System Identification of Human Musculoskeletal Dynamics

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HART Lab
Human-Assistive Robotic Technologies

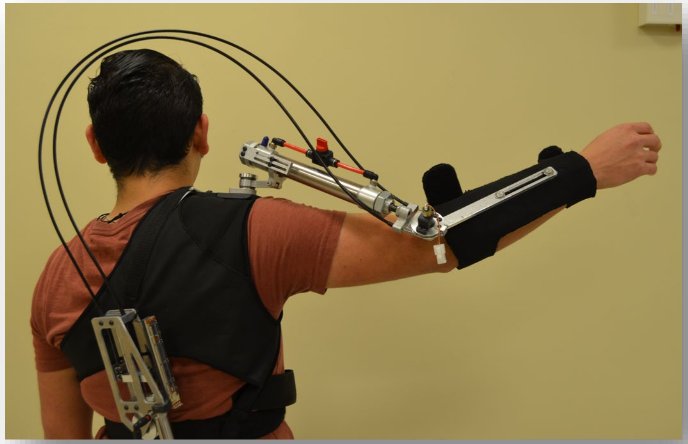
Berkeley
UNIVERSITY OF CALIFORNIA

Why model musculoskeletal dynamics?

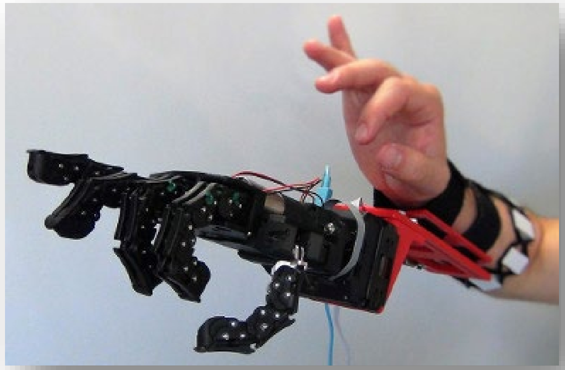
There are many **mechanically** sophisticated, biomimetic devices on the market . . .

UW "Highly Biomimetic Anthropomorphic Robotic Hand"

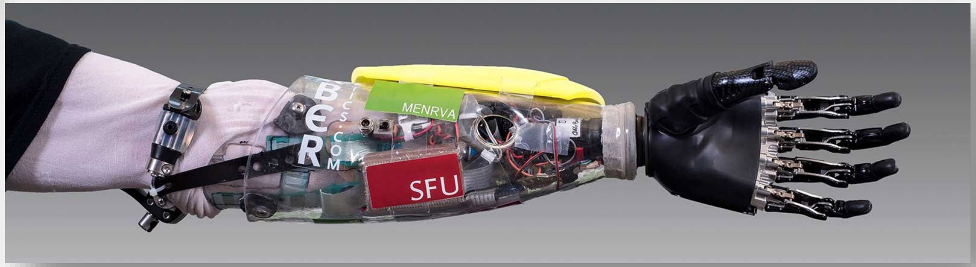
Myomo MyoPro



UCB HART Lab APEX Gamma exoskeleton



PISA-IIT Softhand



Ottobock Bebionic hand

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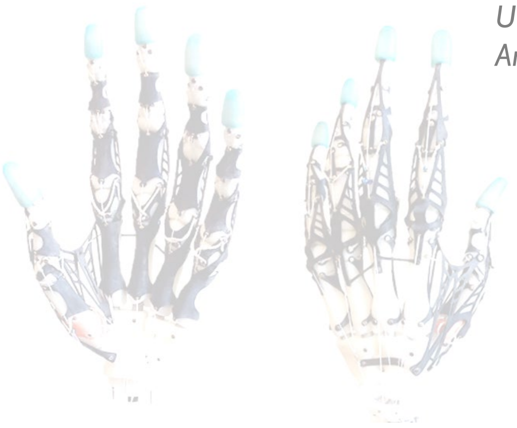

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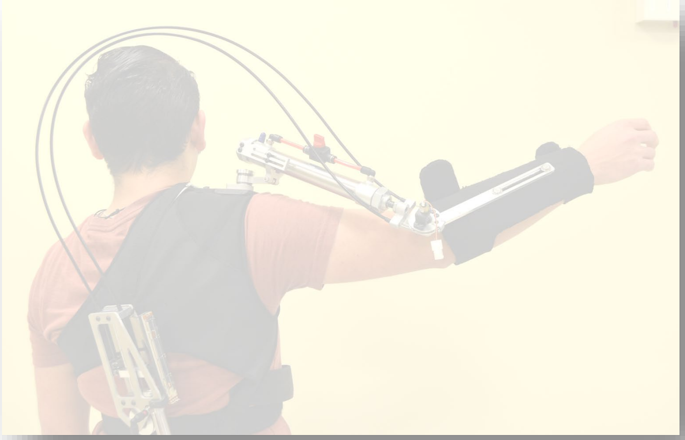

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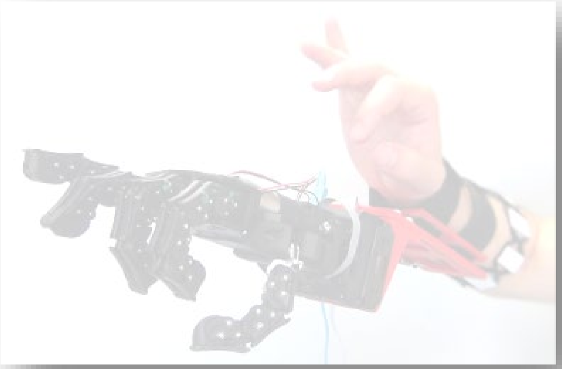

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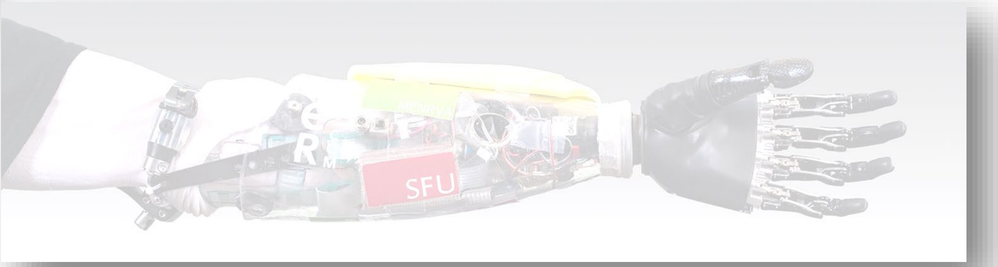

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. . . but we don't know how to **safely** and **expressively** control them.

