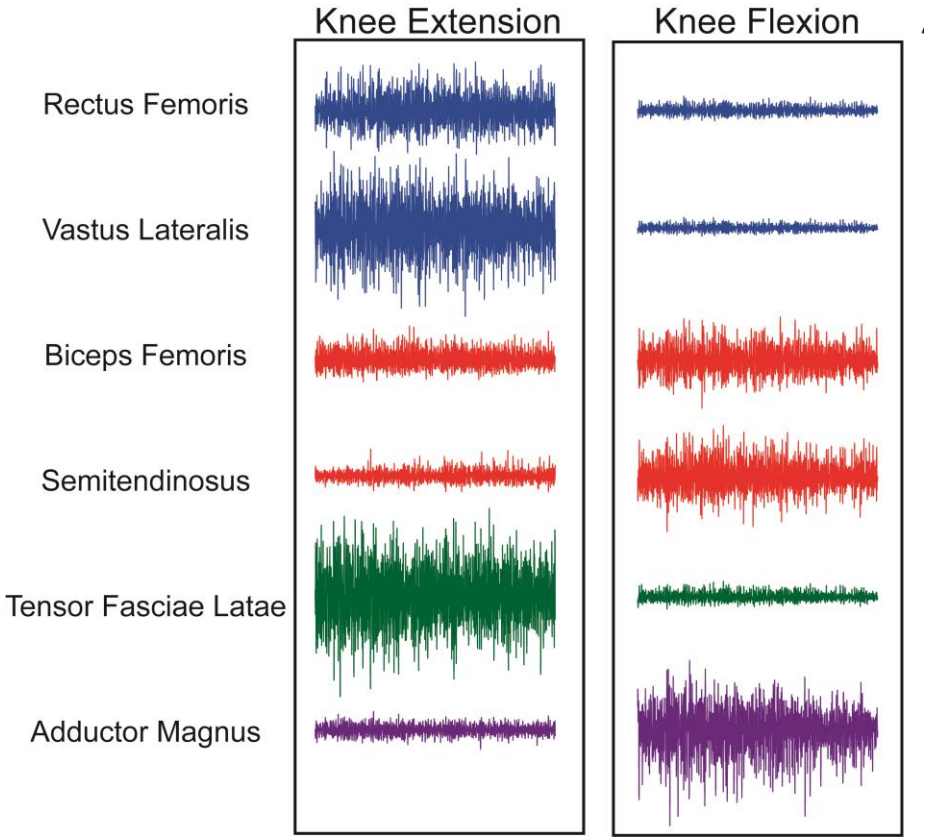
- We have tested approximately 20 different users (2 Veterans) and logged over 1500 hours of patient use
- Ages: 19 – 65 Years
- Time from Amputation: 2 – 44 Years
- Amputation: Short transfemoral to knee disarticulation
- Weight: 93 – 246 lbs

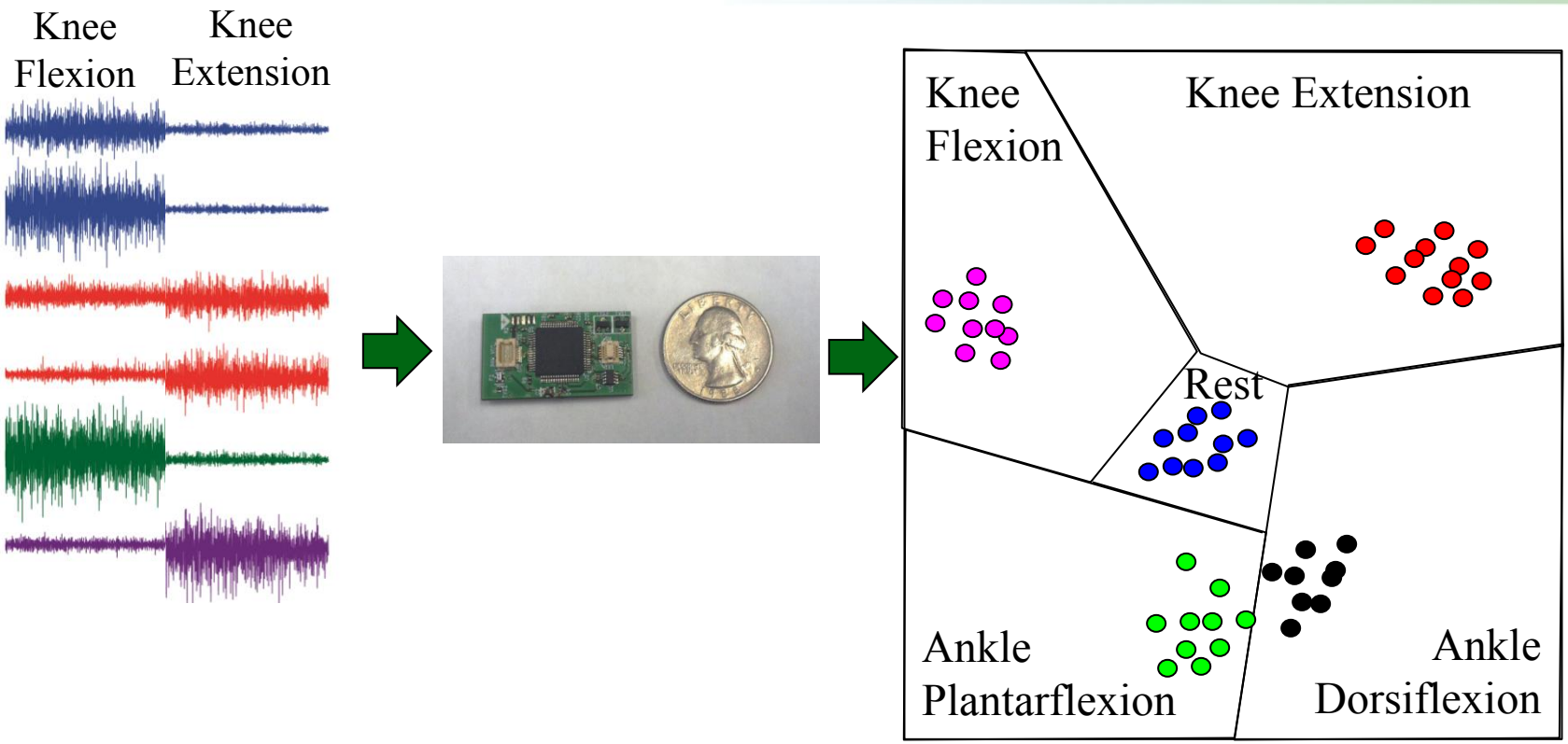
What information remains?

