Human Muscle Force Modeling for Enhanced Assistive Device Control

Laura Hallock
Ruzena Bajcsy
BAIR/CPAR/BDD Internal Weekly Seminar
2018.10.26

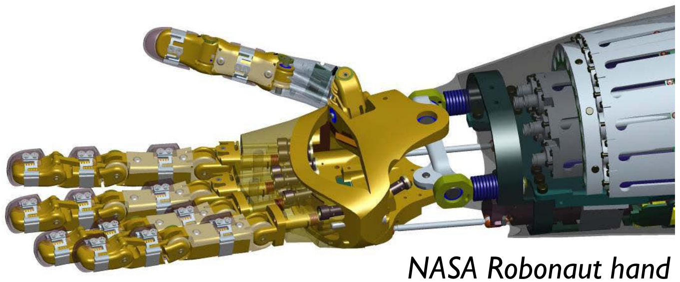
HART Lab
Human-Assistive Robotic Technologies

Berkeley
UNIVERSITY OF CALIFORNIA

Why model musculoskeletal dynamics?

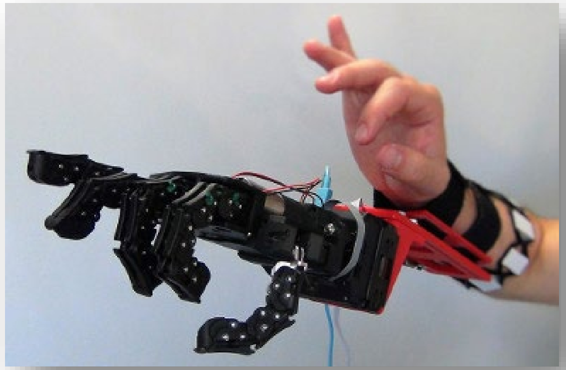
There are many **mechanically** sophisticated, biomimetic devices on the market . . .

UW "Highly Biomimetic Anthropomorphic Robotic Hand"

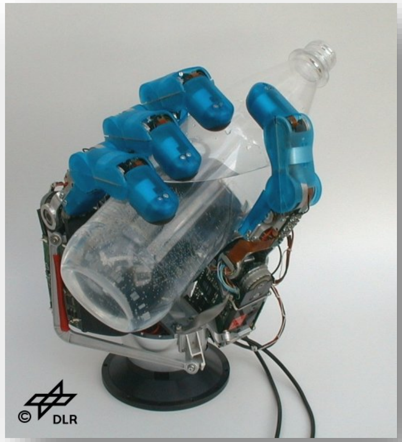


NASA Robonaut hand

Ottobock Bebionic hand



PISA-IIT Softhand

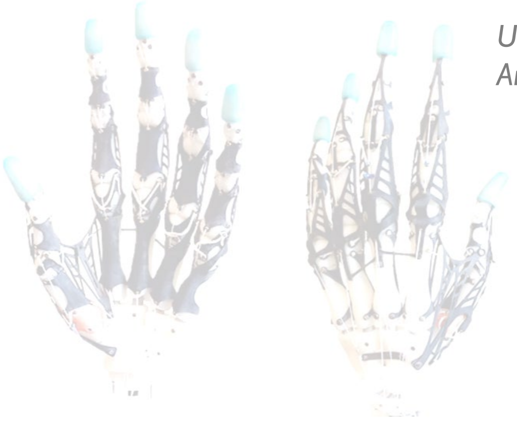


DLR Hand II

Gifu Hand III

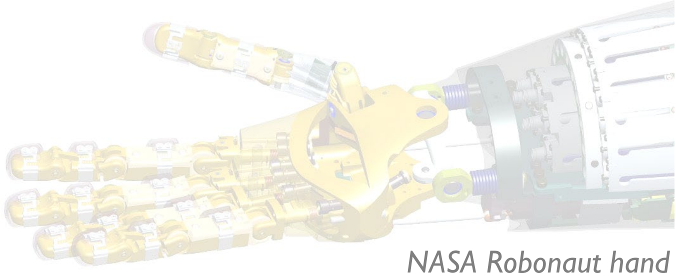
Why model musculoskeletal dynamics?

There are many **mechanically** sophisticated, biomimetic devices on the market . . .

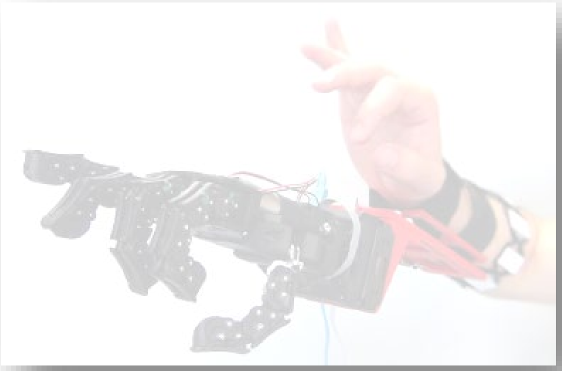


UW "Highly Biomimetic Anthropomorphic Robotic Hand"

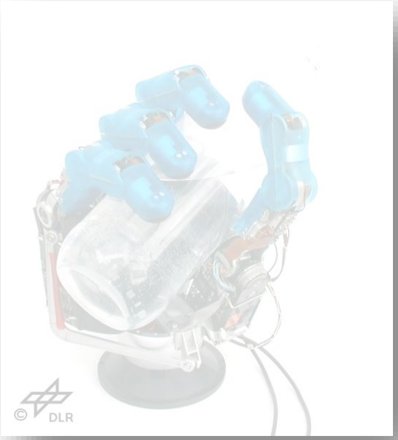
Ottobock Bebionic hand



NASA Robonaut hand



PISA-IIT Softhand



DLR Hand II

Gifu Hand III

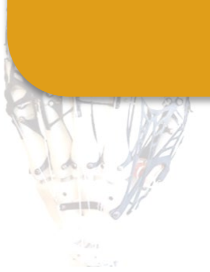
. . . but we don't know how to **control** them.

Why model musculoskeletal dynamics?

There are m

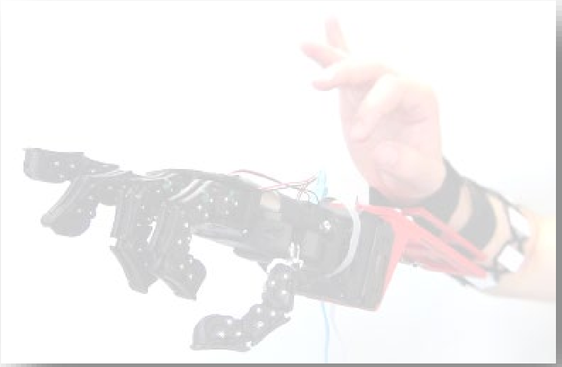
CHALLENGE

How can a human user control **many degrees of freedom**?

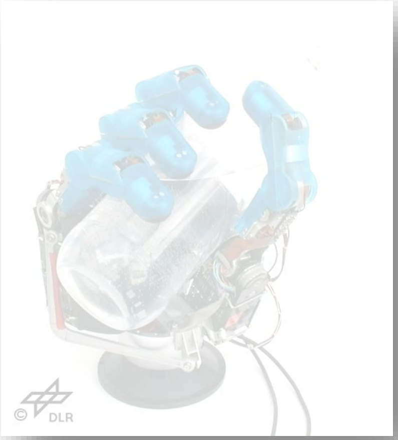


NASA Robonaut hand

Ottobock Bebionic hand



PISA-IIT Softhand



DLR Hand II

Gifu Hand III

. . . but we don't know how to **control** them.

Berkeley
UNIVERSITY OF CALIFORNIA

Why model musculoskeletal dynamics?

There are m

CHALLENGE

How can a human user control **many degrees of freedom**?

NASA Robonaut hand

KEY IDEA

If we can **measure the output force of each muscle**, we should be able to **control an external device of the same complexity**.

Gifu Hand III

PISA-IIT Softhand

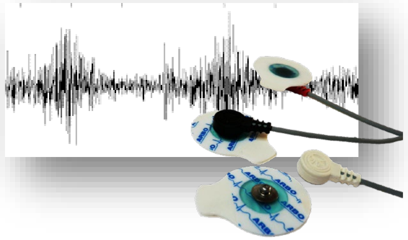
. . . but we don't know how to **control** them.