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There are

CHALLENGE

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

Myomo MyoPro

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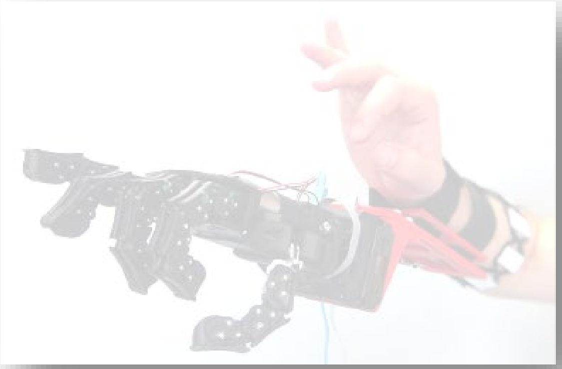

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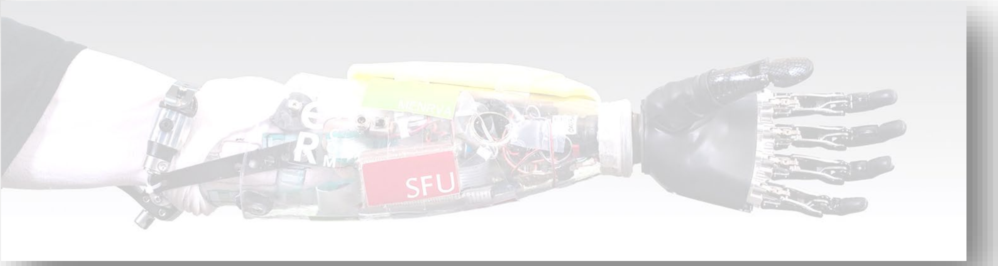

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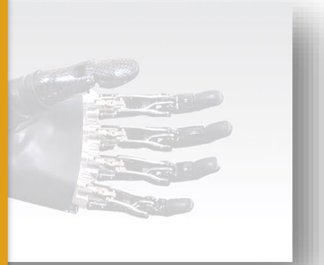
Gamma exoskeleton

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** and **better understand internal forces on the body**.

This is fundamentally a **system identification problem**.



ttobock Bebionic hand

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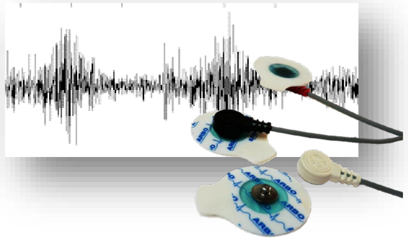
Muscle Force Inference: State-of-the-Art

Neurological Activation

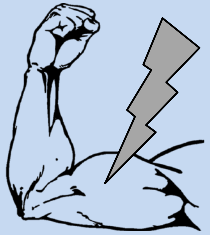
a

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



Contraction Dynamics

$f(\cdot)$



Muscle Output Force

$$F_m = f(a)$$

Muscle Force Inference

Neurological Activation
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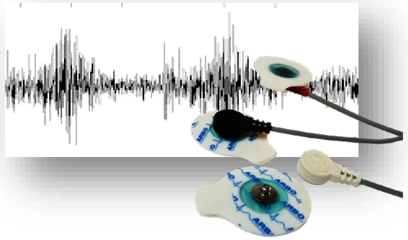

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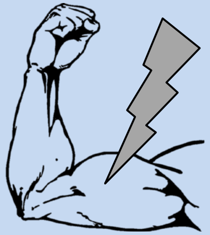
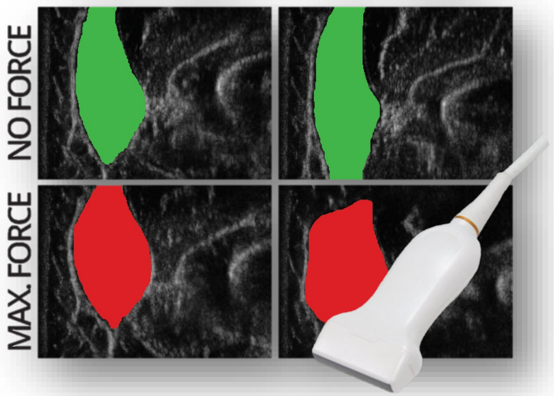


Deformation Dynamics
$g(\cdot)$

Muscle Output Force
$F_m = f(a)$

Muscle Deformation
$D = g(F_m)$

$\theta = 25°$ $\theta = 69°$

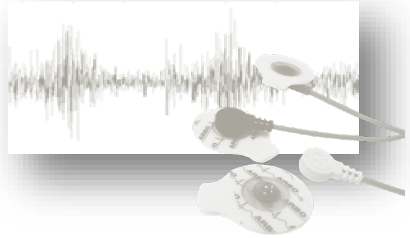


via ***ultrasound***

Muscle Force Inference: Our Approach

Neurological Activation a

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



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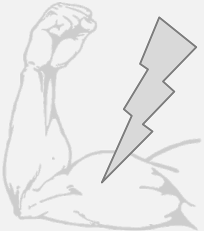


