Enhanced Control for a Lower Limb Prosthesis using High- Density Surface Electromyography

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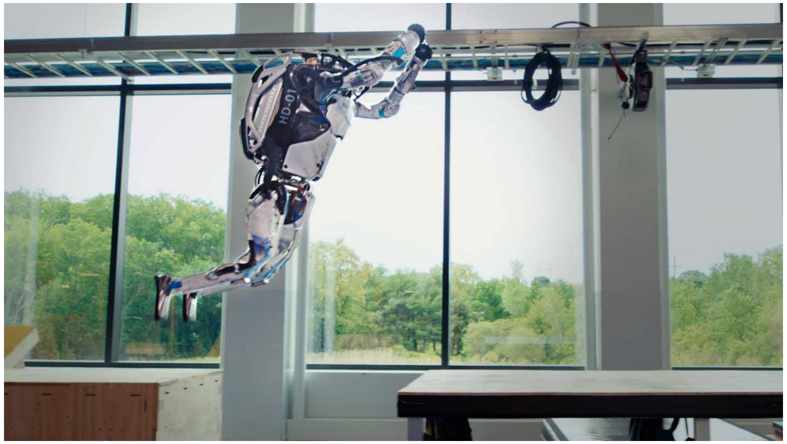
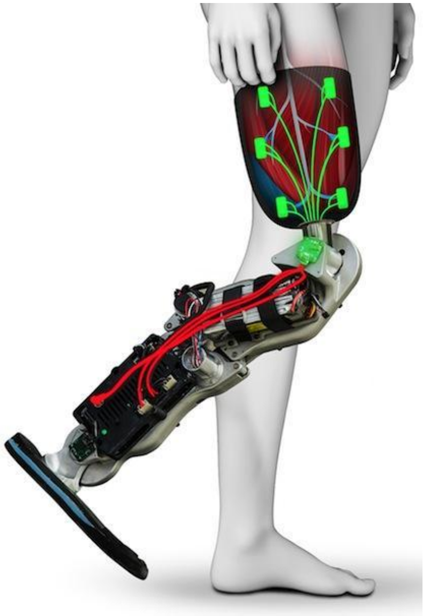
Limb Loss

- Limb loss is a major form of disability currently affecting 2 million Americans, with 159,000 new lower limb amputees each year
- Rehabilitation goal is to restore function and mobility of lost limb
- Multitude of lower limb devices exist with varying levels of function
- Control of devices is currently the limiting factor for high functioning devices

Prosthesis Control

- Control requires communication between the user and device
- Current devices have control that can be difficult in daily use
  - Require direct user input via gestures, buttons, apps, etc
- Seamless and robust control schemes are needed
  - Mode identification and volitional
- Lower limb control requires maximum safety

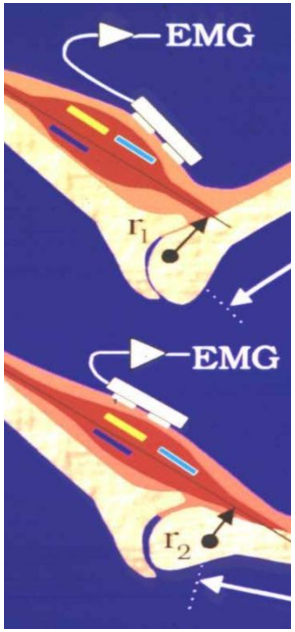




Todd Kuiken
https://www.wired.com/images_blogs/design/2013/10/leg1.jpg

Electromyography

- Control signals from the muscles are ideal to provide control communication
  - Electromyography (EMG) can detect electrical signals from muscle contraction
- Surface EMG (sEMG) takes input from user
  - Zero lag, direct response (Parri, 2017)
  - IMU, Load Cells, Pressure sensors are reactive
- sEMG signals are prone to variance, not robust for control
  - Motion artifact, impedance, daily variation
- Standard sEMG uses a single signal from each muscle group
- HDsEMG can record an array of signals



(Delsys, 2008)

Standard bi-polar sEMG sensor (Top)

HDsEMG array (Bottom).