Muscle Force Inference: State-of-the-Art

Neurological Activation

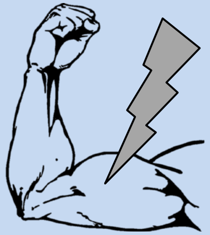
a

via ***electro-myography (EMG)***



Contraction Dynamics

$f(\cdot)$

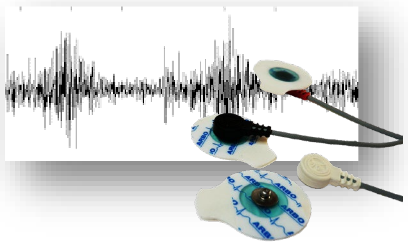


Muscle Output Force

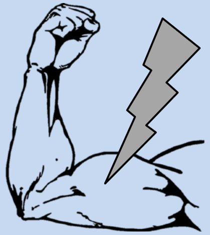
$F_m = f(a)$

Muscle Force Inference: State-of-the-Art

Neurological Activation
a
via ***electro-myography (EMG)***



Contraction Dynamics
$f(\cdot)$

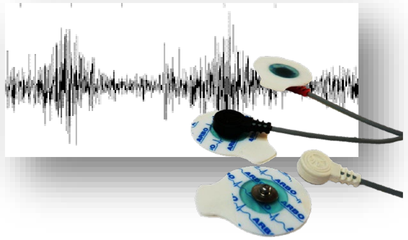


Muscle Output Force
$F_m = f(a)$

EMG is:
- noisy
- sensitive to electrode placement
- aggregate
- based on neurological signals (neurological disorder → poor signal)

Muscle Force Inference

Neurological Activation
a
via ***electro-myography (EMG)***



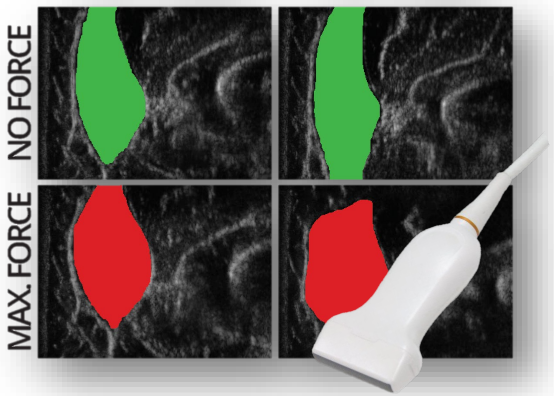
Contraction Dynamics
$f(\cdot)$

Muscle Output Force
$F_m = f(a)$

Deformation Dynamics
$g(\cdot)$

Muscle Deformation
$D = g(F_m)$

$\theta = 25°$ $\theta = 69°$



via ***ultrasound***

Vibration Dynamics
$h(\cdot)$

Muscle Vibration
$V = h(F_m)$

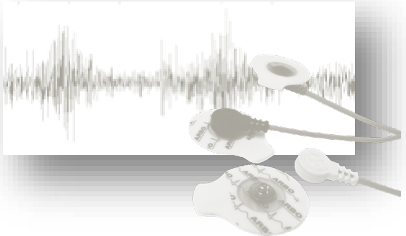
via ***acoustic myography (AMG)***

Muscle Force Inference: Our Approach

Neurological Activation

a

via ***electro-myography (EMG)***



Contraction Dynamics

$f(\cdot)$

Deformation Dynamics

$g(\cdot)$

Vibration Dynamics

$h(\cdot)$

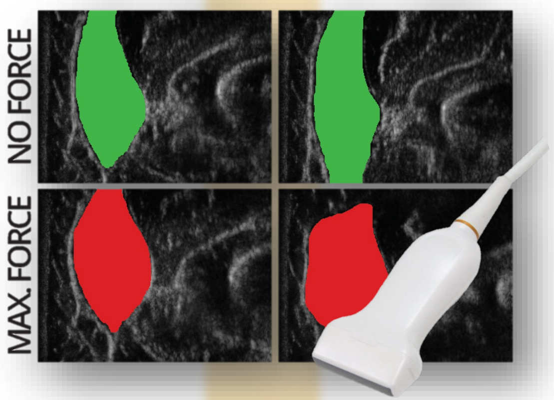
Muscle Output Force

$$F_m = f(a) = g^{-1}(D) = h^{-1}(V)$$

Muscle Deformation

$$D = g(F_m)$$

$\theta = 25°$ $\theta = 69°$



via ***ultrasound***

Muscle Vibration

$$V = h(F_m)$$

via ***acoustic myography (AMG)***

Both deformation and vibration are **mechanical signals**, allowing for measurement of muscle force **without considering the neurological feedback loop**. (Until we want to explicitly study it!)

Muscle Force Inference: Our Approach

Muscle Output Force

$$F_m = f(a) = g^{-1}(D) = h^{-1}(V)$$

Neurological Activation a

via ***electro-myography (EMG)***

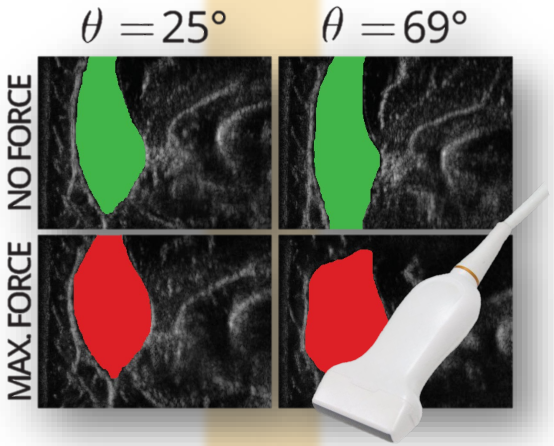
Contraction Dynamics $f(\cdot)$

Deformation Dynamics $g(\cdot)$

Vibration Dynamics $h(\cdot)$

Muscle Deformation

$$D = g(F_m)$$



via ***ultrasound***

Muscle Vibration

$$V = h(F_m)$$

via ***acoustic myography (AMG)***

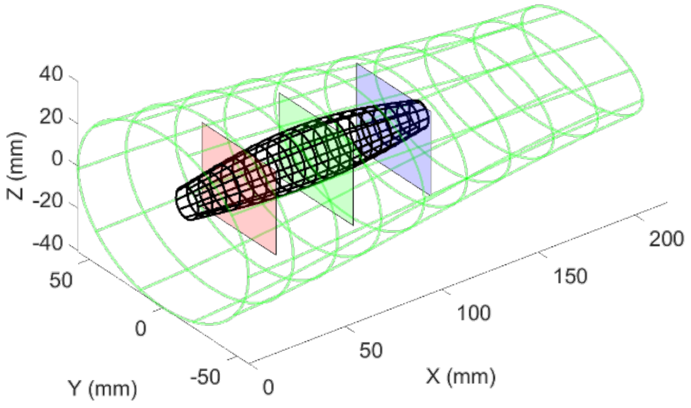
Both deformation and vibration are **mechanical signals**, allowing for measurement of muscle force **without considering the neurological feedback loop**. (Until we want to explicitly study it!)

Deformation signal is **highly localized**!