Deformation Dynamics

$g(\cdot)$

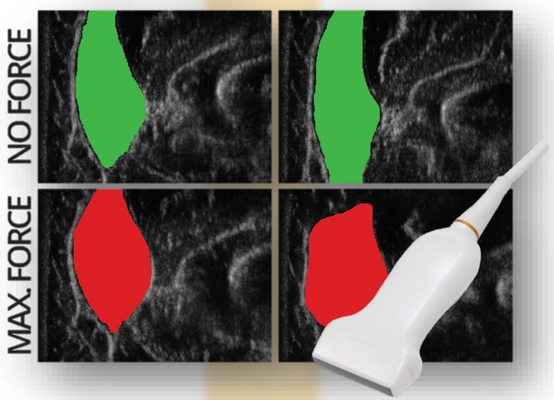
Muscle Output Force

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

Muscle Deformation

$$D = g(F_m)$$

$\theta = 25°$ $\theta = 69°$

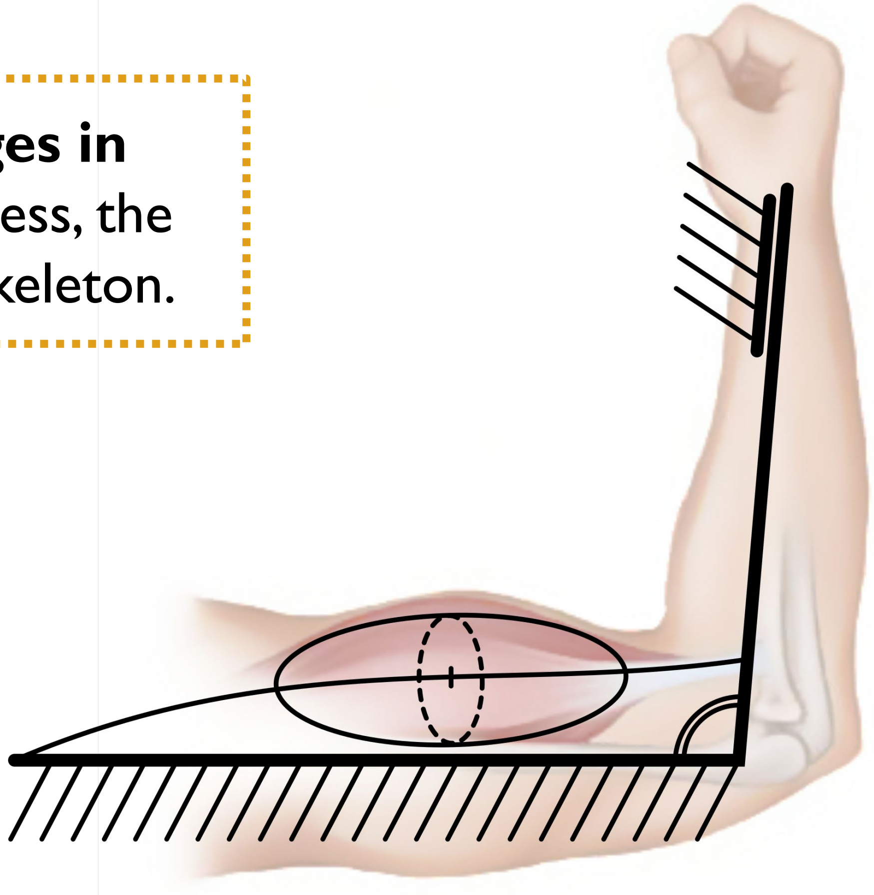


via ***ultrasound***

Deformation is a **highly localized mechanical signal**, allowing for measurement of muscle force **without considering the neurological feedback loop**. (Until we want to explicitly study it!)

What should $g(\cdot)$ look like?

Changes in muscle shape reflect changes in tendon length, and therefore tendon stiffness, the method by which force is imparted to the skeleton.



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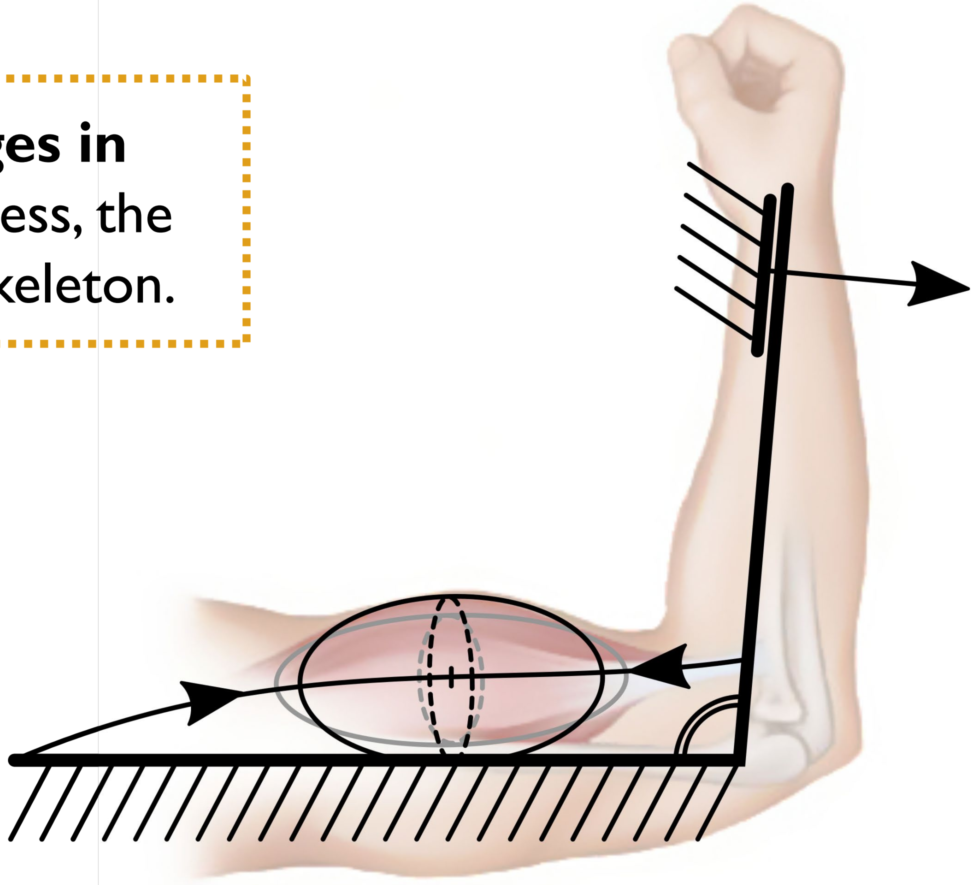
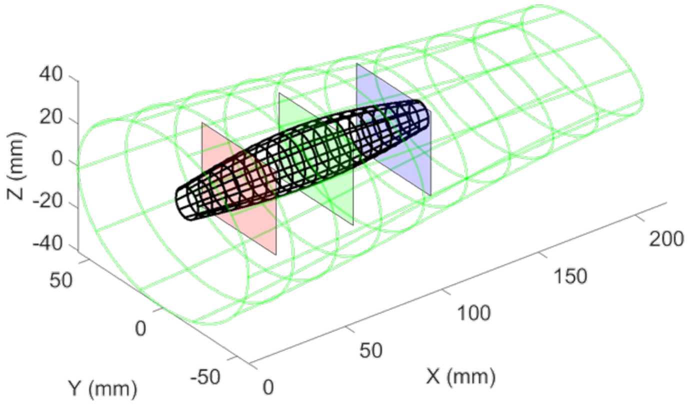