Hypothesis and Objectives

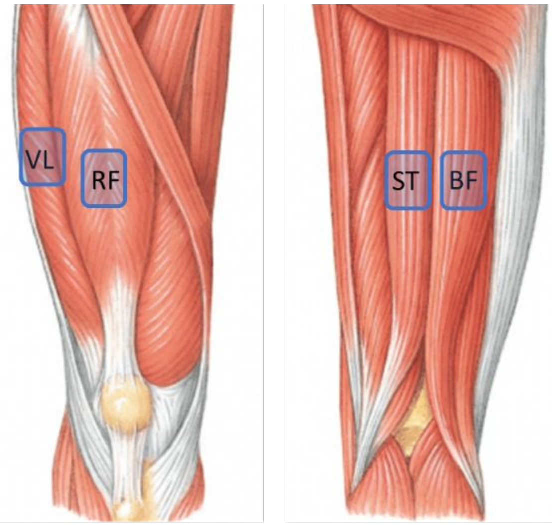
- HDsEMG can be used to provide more robust control signals for lower limb prostheses compared to Standard sEMG

<u>Specifically</u>

- HDsEMG will provide higher quality signals
- HDsEMG will allow for signal compensation due to dislocation
- HDsEMG will provide higher accuracy with Machine Learning to predict activity and intent

Methods

- Human Experimental Protocol
  - 7 Control Participants
  - sEMG on two knee extensors + flexors
- Sensors in two locations
  - Optimal and 1 cm displaced distally
- Activities of daily living
  - Walking, turning, sit-to-stand, stand-to-sit, stairs, ramp, squats



Extensors: Rectus Femoris. Vastus Lateralis

Flexors: Semitendinosus, Bicep Femoris.

Consent+ Initial Setup → ADLs → Adjust sEMG Placement → ADLs → Adjust sEMG Placement → ADLs → Adjust sEMG Placement → ADLs → Done

Signal Quality Measures

- Signal Quality
  - Signal to Noise Ratio (SNR): How clean is the signal
- Signal Strength
  - Root-Mean Square (RMS): How powerful
- Signals Tested
  - Single Standard sEMG
  - Single HDsEMG with highest SNR

(Sinderby, 1995)

Signal Quality Results

- Signal to Noise Ratio (SNR)
  - Standard sEMG = 5.0 ± 2.0 dB
  - HDsEMG = 12.6 ± 2.0 dB
  - Anything higher than 10 dB = clean (Sinderby, 1995)
- Signal Strength (RMS)
  - Standard sEMG = 0.039 ± 0.015
  - HDsEMG = 0.019 ± 0.011