Deformation Modeling Challenges

1. Observed deformation **varies substantially with sensor location**.

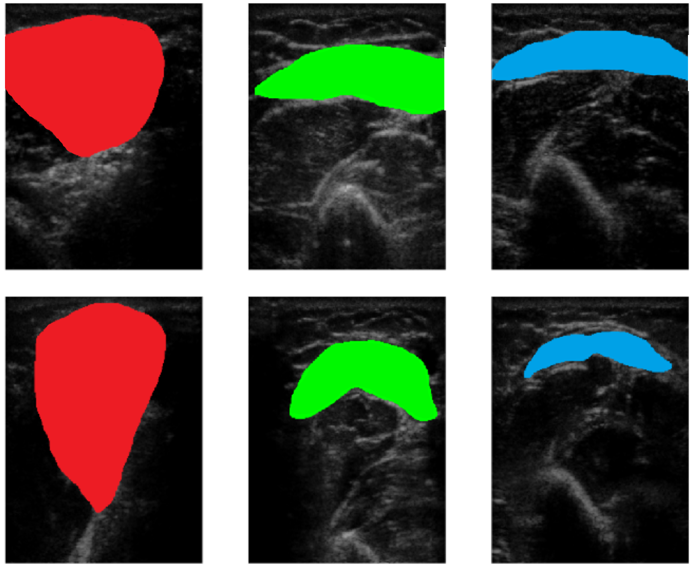
3D View

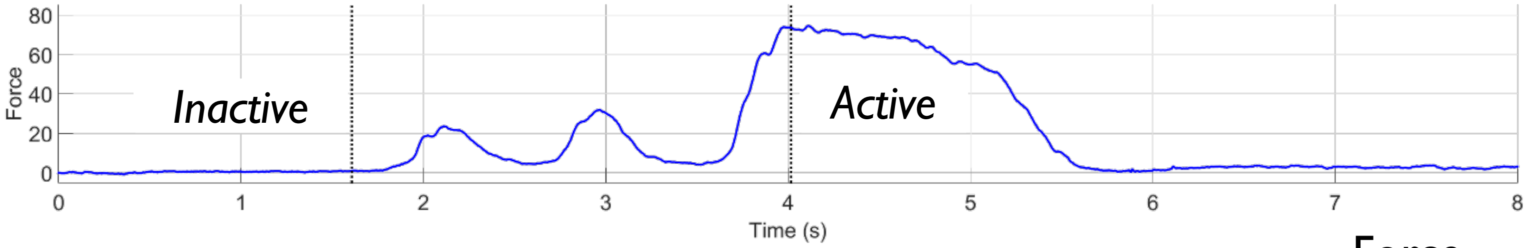


Muscle Cross-Section *(Brachioradialis)*

Inactive

Active



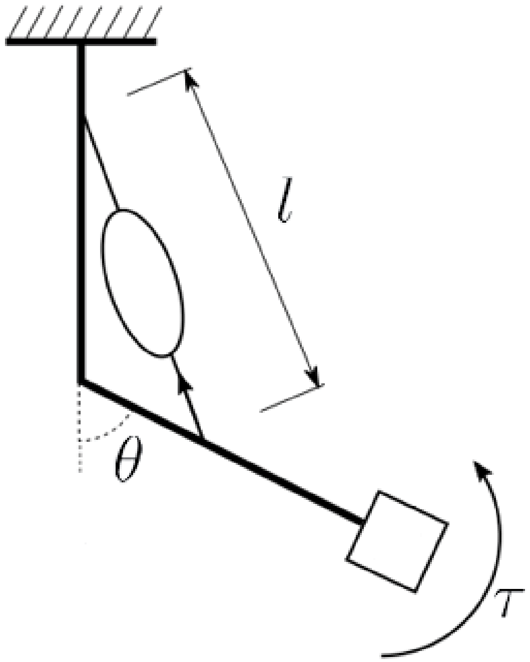


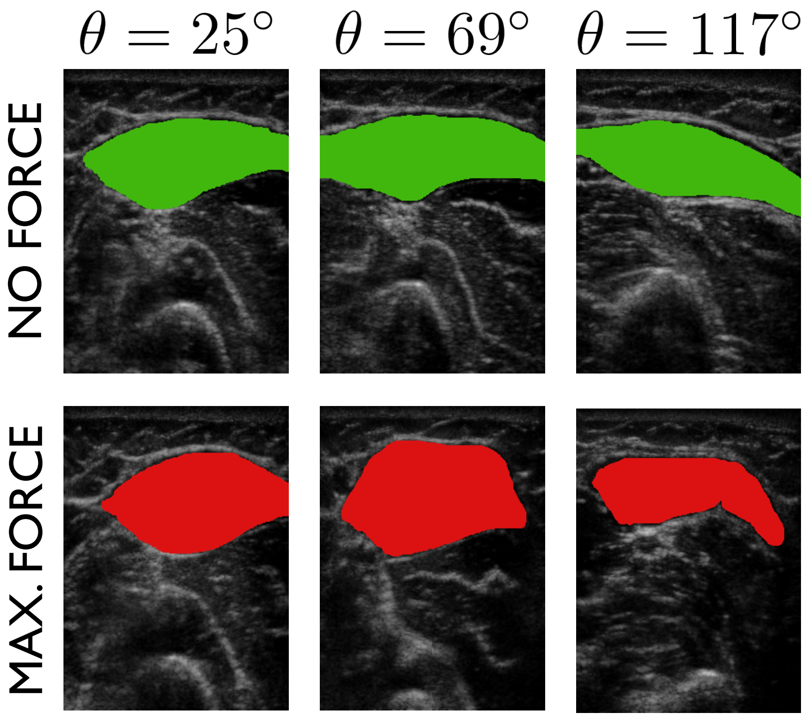
Force

Deformation Modeling Challenges

1. Observed deformation **varies substantially with sensor location**.

2. Deformation occurs under changes in both **kinematic configuration** and **force output**.





Deformation Modeling Challenges

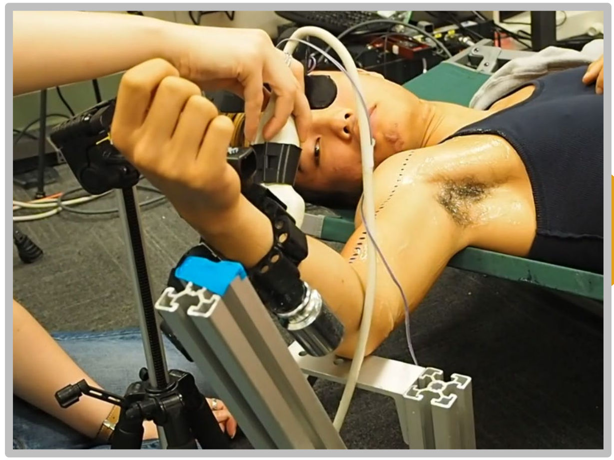
1. Observed deformation **varies substantially with sensor location**.

2. Deformation occurs under changes in both **kinematic configuration** and **force output**.

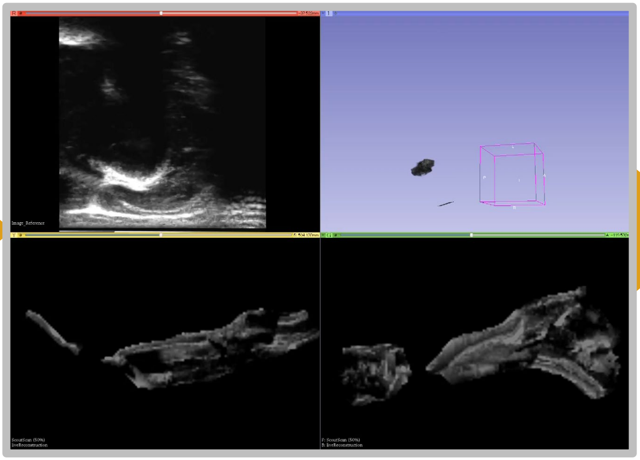
To build a model that can robustly infer muscle force, we need to observe the **entire muscle** under **multiple** (ideally, factorial) **joint positions** and **loading conditions**.

Approach: Ultrasound + Motion Capture

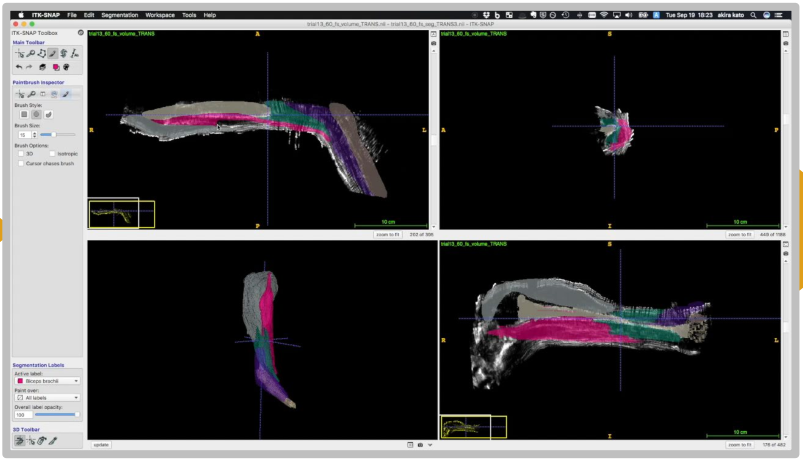
Raw Data Collection
via Ultrasound & Motion Capture