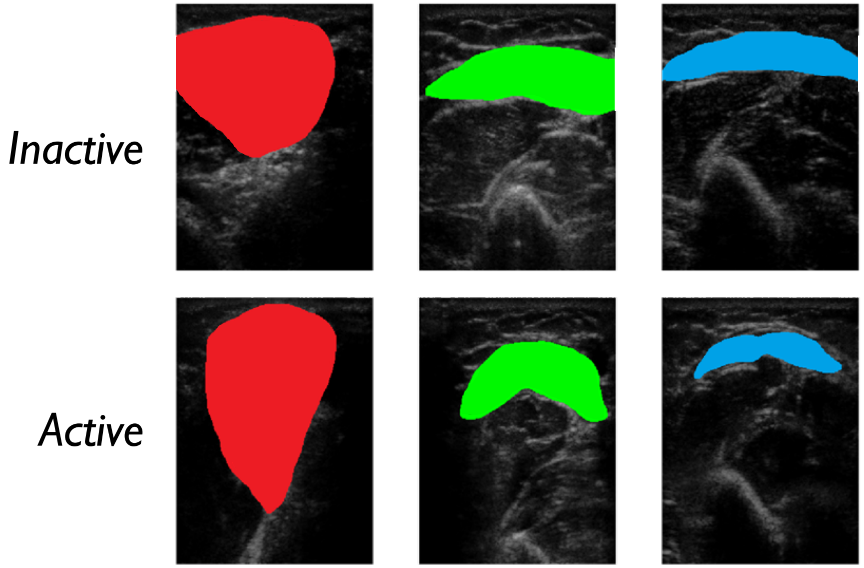
Deformation Modeling Challenges

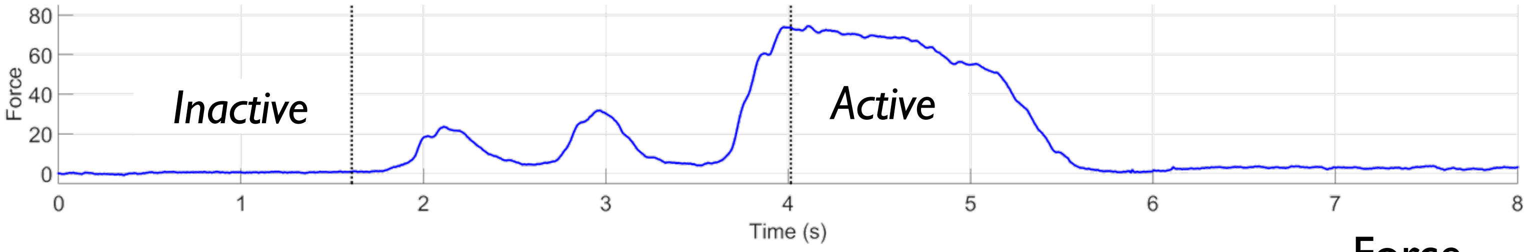
1. Observed deformation **varies substantially with sensor location**.

3D View



Muscle Cross-Section *(Brachioradialis)*



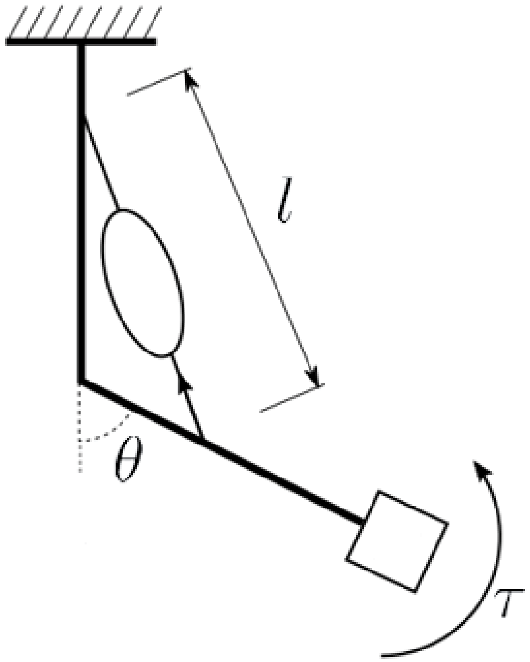


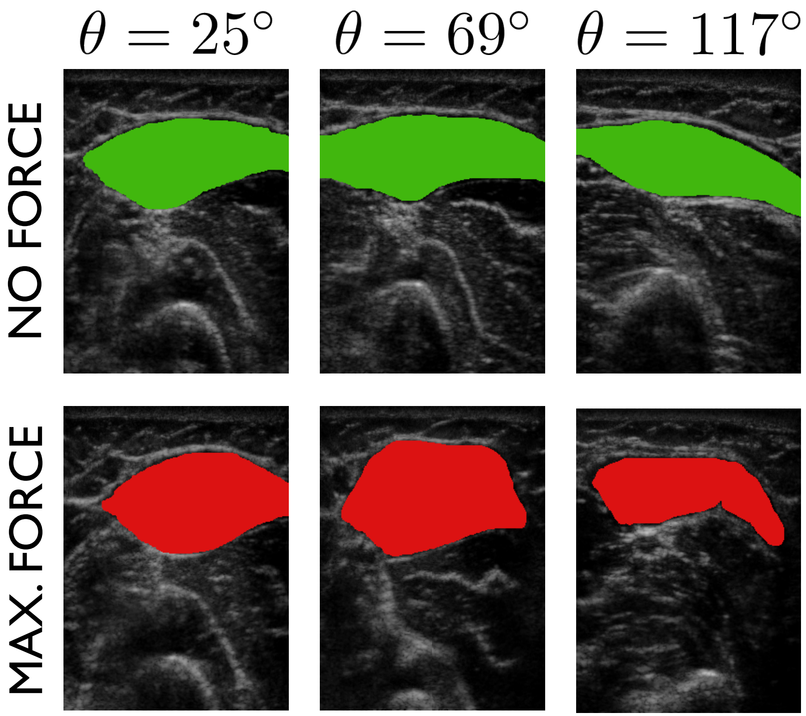
Force

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

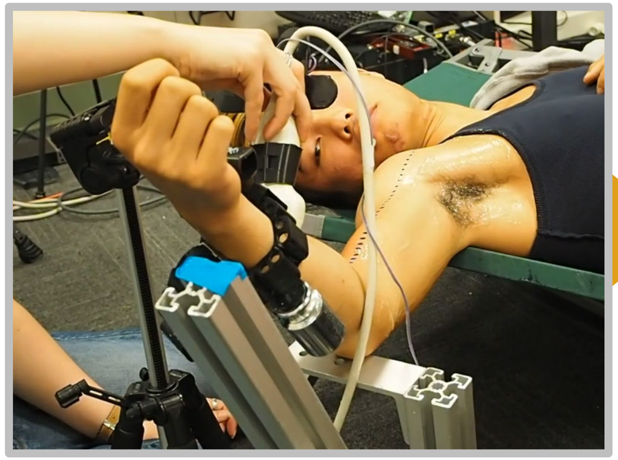
1. Observed deformation **varies substantially with sensor location**.

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

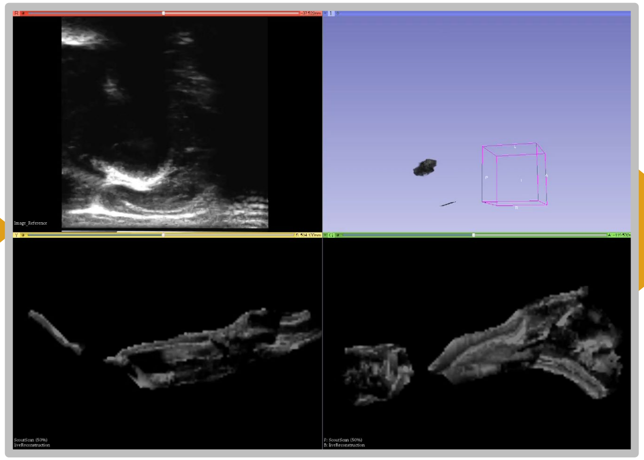
To build a model that can robustly infer muscle force, we need to observe the **entire muscle** under **multiple** (ideally, factorial) **joint positions** and **loading conditions**.