Myoelectric control sites

Embedded electrodes



Pattern Recognition



EMG Signals → Data Windowing → Feature Extraction → Classification → Intent

Independent Control

Hargrove et al., *JAMA*, 2011

Targeted Muscle Reinnervation

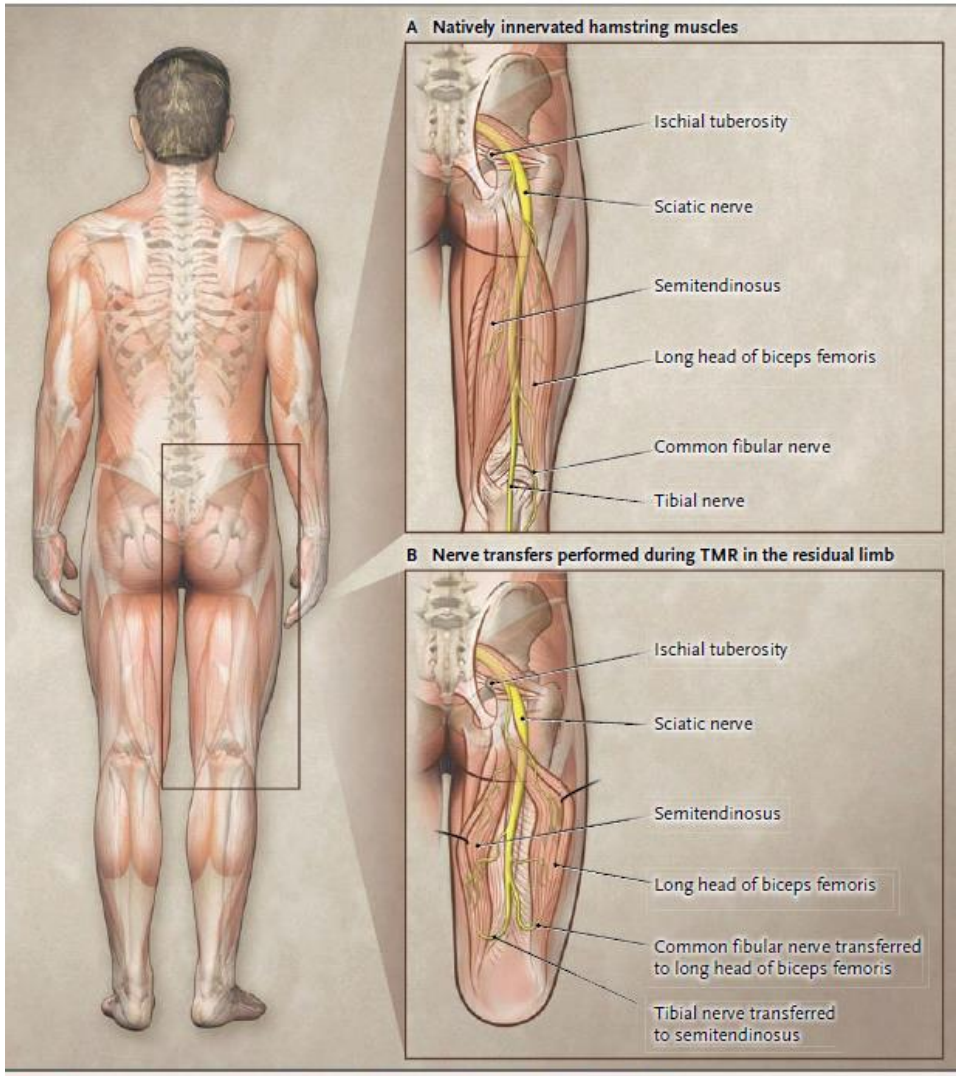


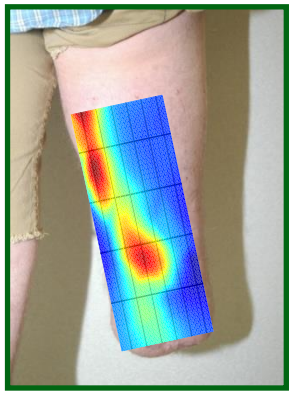
Figure 1. Natively Innervated and Surgically Reinnervated Residual Thigh Muscles.
Posterior views of the anatomy of the upper thigh show natively innervated hamstring muscles (Panel A) and nerve transfers performed during targeted muscle reinnervation (TMR) surgery (Panel B) in the residual limb.

1. NEURAL SIGNALS STILL EXIST
2. AVAILABLE MUSCLE SITES (Biological Amplifiers)
3. INTUITIVE CONTROL

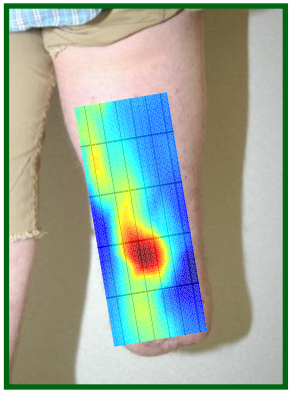
Additional Neural Information: TMR

- Tested 2 patients after TMR surgery
  - Allows access to neural control of the ankle