Volumetric Reconstruction
via PLUS Toolkit



Tissue Segmentation
in ITK-SNAP



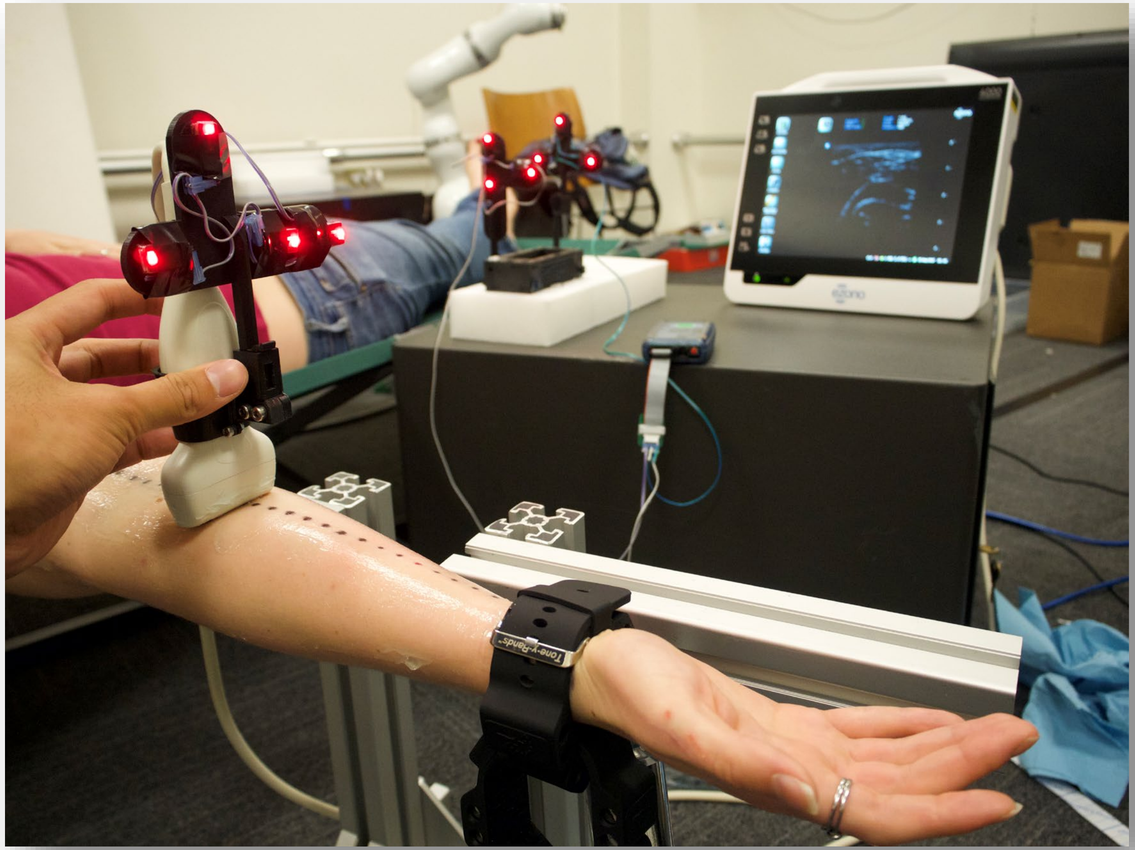
Using **motion capture** to track the **ultrasound probe position**, we can generate **full 3D scans** of the arm under **static conditions**.

Approach: Data Selection

Model target: elbow flexors (*biceps brachii*, *brachialis*, *brachioradialis*)

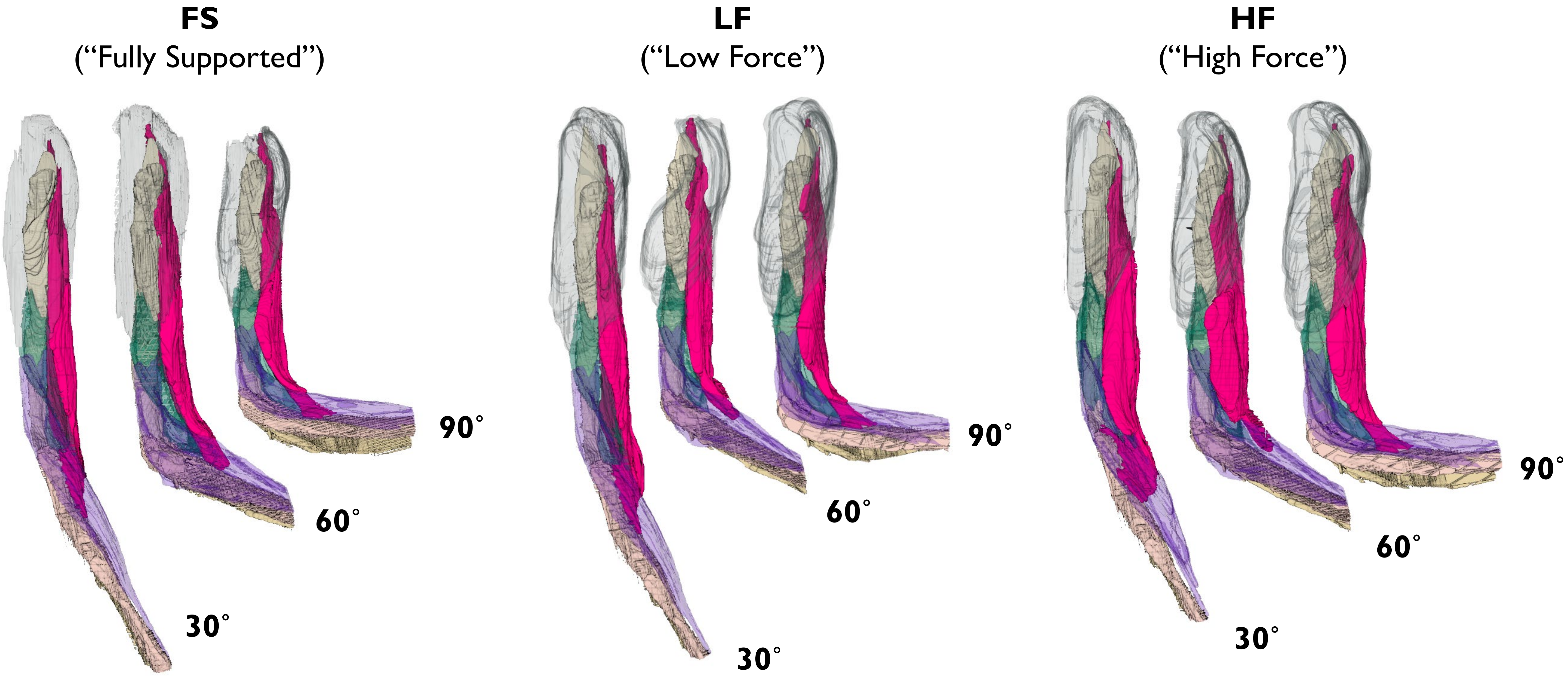
Data set:

- 3 subjects (1 F, 2 M)
- full arm ultrasound volumetric scan
- 4 elbow flexion angles, 0–90°
- 5 loading conditions
  - ***FS***: fully supported
  - ***GC***: gravity compensation only
  - ***LF***: light wrist weight (~225g)
  - ***MF***: medium wrist weight (~725g)
  - ***HF***: heavy wrist weight (~950g)