Approach: Ultrasound + Motion Capture

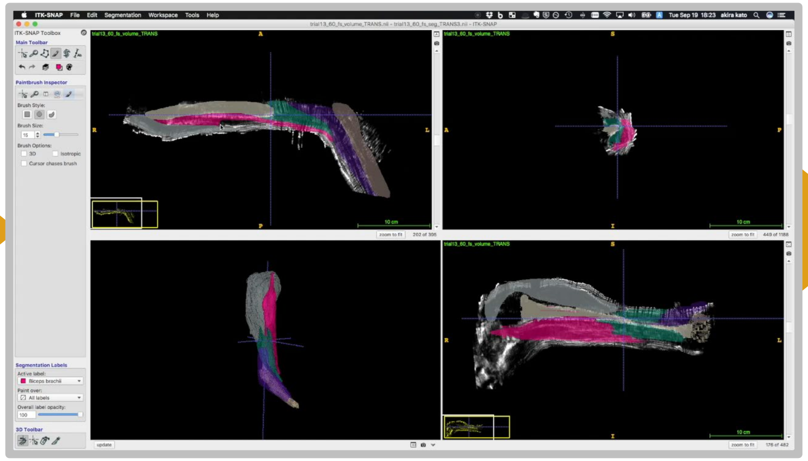
Raw Data Collection
via Ultrasound & Motion Capture



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**.

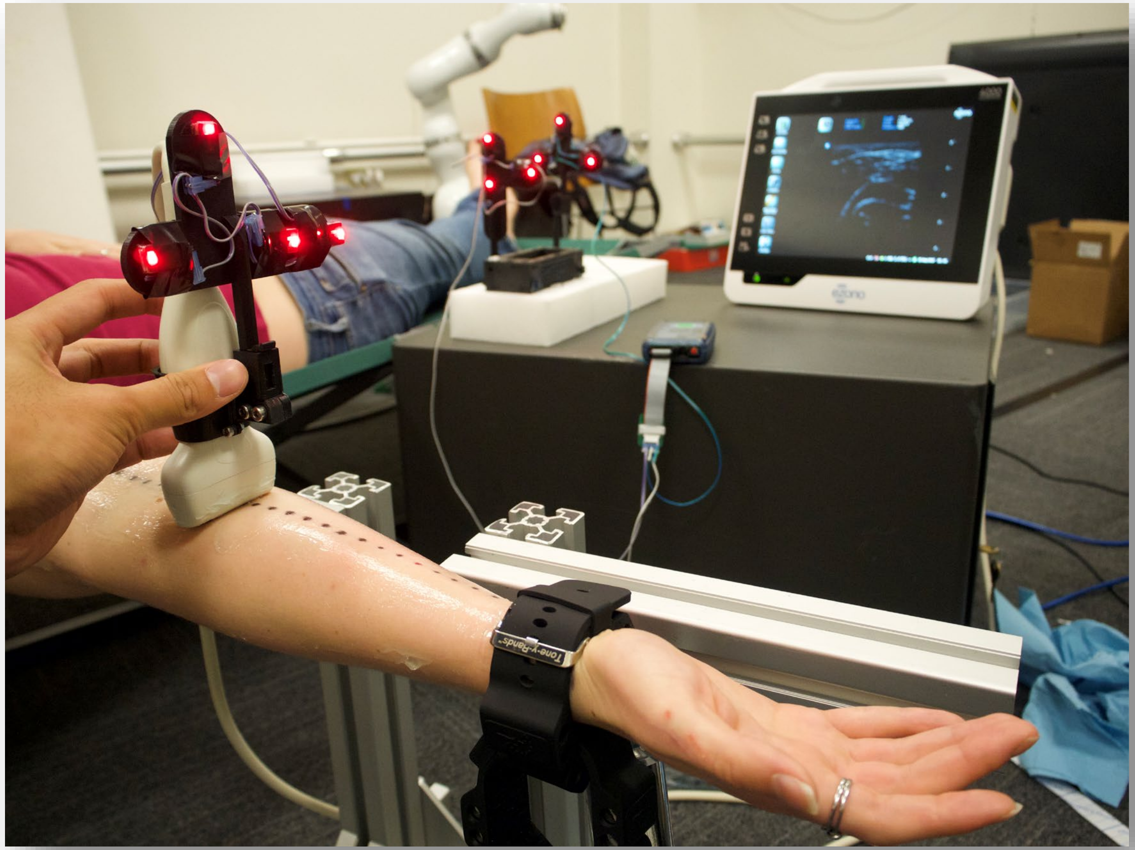
*[**Hallock**, Kato, Bajcsy, ICRA 2018]*

Approach: Data Selection

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

Data set:

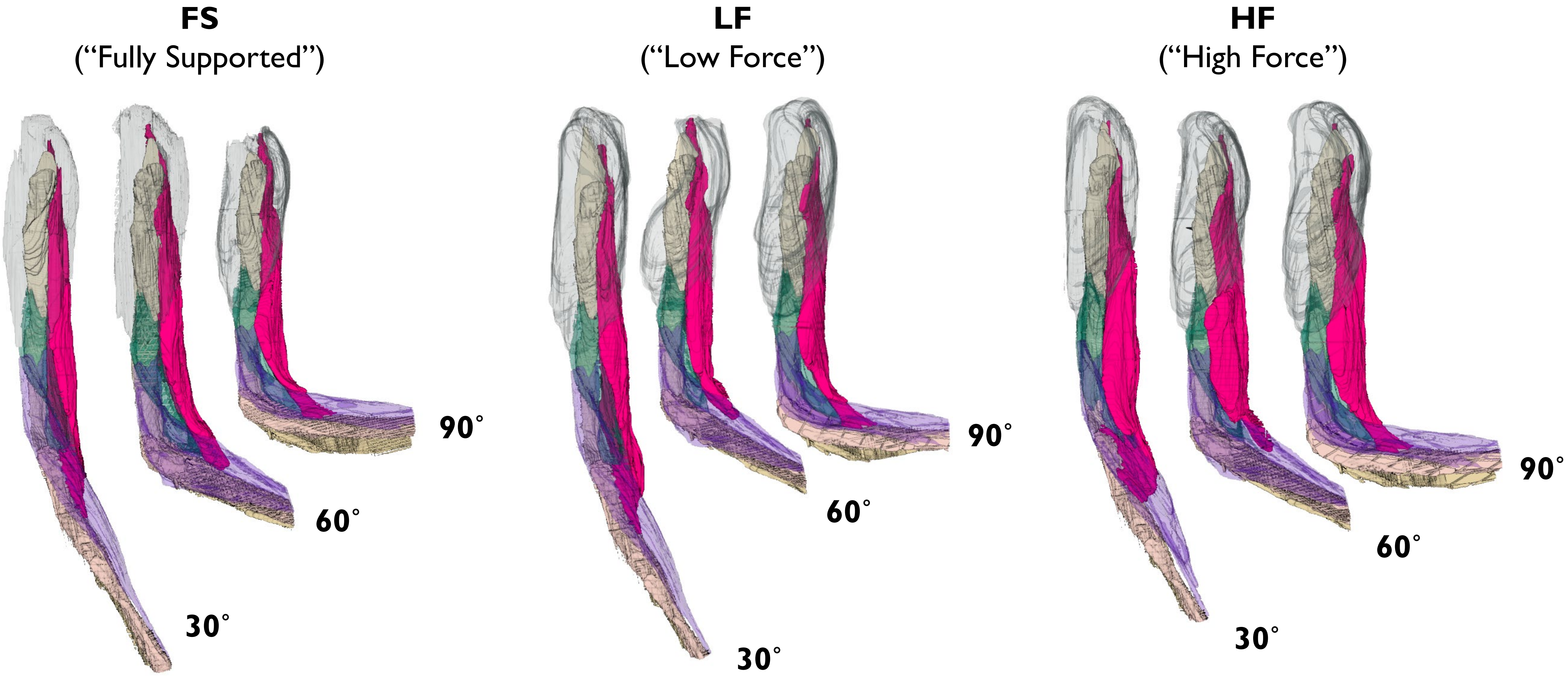
- 3 subjects (1 F, 2 M)
- full arm ultrasound volumetric scan
- 4 elbow flexion angles, 0–90°
- 5 loading conditions
  - ***FS***: fully supported
  - ***GC***: gravity compensation only
  - ***LF***: light wrist weight (~225g)
  - ***MF***: medium wrist weight (~725g)
  - ***HF***: heavy wrist weight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



Ultrasound volumetric data collection, HART Lab 2017

*[**Hallock**, Kato, Bajcsy, ICRA 2018]*

Preliminary Results: Qualitative



[**Hallock**, Kato, Bajcsy, ICRA 2018]

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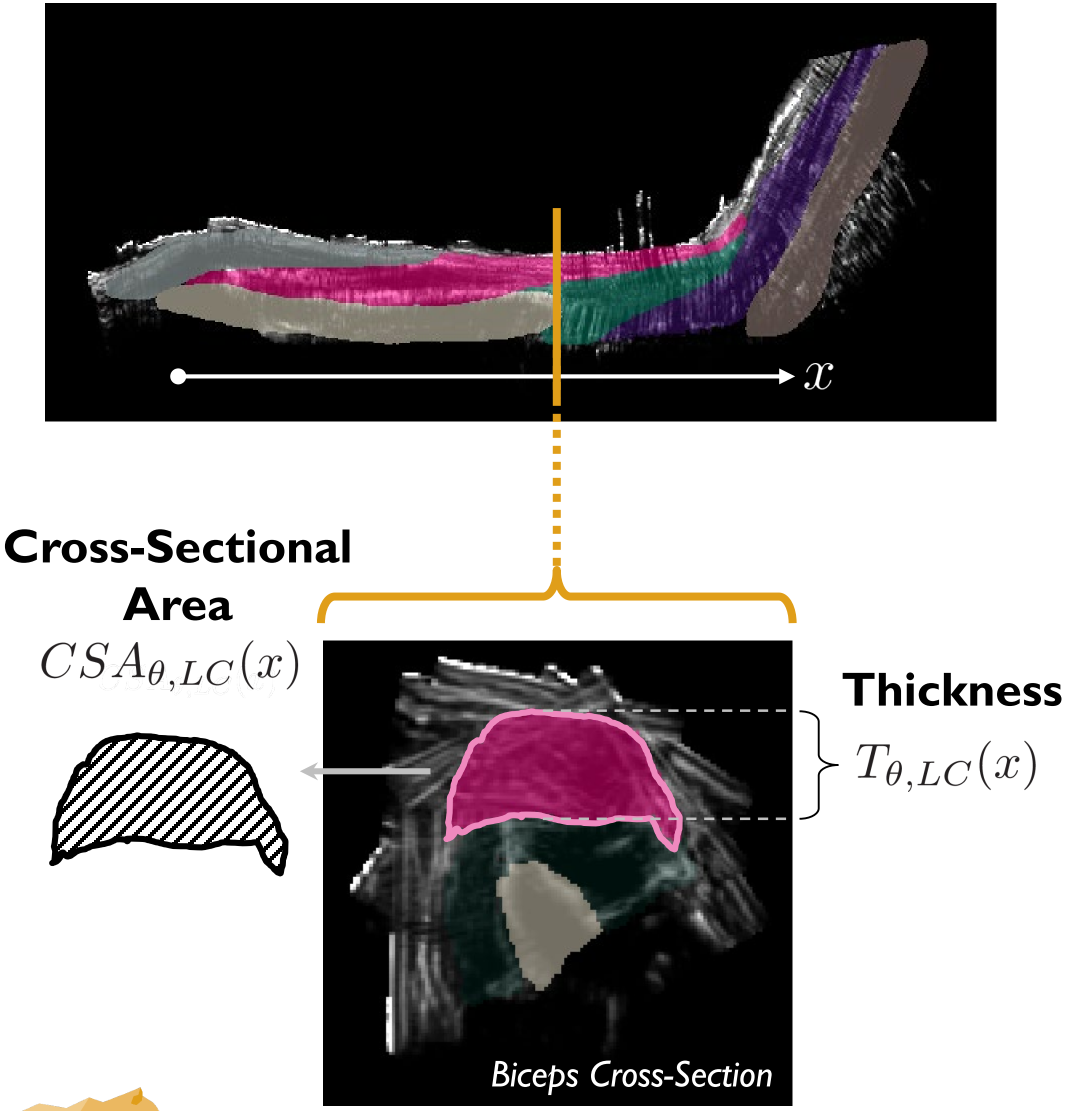
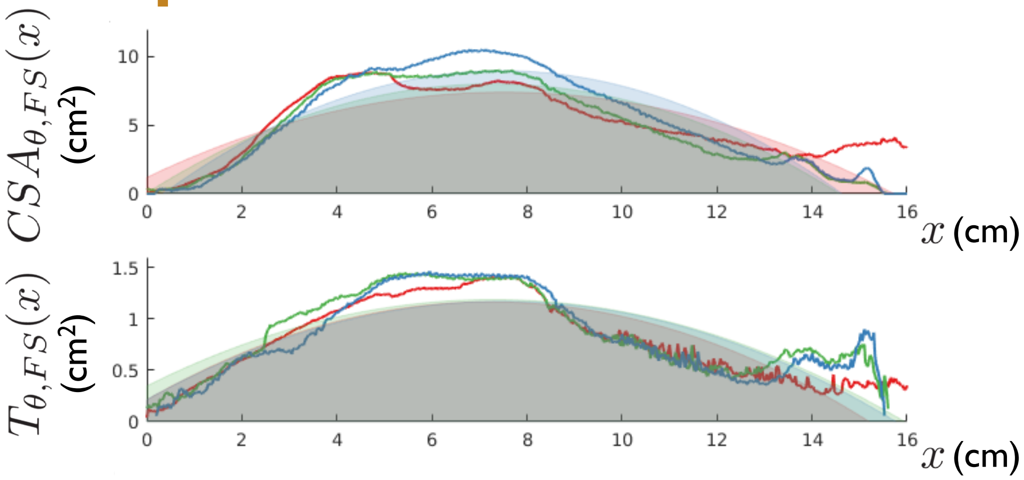
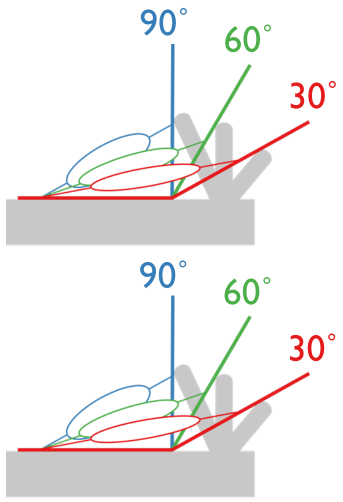
Preliminary Results: Simplest Models