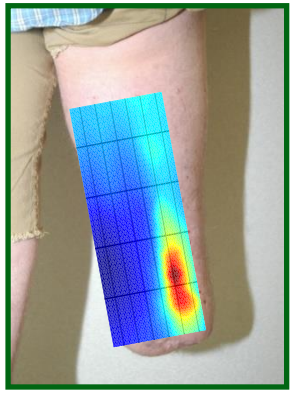
Knee Flex

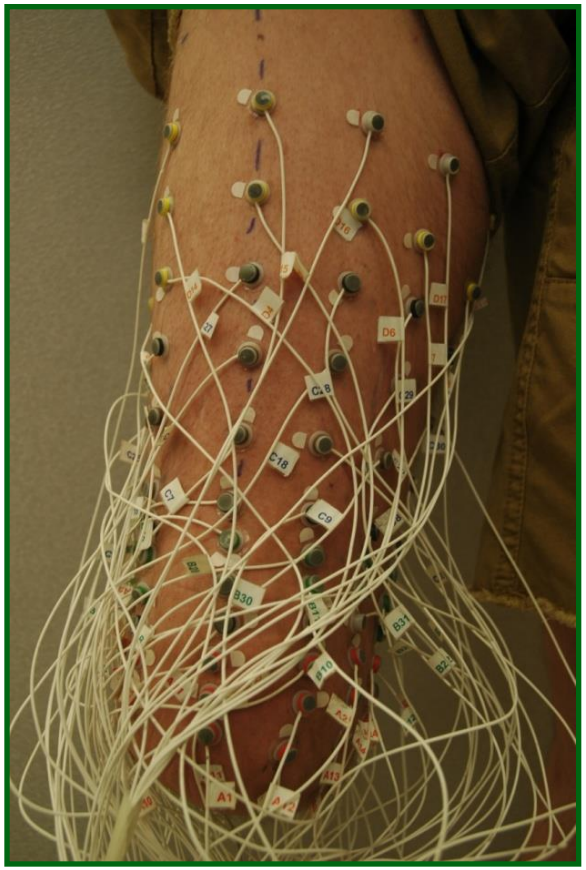


Ankle Dorsiflex



Ankle Plantarflex

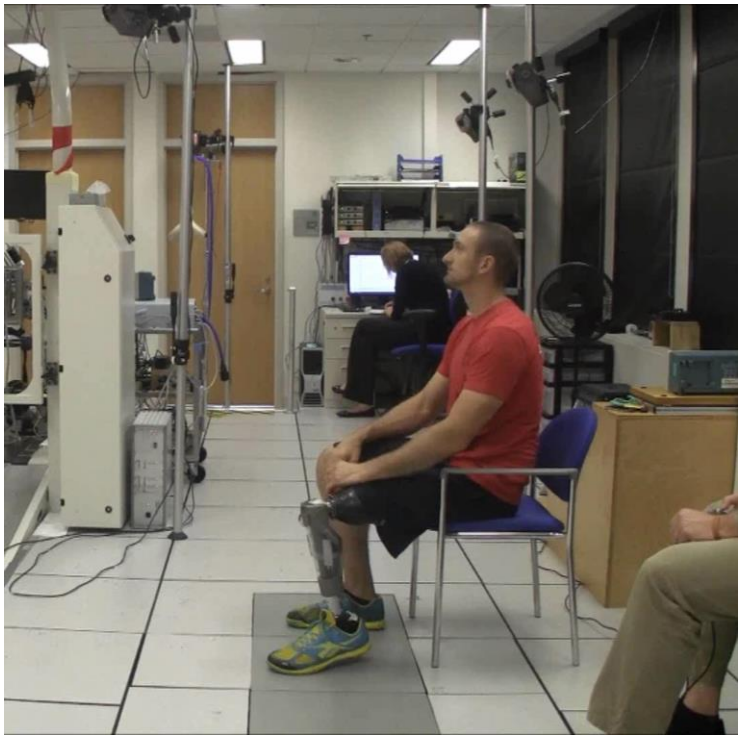


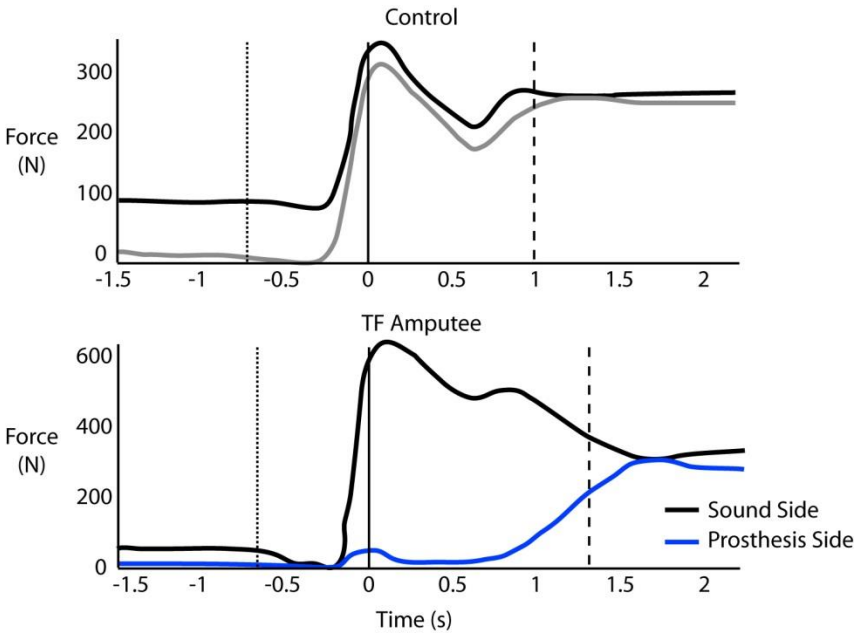


TMR Independent Control

Sit-to-Stand

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

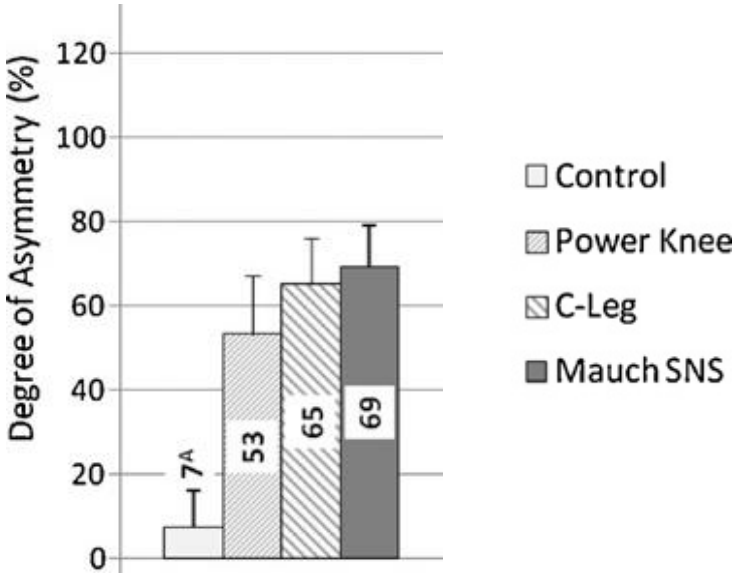




Burger et al. 2005

Powered Prostheses

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



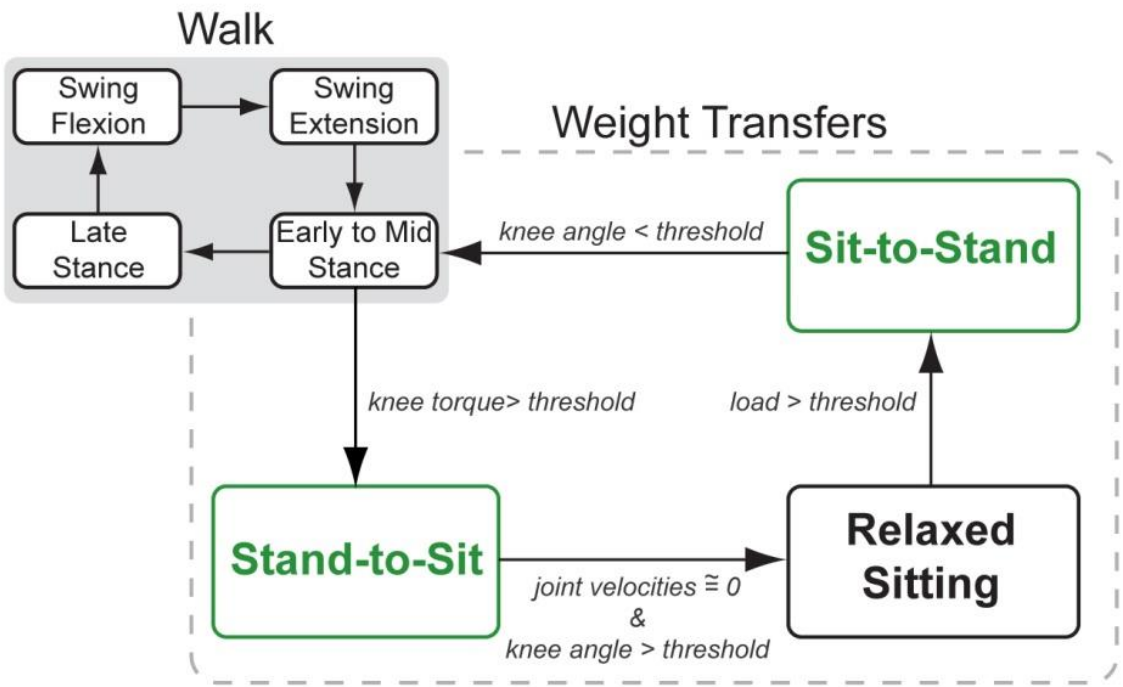
Vertical Ground Reaction Force

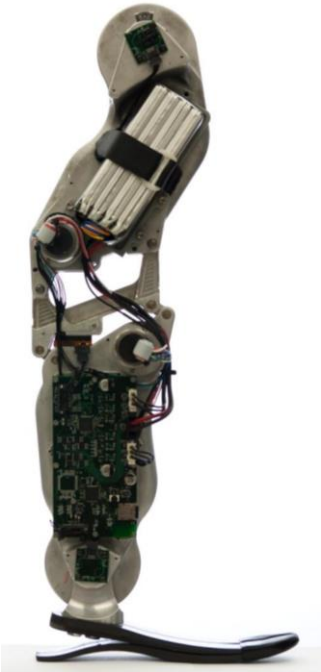
Highsmith et al. 2011

(positive asymmetry values represented greater force through the intact side)