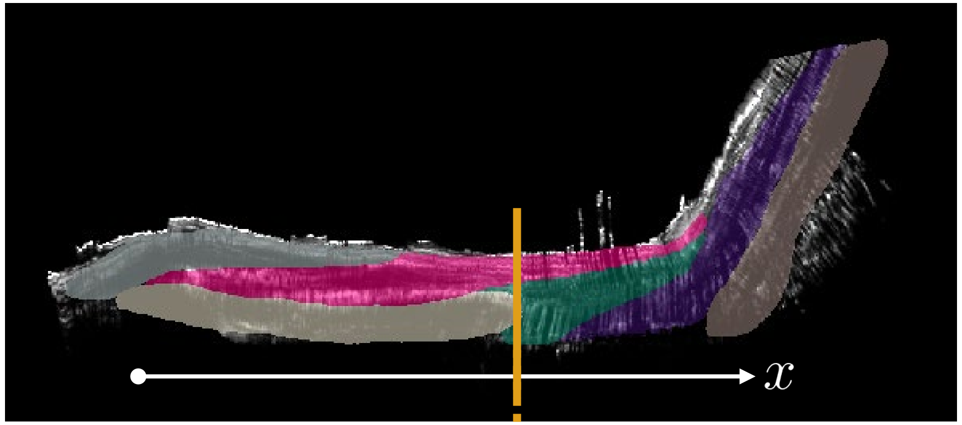


Ultrasound volumetric data collection, HART Lab 2017

Preliminary Results: Qualitative

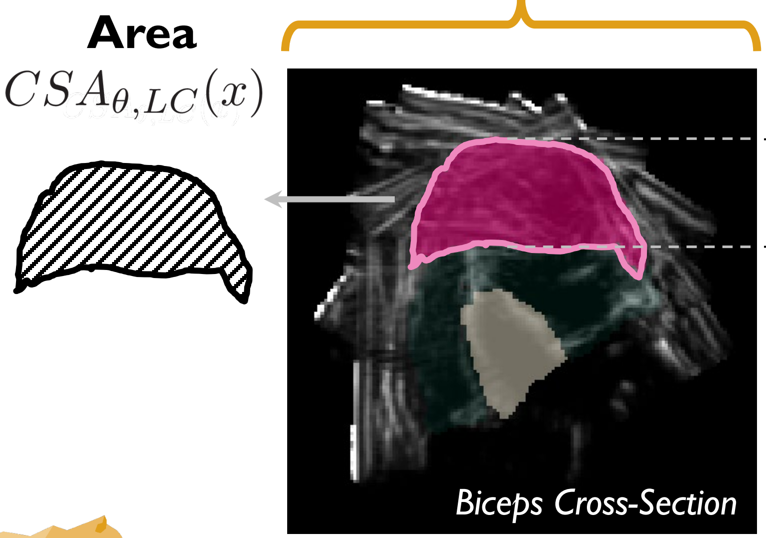


Preliminary Results: Simplest Models



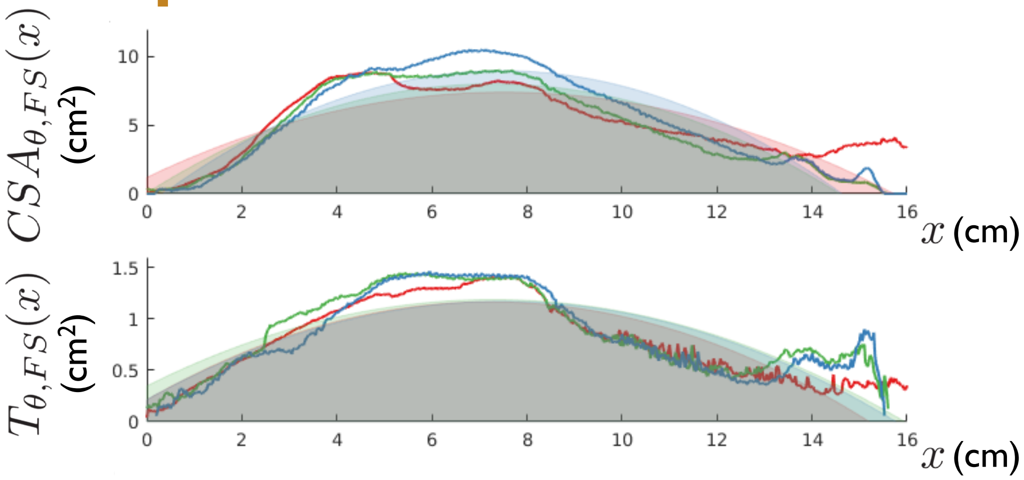
Cross-Sectional Area

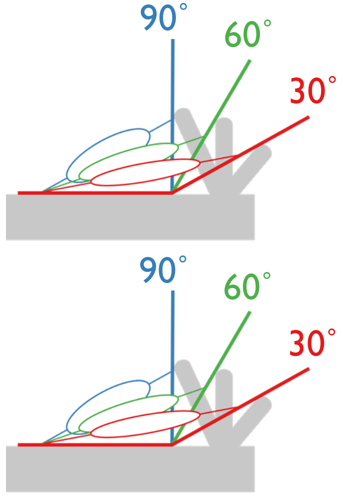
$CSA_{\theta,LC}(x)$



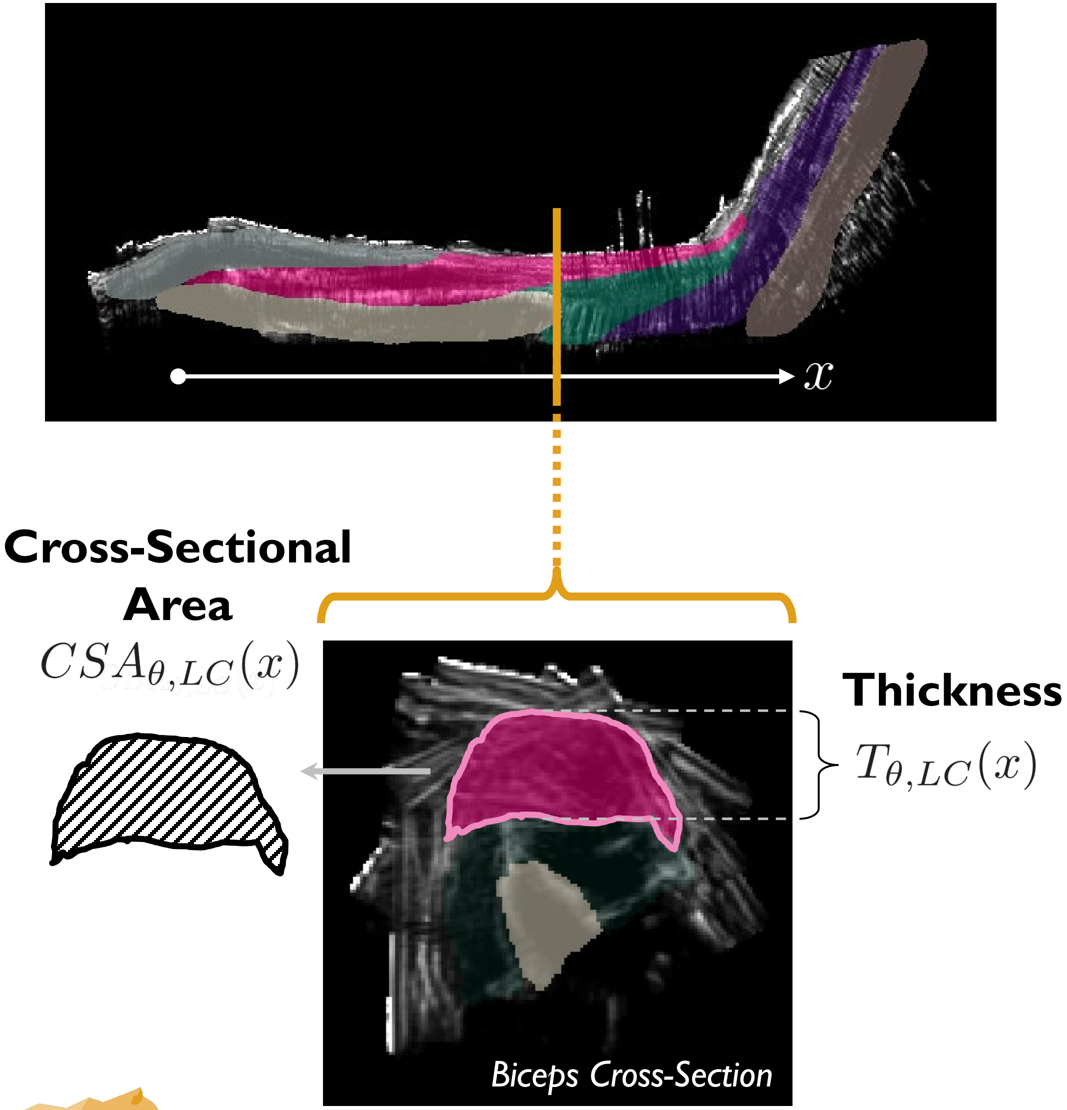
Thickness

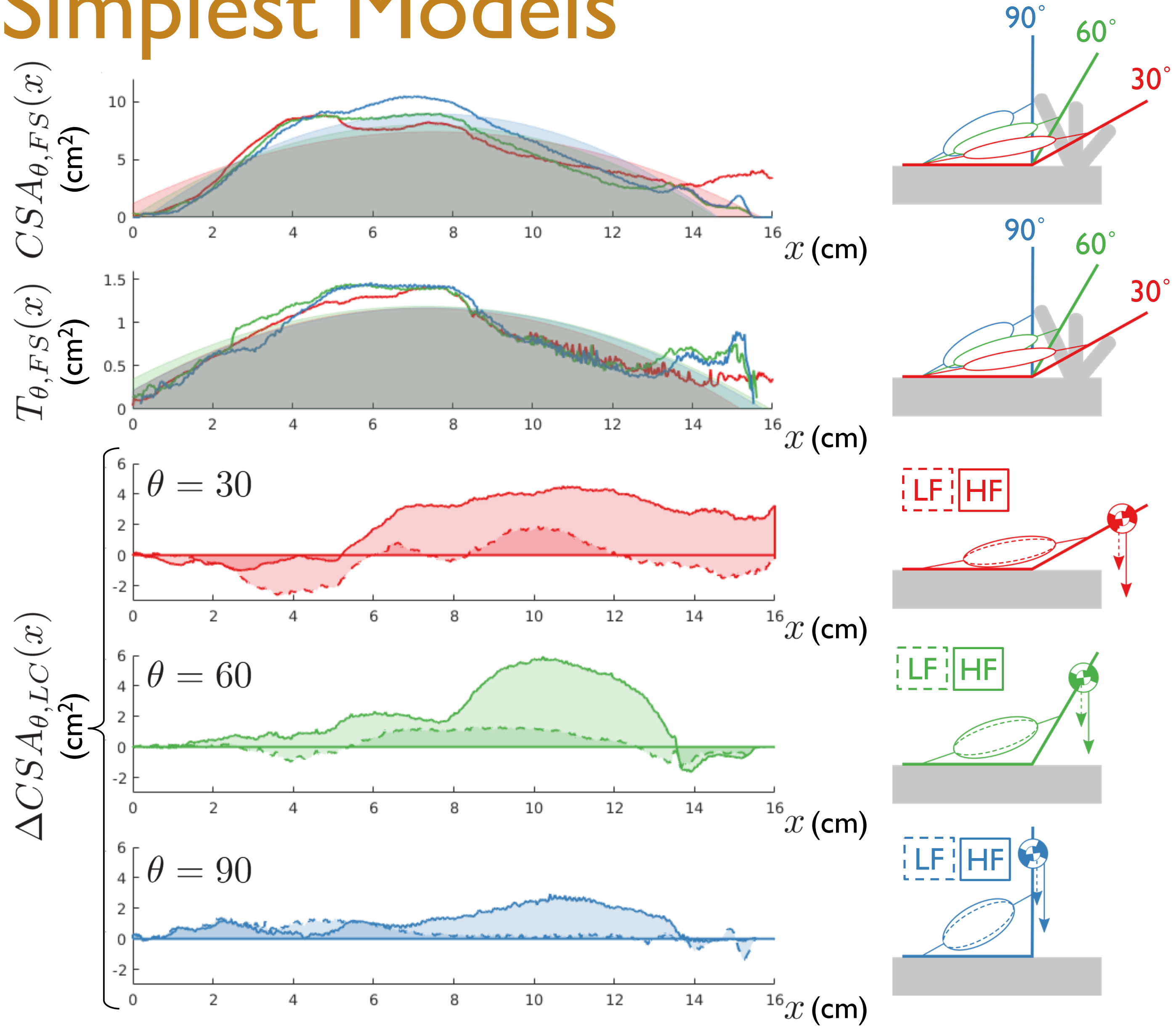
$T_{\theta,LC}(x)$



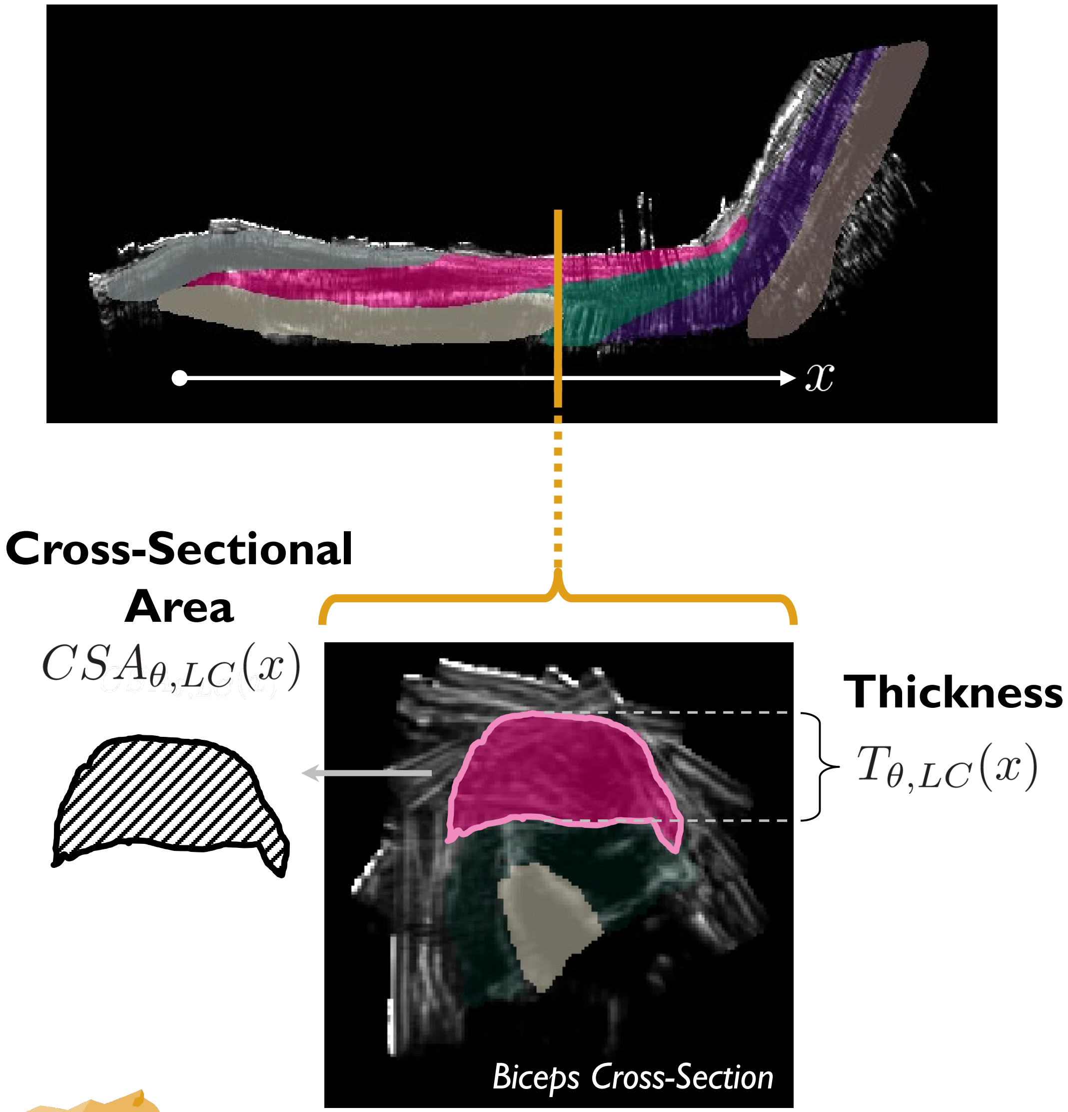


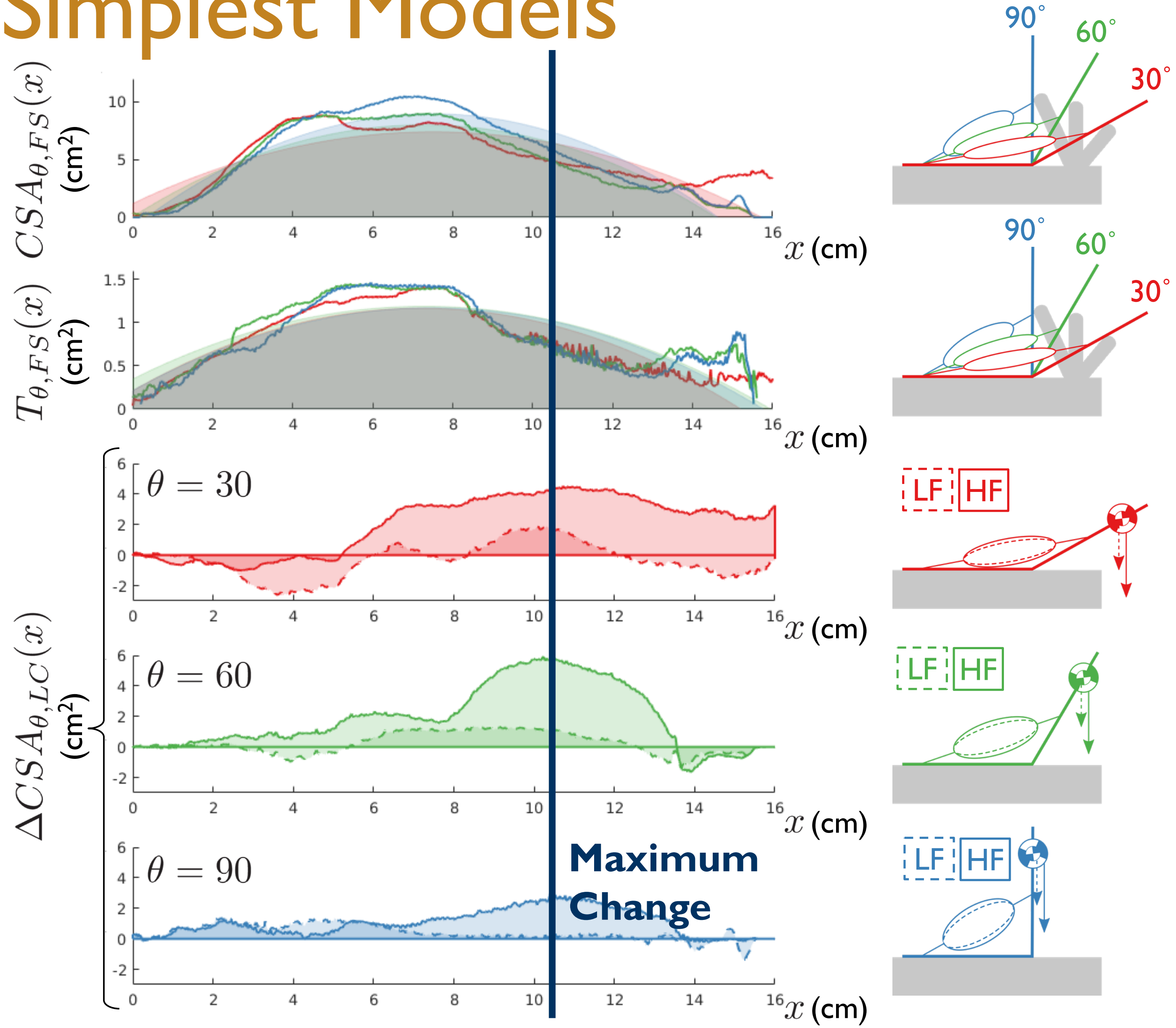
Preliminary Results: Simplest Models



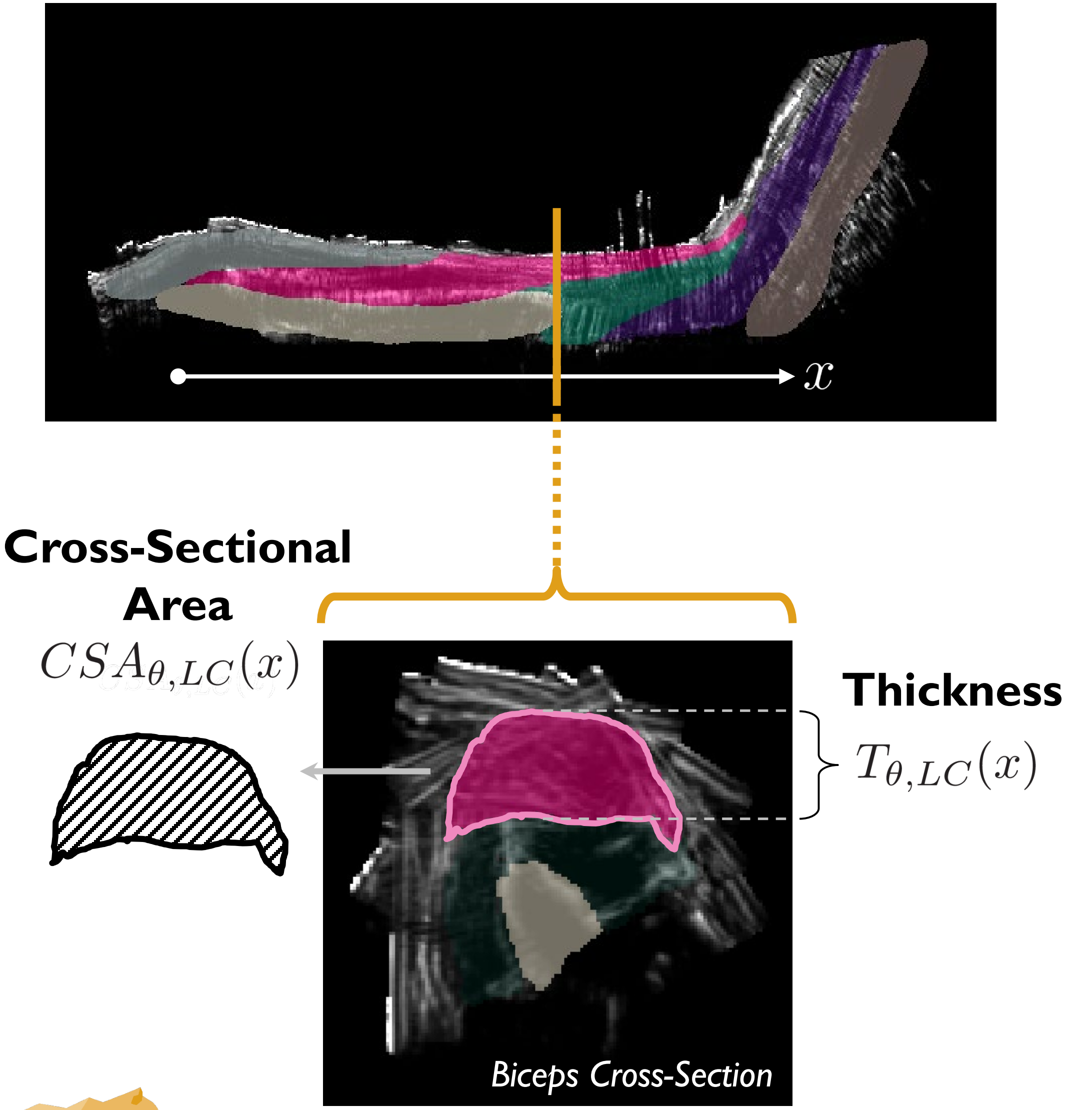


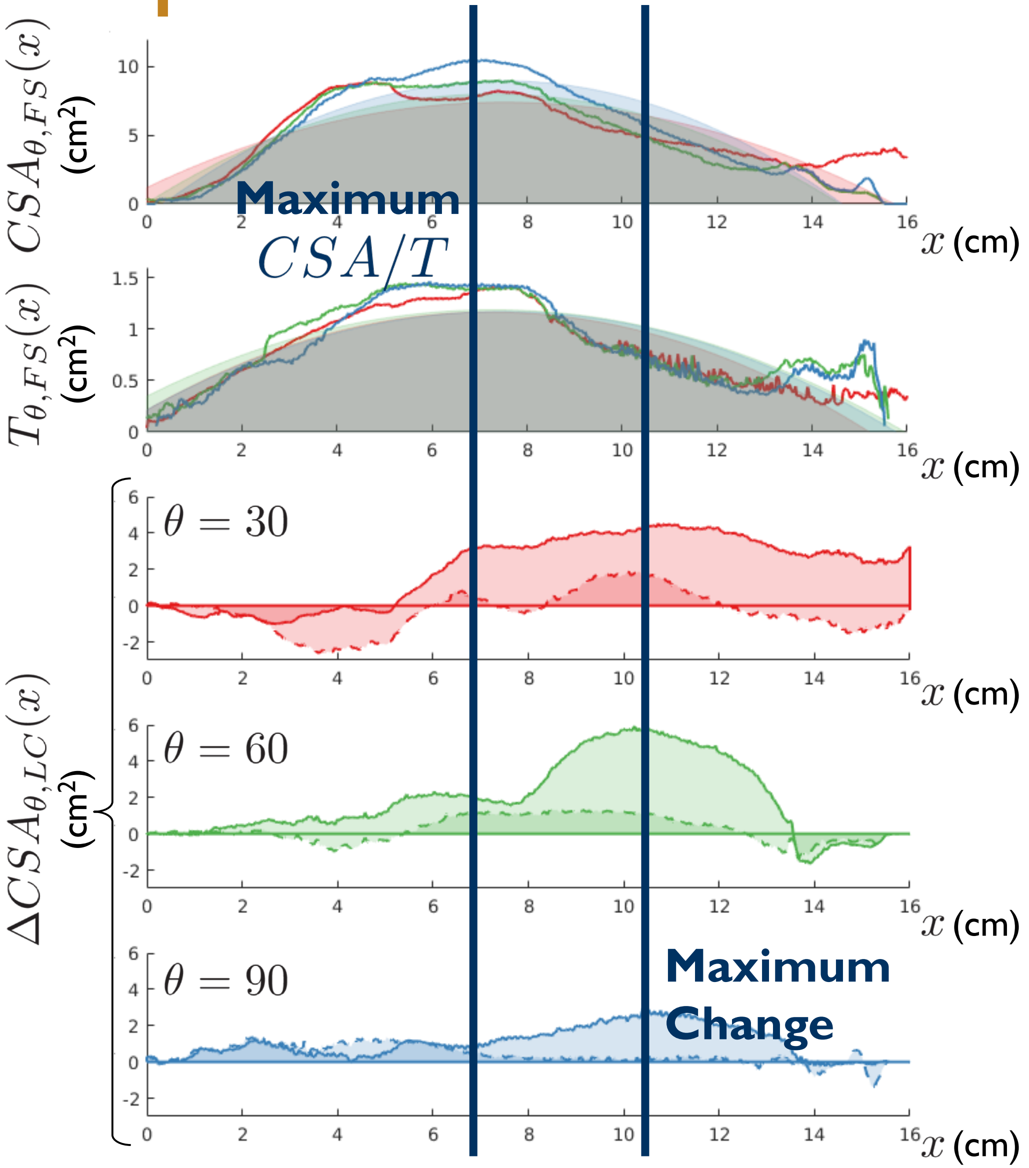
Preliminary Results: Simplest Models

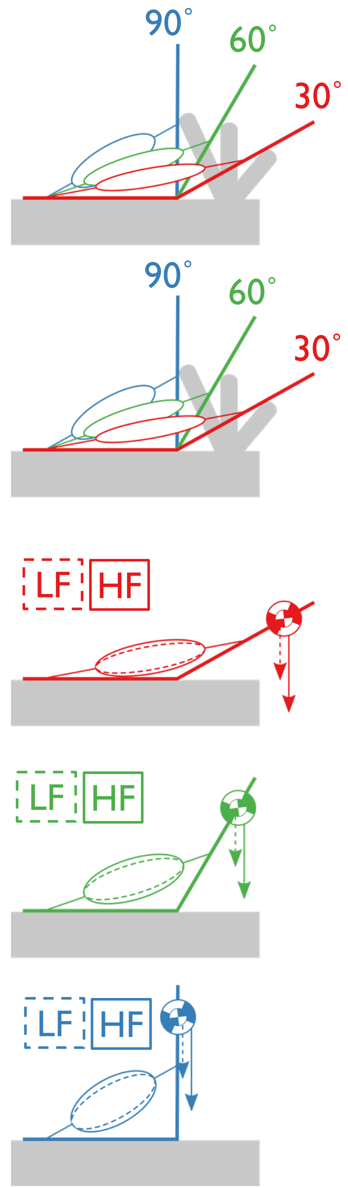




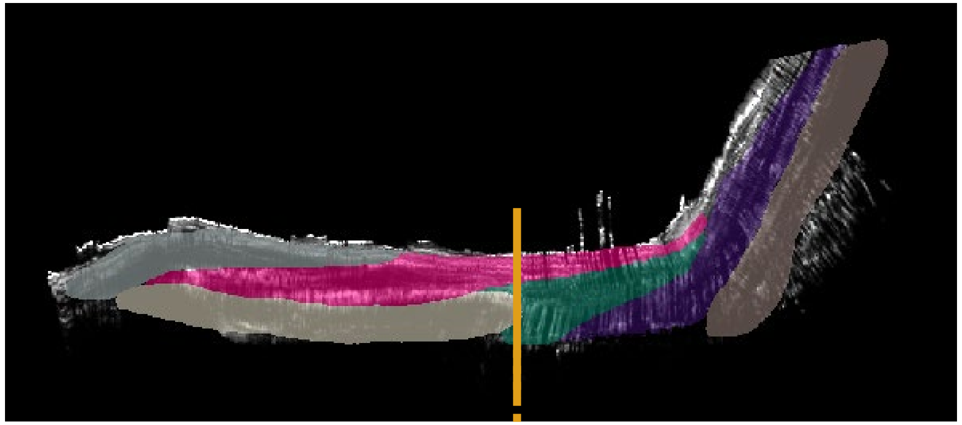
Preliminary Results: Simplest Models





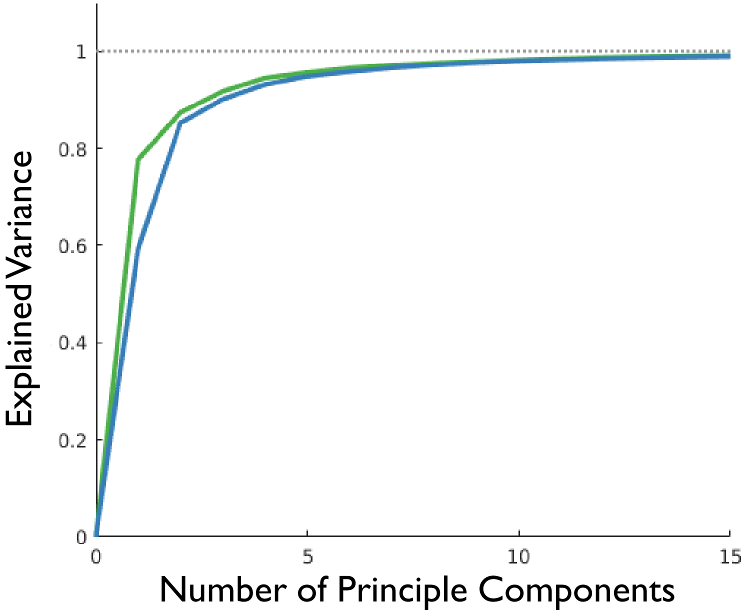