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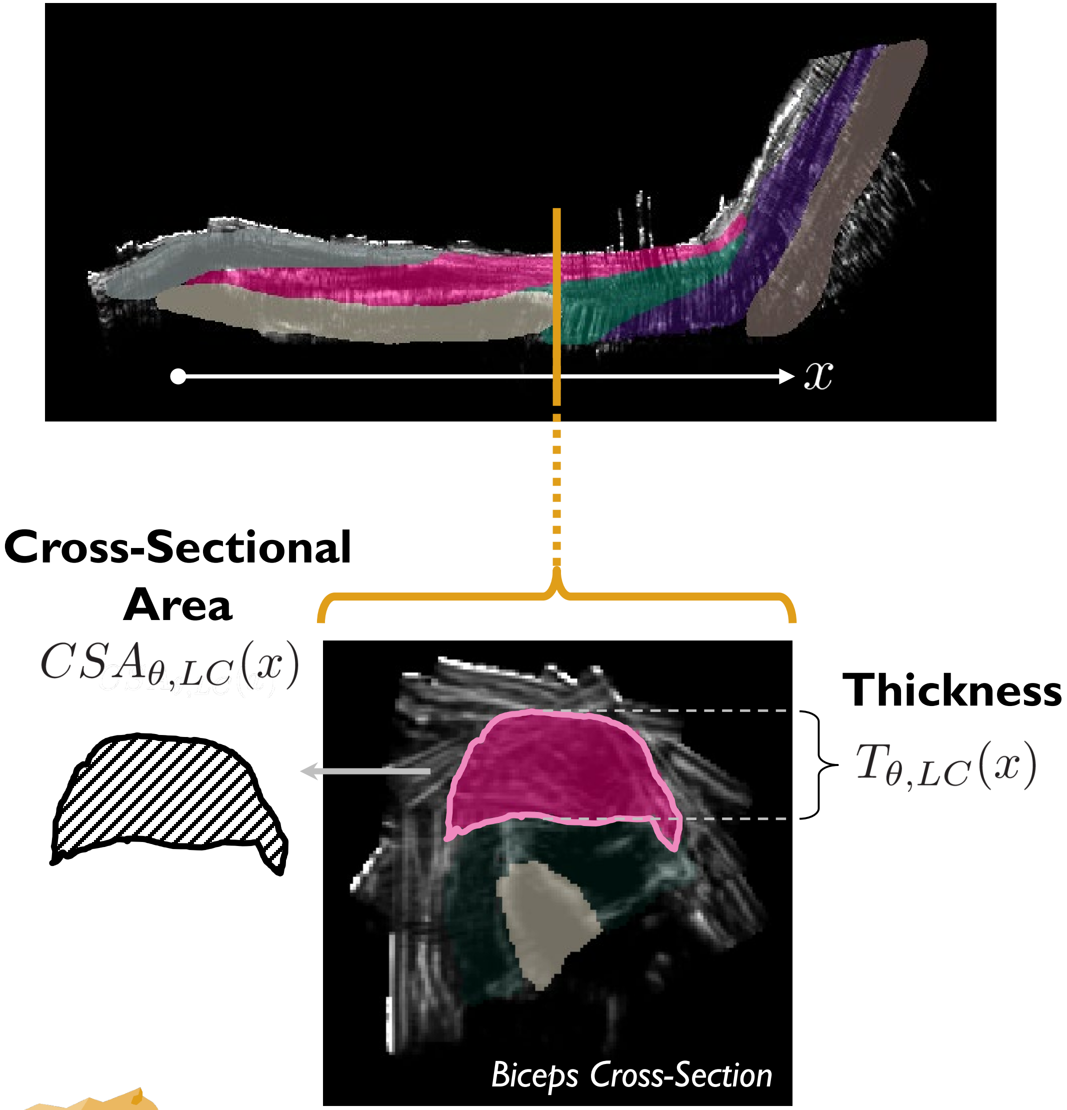