Powered Knee and Ankle Control

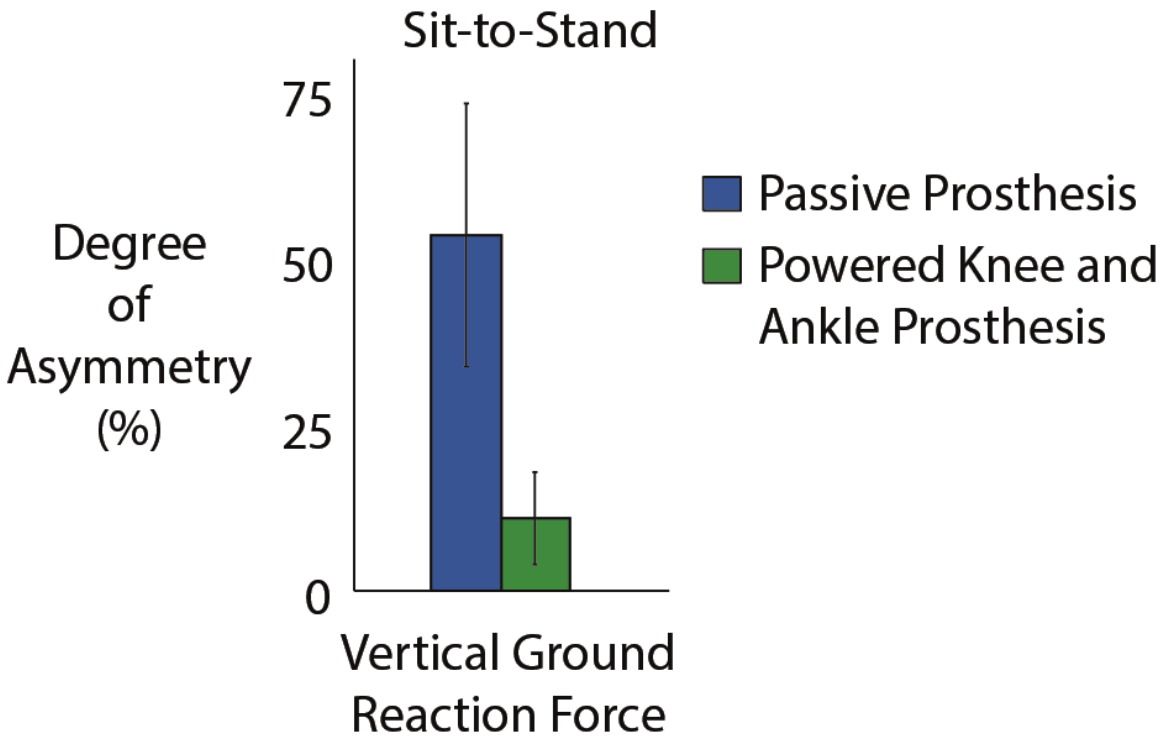
- Flexibility to tune the prosthesis and provide power generation/dissipation in different modes





Sit-to-Stand: Ground Reaction Forces

- More symmetric weight distribution using the Powered Knee and Ankle Prosthesis to stand up

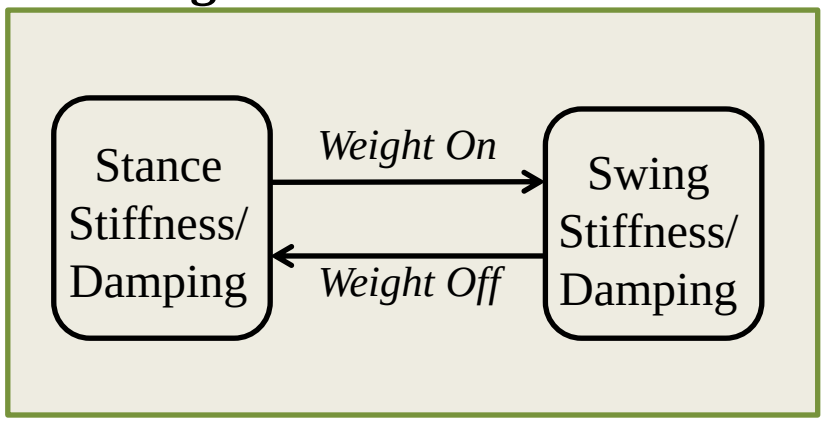


(positive asymmetry values represented greater force through the intact side)

Sit-to-Stand

Computerized Control of Legs

Walking Controller

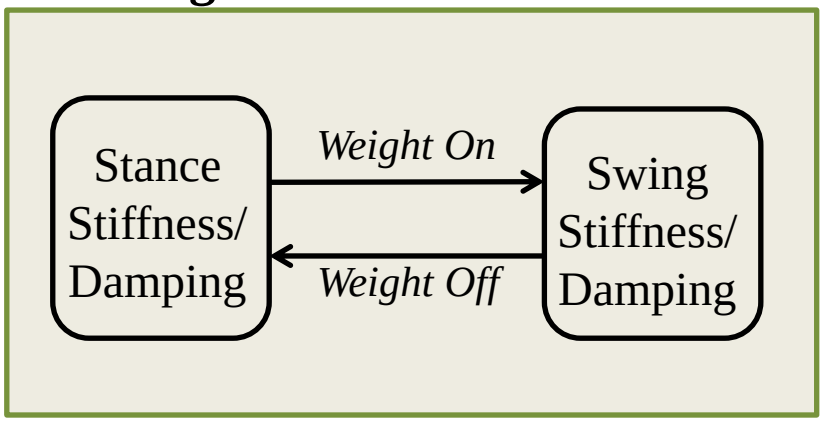


Stated Based Control

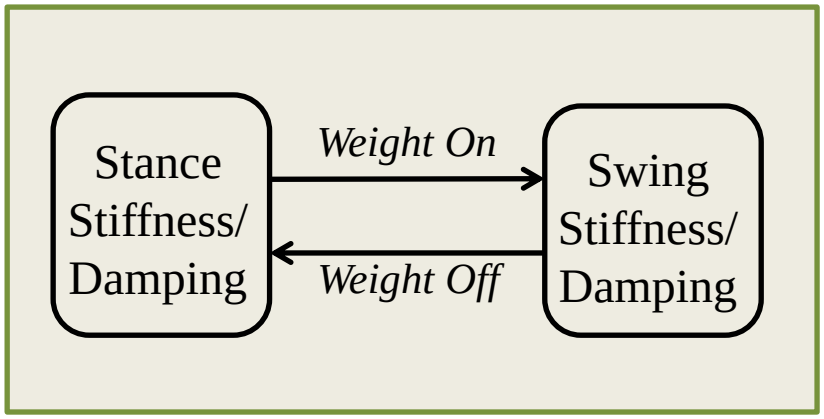
- Straightforward to control the stiffness or damping of the device based 'mechanical sensors like load cells.