Preliminary Results: Statistical Shape Modeling



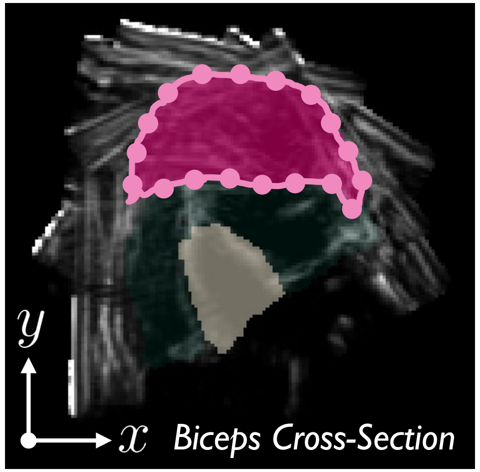
SHAPE DECOMPOSITION :

$$S = \underbrace{\overset{\text{mean shape}}{\overbrace{\bar{S}}} + P}_{\text{eigenvectors of covariance}}\overset{\text{weight vector}}{\overbrace{b}}$$



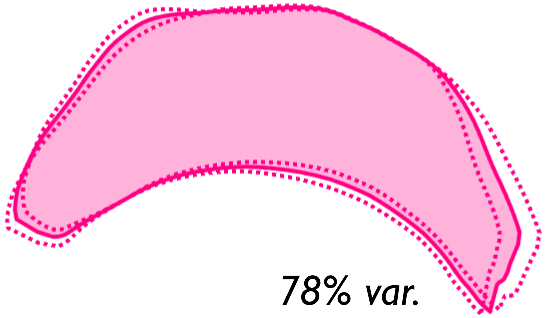
Shape

$$S = \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ y_1 \\ \vdots \\ y_n \end{bmatrix}$$

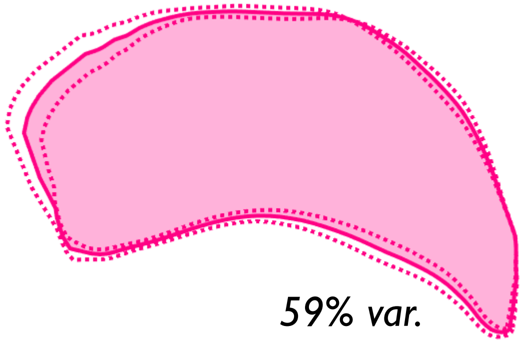


First Shape Modes

No Force, Vary Angle



30° Angle, Vary Force



Current / Future Work: Big Questions

- **Translational**: If we measure kinematic configuration using other sensors (e.g., motion capture), can we **infer a clean relationship between force and deformation** that can be used as a control signal?