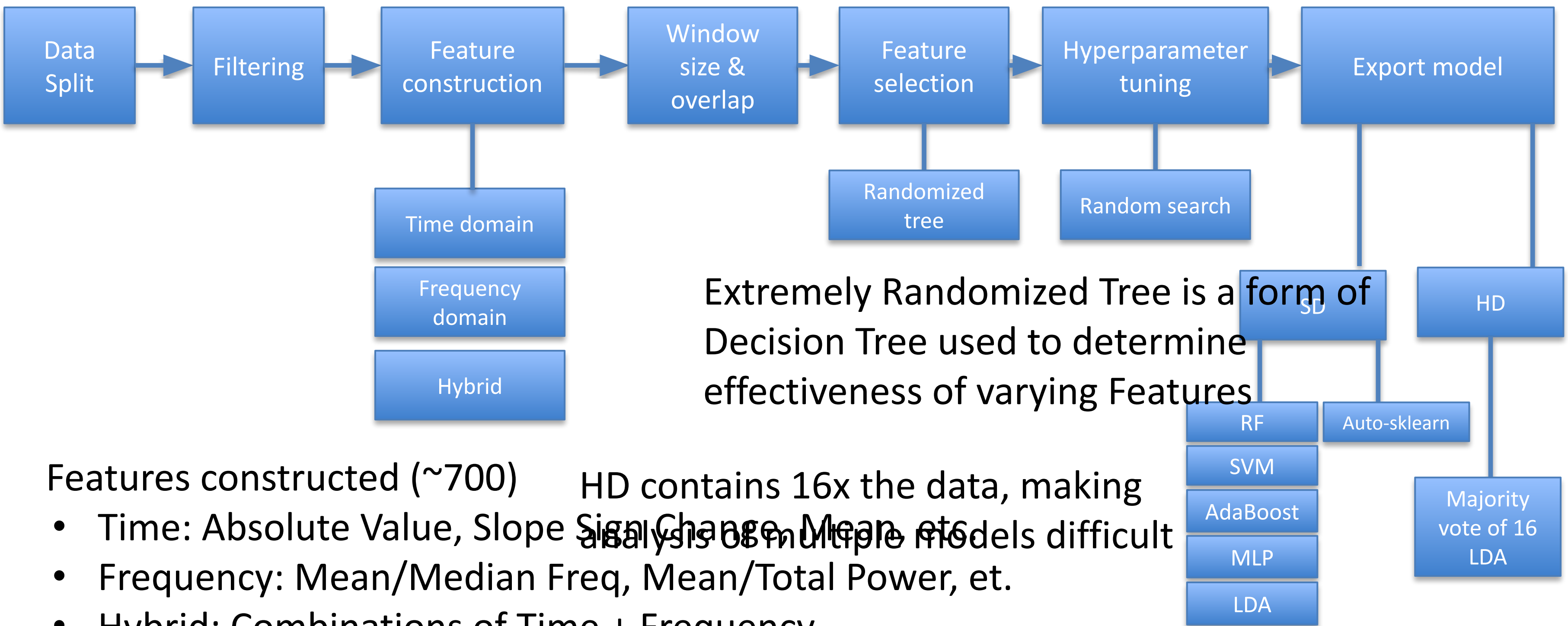
Machine Learning Data

Data was split into Training and Testing (70/30)

A moving average filter was applied to reduce noise

Window was set to 480 samples with overlap of 470 samples
Corresponded with average stride time

Gamma, Kernal Type, Learning Rate, Hidden Layer Size



Extremely Randomized Tree is a form of Decision Tree used to determine effectiveness of varying Features

Features constructed (~700)

- Time: Absolute Value, Slope Sign Change, Mean, etc.
- Frequency: Mean/Median Freq, Mean/Total Power, et.
- Hybrid: Combinations of Time + Frequency

HD contains 16x the data, making analysis of multiple models difficult

Final models were compared 3-fold cross-validation

McNamar Tests indicated significance between models

Results

Outcomes from Single Subject

	SDsEMG		HDsEMG	
Sensor Placement	**Optimal**	**Displaced**	**Optimal**	**Displaced**
Accuracy	68%	70%	67%	62%
Sample Count	37	37	33	26
Final Model	Random Forest	Auto-SKLearn	Linear Discriminant Analysis	Linear Discriminant Analysis

- Accuracy= $\frac{\#\, Correct\ Classifications}{Total\ \#\, Windows\ Classified}$
- Sample Count is the number of Windows for each data set
- Final Model is the Classifier chosen

Significance and Conclusion

- Quality and Strength
  - HDsEMG is higher quality with lower strength than SDsEMG
- Machine Learning
  - Accuracy for predicting activity is currently being evaluated
  - Single subject shows little change in accuracy
- More work is needed to determine optimal method for utilizing HDsEMG content

Questions?

Thank you to Mojtaba Mohasel and Fred Christensen.
This work represents the goals of their graduate work at MSU

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