Computerized Control of Legs

Walking Controller



Stair Descent Controller

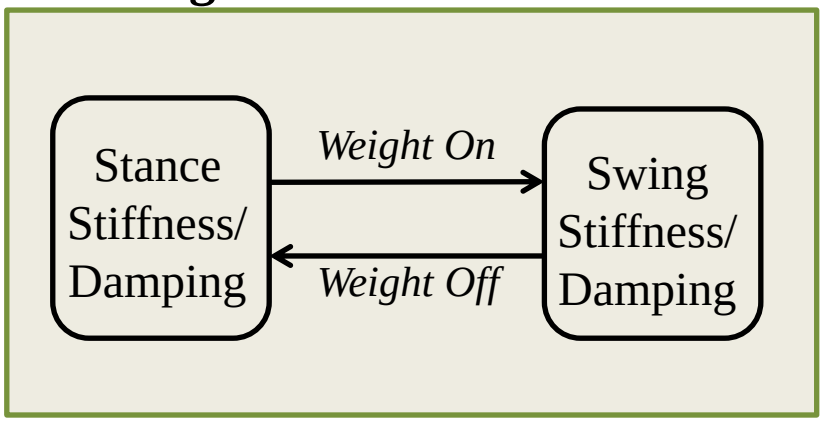


Stated Based Control

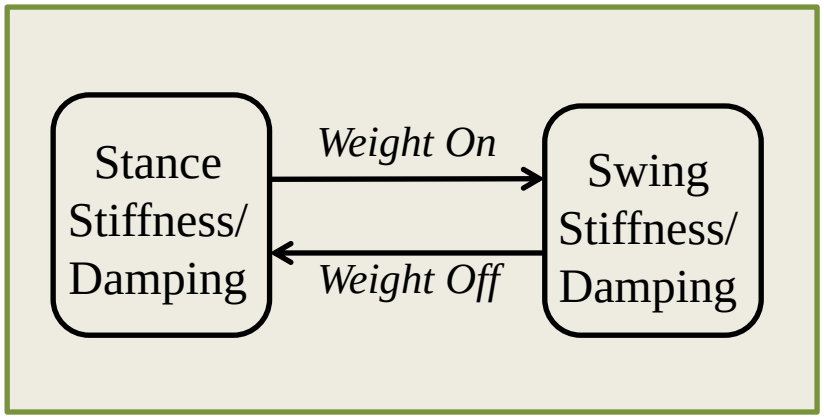
- Straightforward to control the stiffness or damping of the device based 'mechanical' sensors like load cells.
- The 'impedance' changes for each type of ambulation activity.

Computerized Control of Legs

Walking Controller



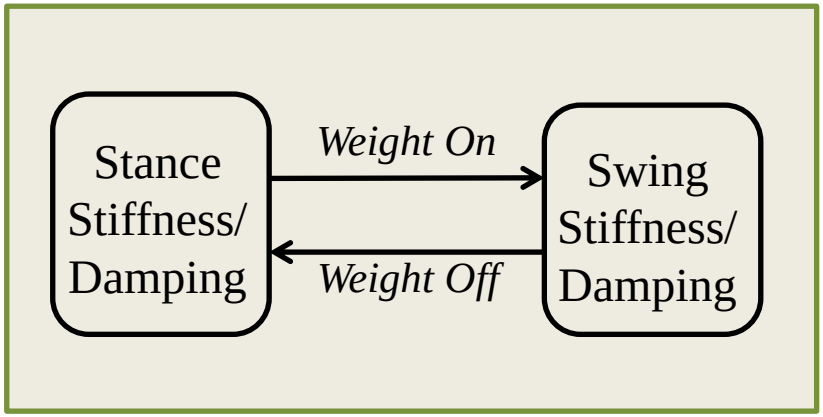
Stair Descent Controller



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 straight-forward to use mechanical sensors to *naturally* transition between activities.