- **Basic**: Can these muscle force measures be used to **build better models of neuromuscular contraction dynamics** and **better interpret {EMG, fMRI, EEG, etc.} signals**?

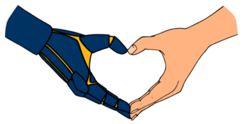
Current / Future Work: Big Questions

- **Translational**: If we measure kinematic configuration using other sensors (e.g., motion capture), can we **infer a clean relationship between force and deformation** that can be used as a control signal?
- **Basic**: Can these muscle force measures be used to **build better models of neuromuscular contraction dynamics** and **better interpret {EMG, fMRI, EEG, etc.} signals**?

{lhallock, bajcsy} @ eecs.berkeley.edu

hart.berkeley.edu

THANKS TO:
Gregorij Kurillo
Akira Kato
Sara Fridovich-Keil
Jeffrey Zhang
Daniel Ho
Ian McDonald
Yonatan Nozik
Sai Mandava
Chris Mitchell
Thomas Li
David Wang
Sachiko Matsumoto
Nandita Iyer
Stella Seo
Prerana Kiran
Shivani Sharma
Michelle He
Evan Shu
Jason Liu
Aaron Sy



Download the full data set at
hart.berkeley.edu/datasets

Papers

L.A. Hallock, A. Kato, and R. Bajcsy. "Empirical Quantification and Modeling of Muscle Deformation: Toward Ultrasound-Driven Assistive Device Control." *IEEE International Conference on Robotics and Automation (ICRA)*, 2018.

L.A. Hallock and R. Bajcsy. "A Preliminary Evaluation of Acoustic Myography for Real-Time Muscle Force Inference." *International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018. (late-breaking report)

L.A. Hallock, R.P. Matthew, S. Seko, and R. Bajcsy. "Sensor-Driven Musculoskeletal Dynamic Modeling." *International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016. (late-breaking report)

Sponsors

SIEMENS

NSF

BAIR

BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

GRFP

NSF GRADUATE RESEARCH FELLOWSHIP PROGRAM