Stair Ascent Controller

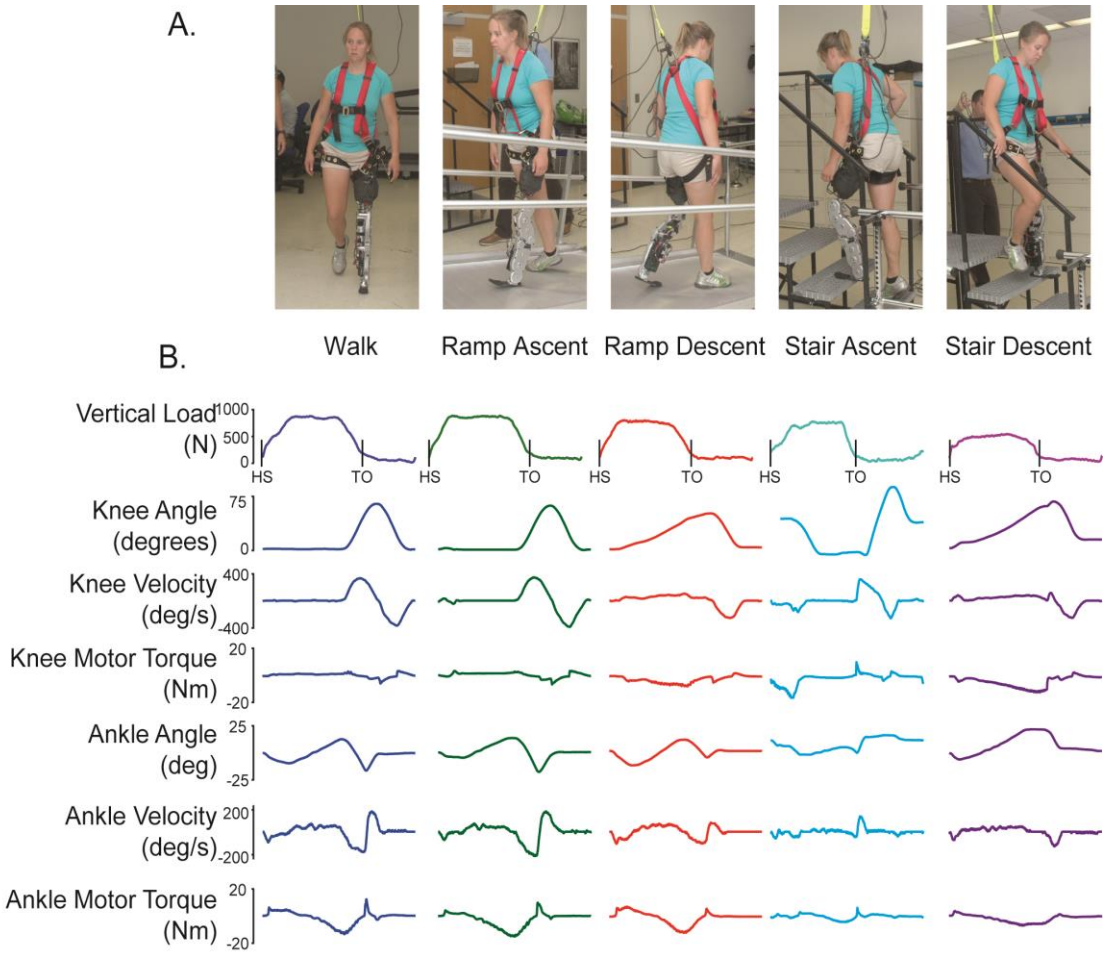


Activity Mode Estimation

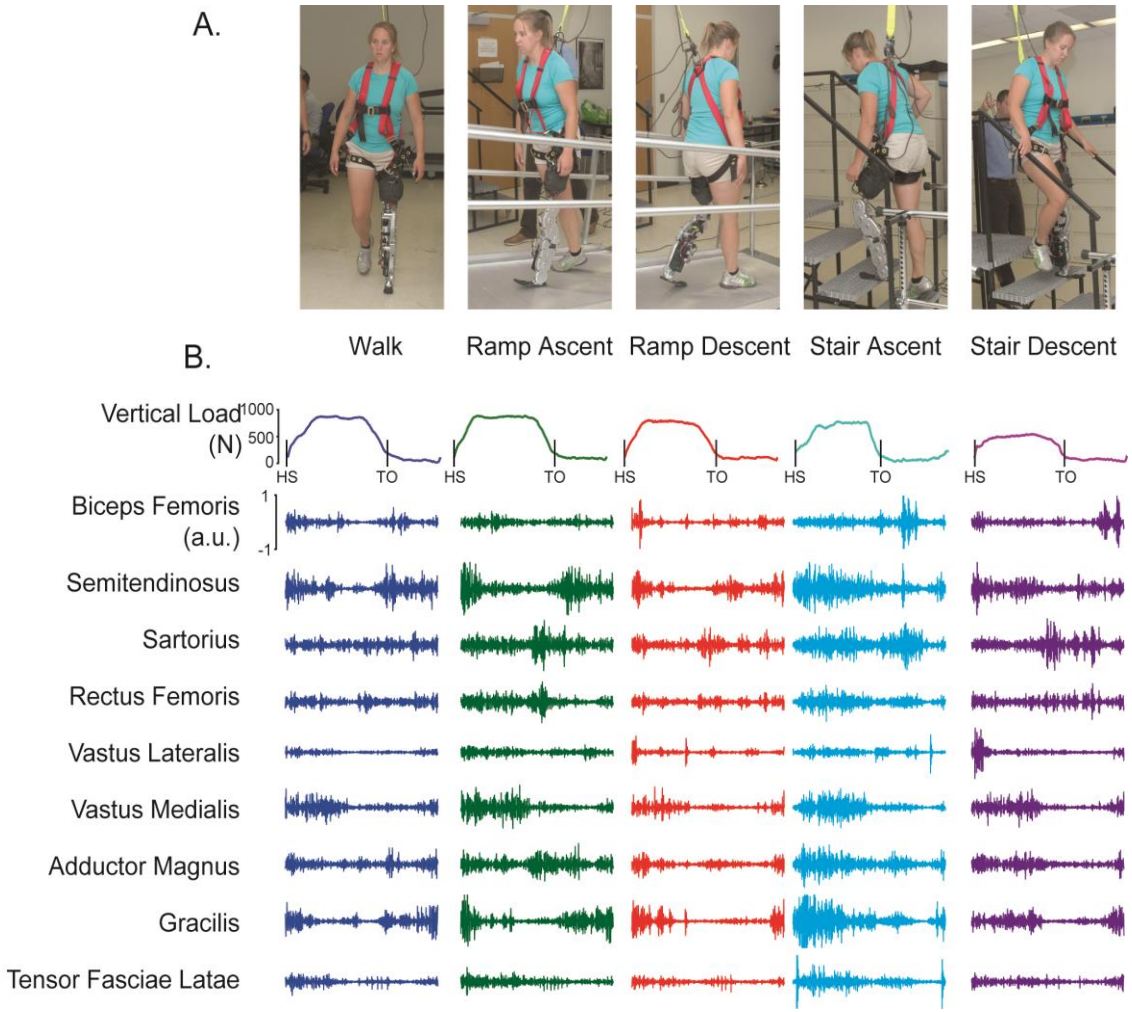
Approaches used to Select Ambulation Activities

- 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

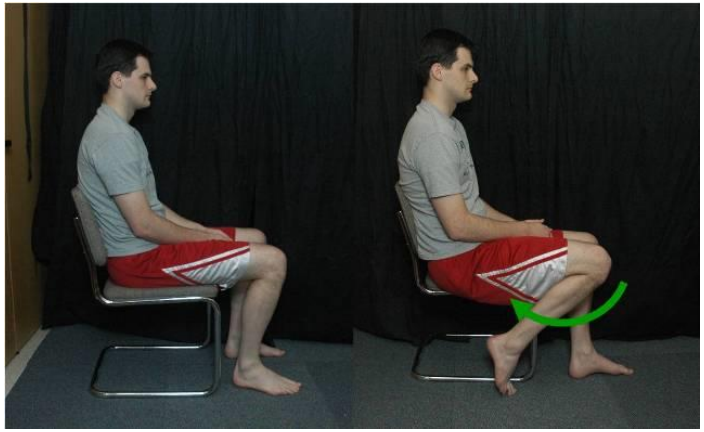


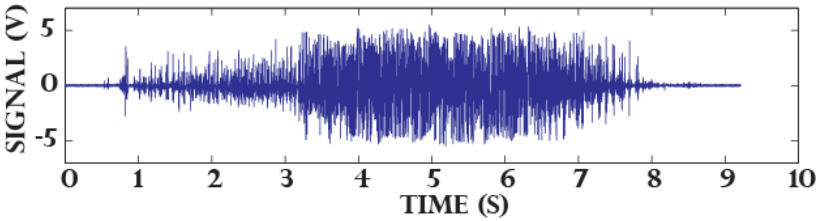
EMG Signal Patterns



Lower Limb EMG

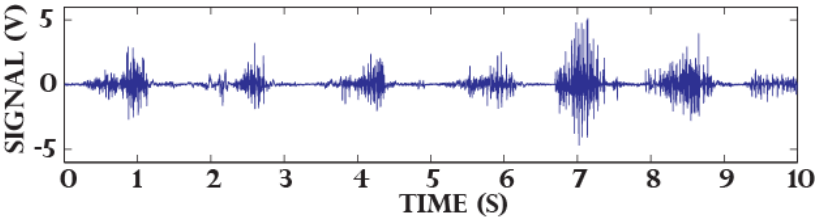
Non-Weight-Bearing Task
"Knee Flexion"





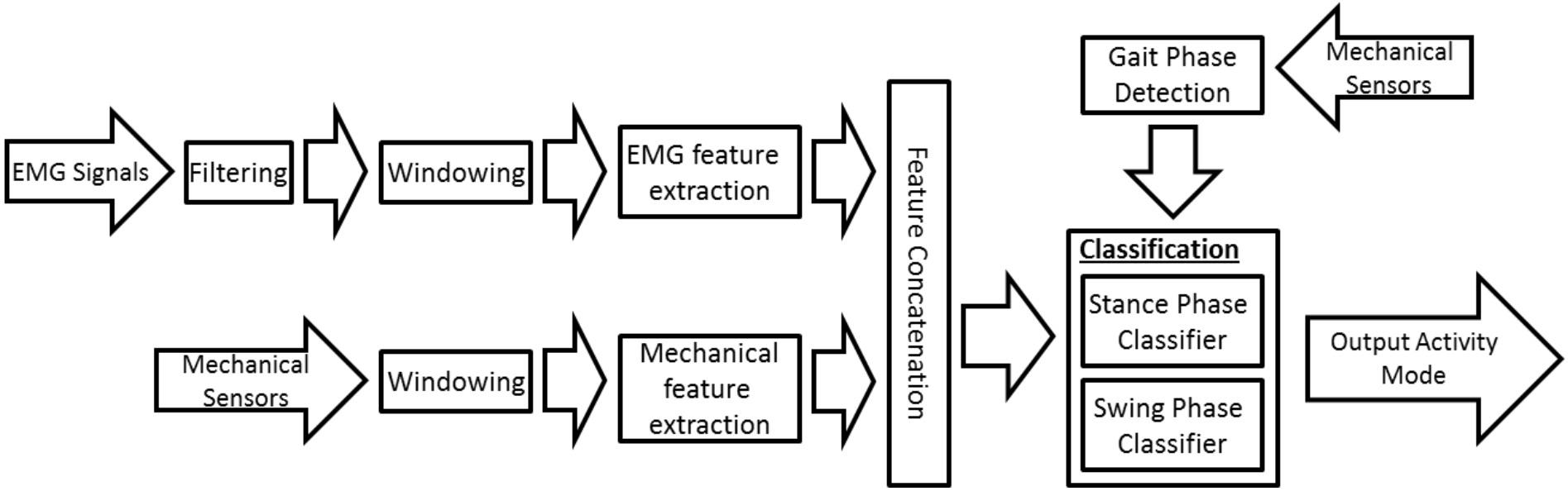
- 'Constant' amplitude within a task
- Suitable for pattern recognition

Ambulation Task:
"Walking"



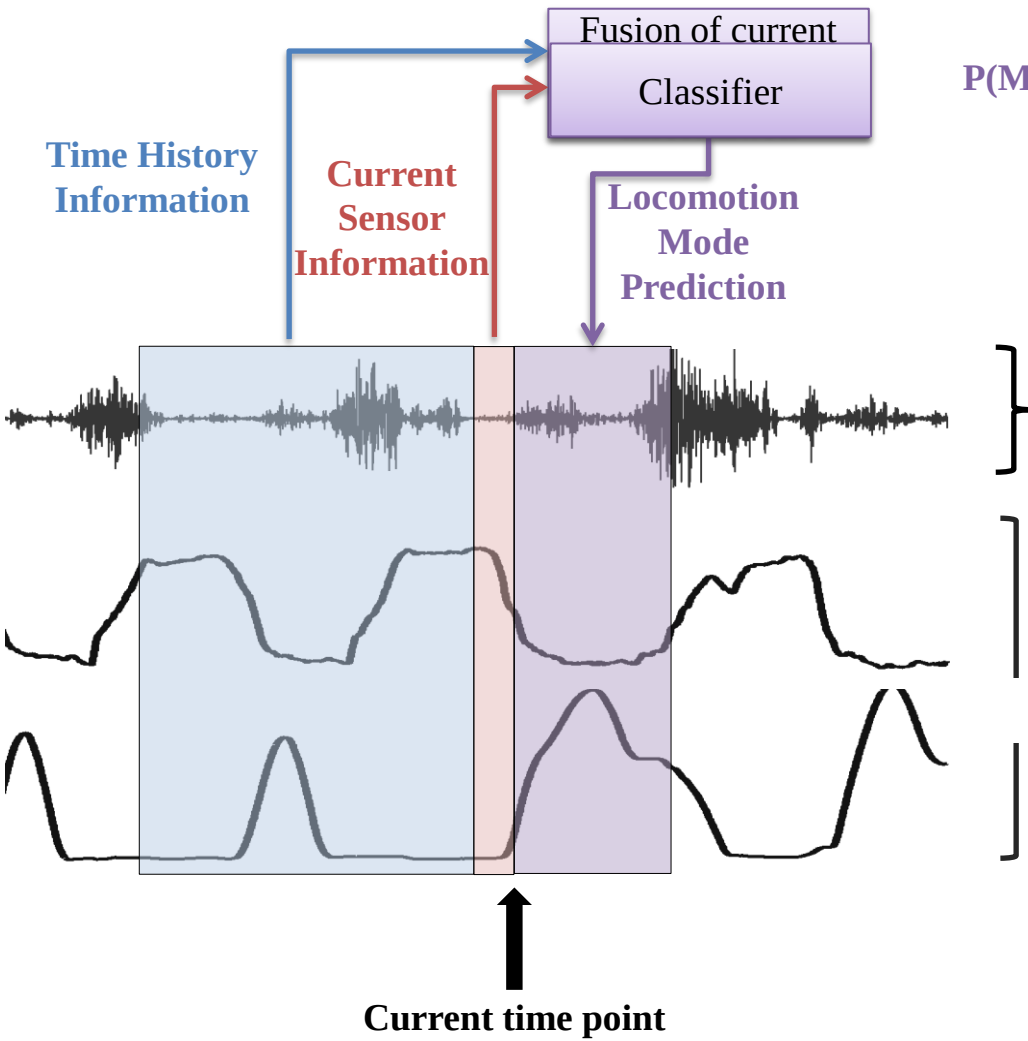
- Time-varying and quasi-cyclic within one task
- Signals are very 'noisy'

Phase Based Classification



Helen Huang
NC State

Classification Method with Time History Information



Bayes Law

P(Mode | Sensors) = n * P(Sensors | Mode) * P(Mode)

- P(Mode | Sensors) → Posterior Probability
- P(Sensors | Mode) → Sensor Model (Current)
- P(Mode) → Prior Probability (Time History)

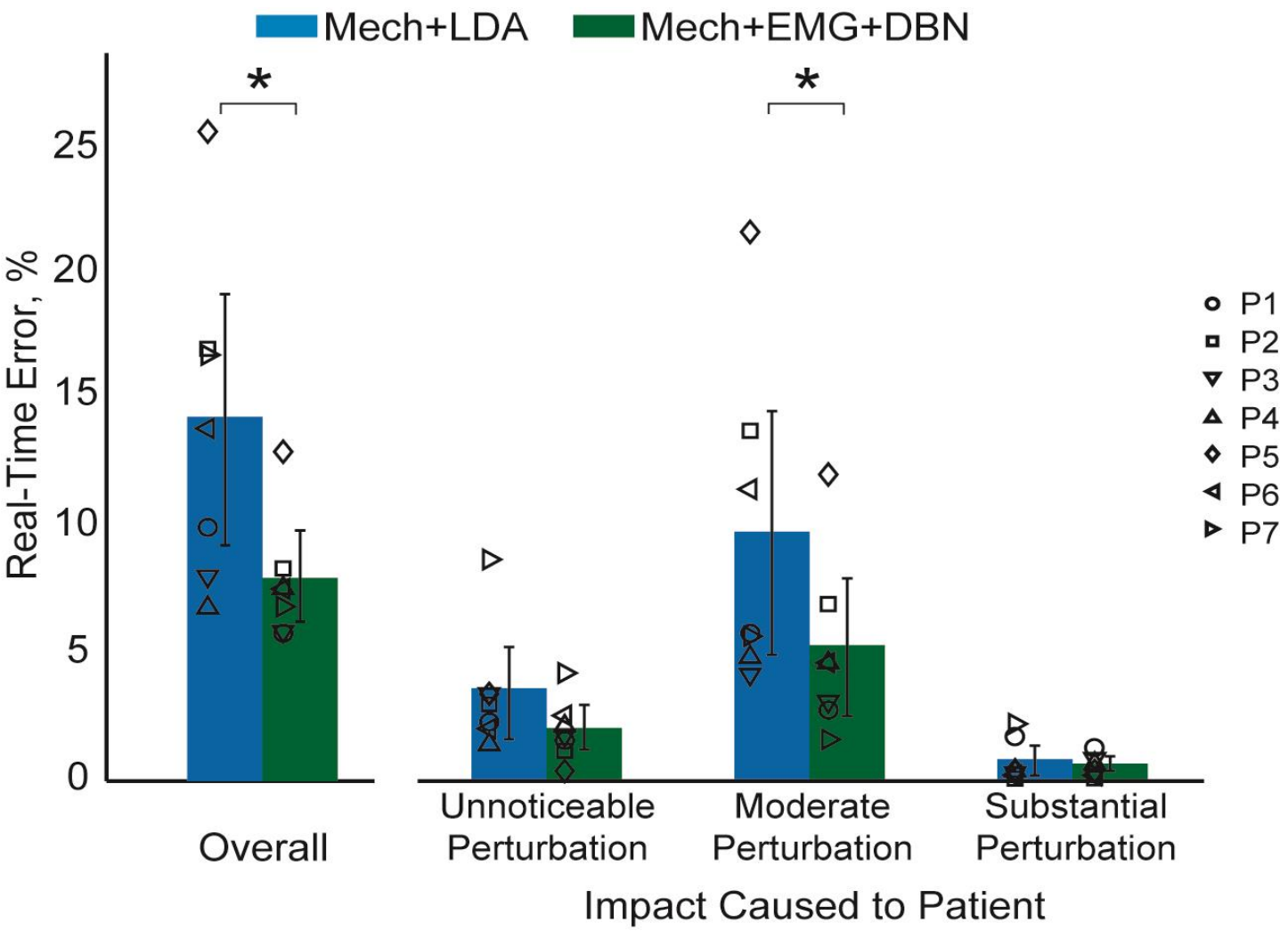
Propagation of Time History

Prior = Posterior * Transitional Probability Matrix

Aaron Young


Native Muscles
Reinnervated Muscles
4
3
2
1
0
-1
-2
-3
-4
5s
4s
3s
2s
1s
0s

Online Classification



‘Transitional’ Error

‘Steady-State’ Error

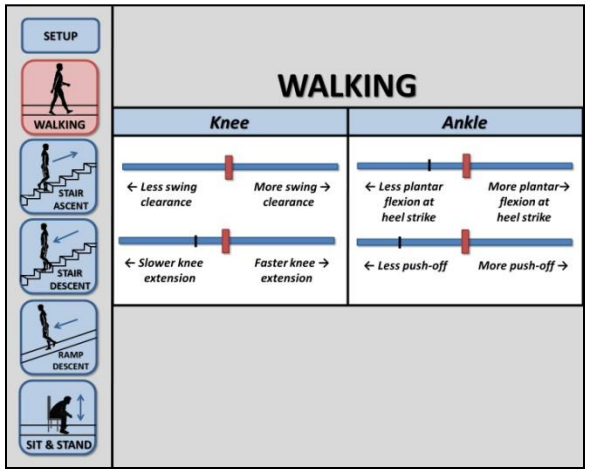
Long Duration Use

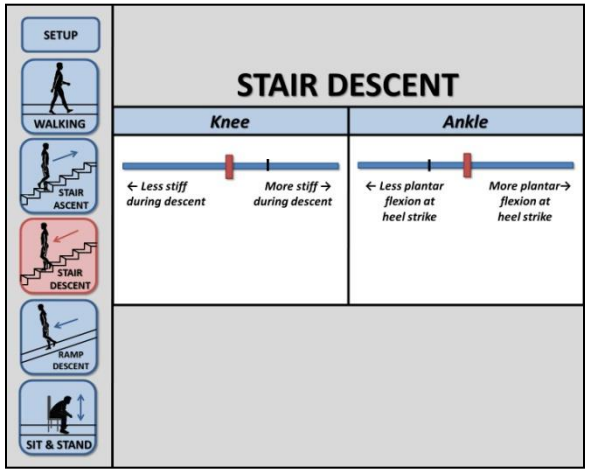
Clinical Calibration Considerations

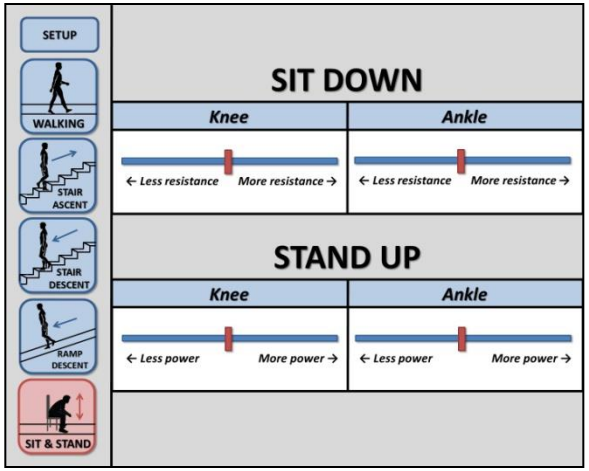
- Experience tuning powered knee and ankle prosthesis for:
  - Level ground walking
  - Ramp ascent and descent
  - Stair ascent and descent
  - Sit-to-stand and Stand-to-sit
- 85% reduction in tuning parameters
  - Developed impedance parameter functions scalable to body weight, ambulation speed, and 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

This work is supported by:

- US Army's Telemedicine and Advanced Technology Research Center
  - Grant number 81XWH-09-2-0020

Rehabilitation Institute *of* Chicago