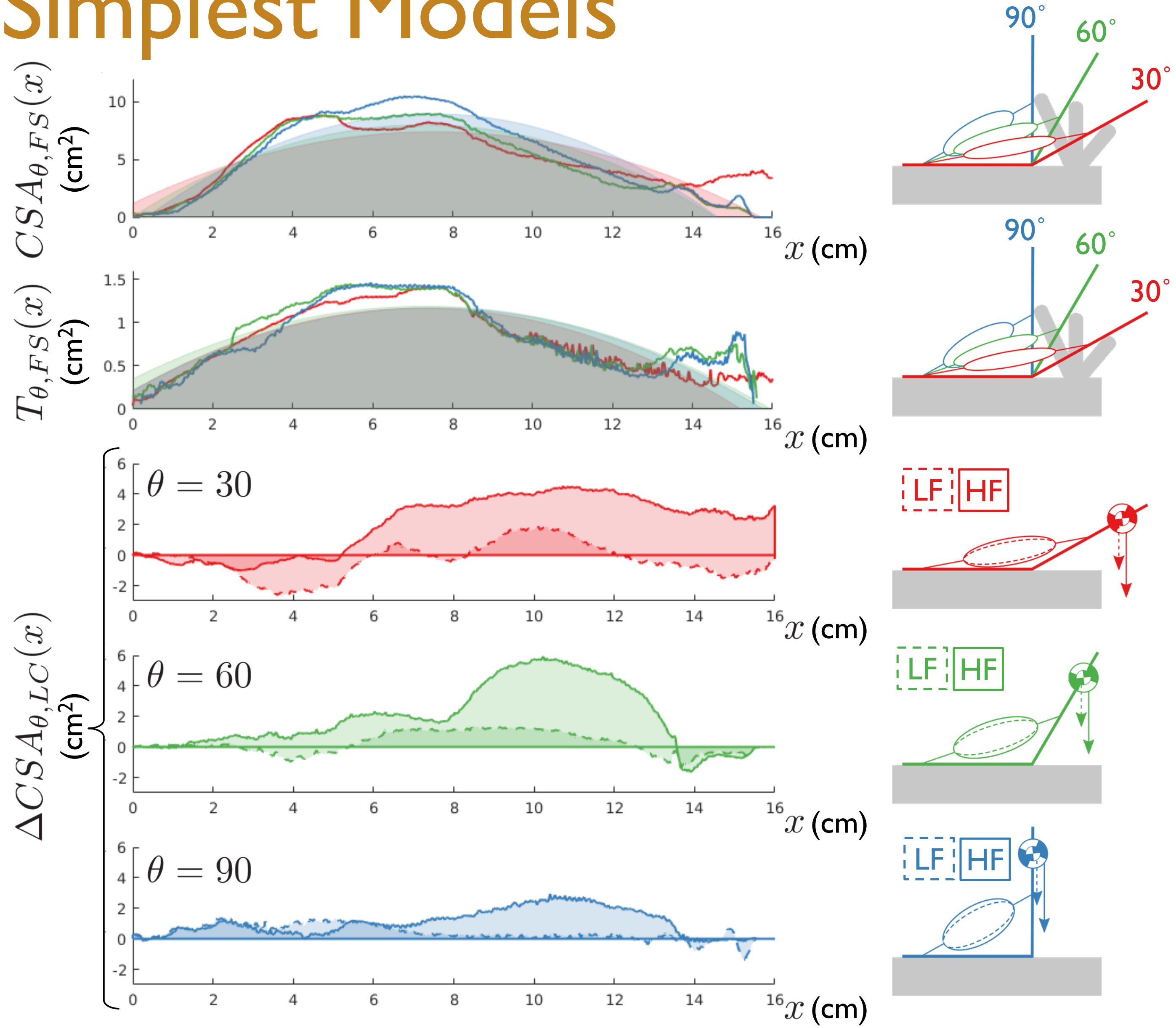

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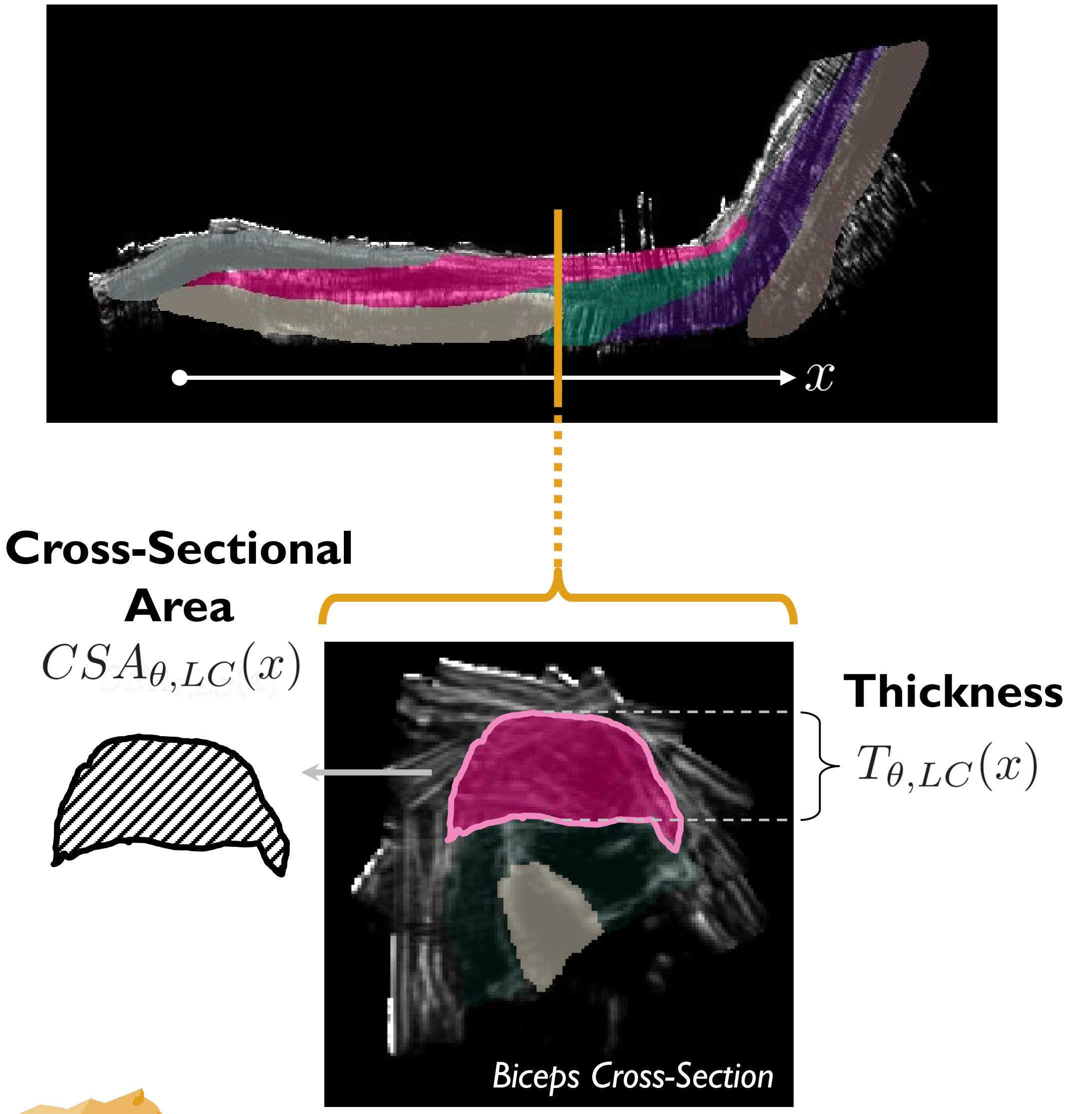

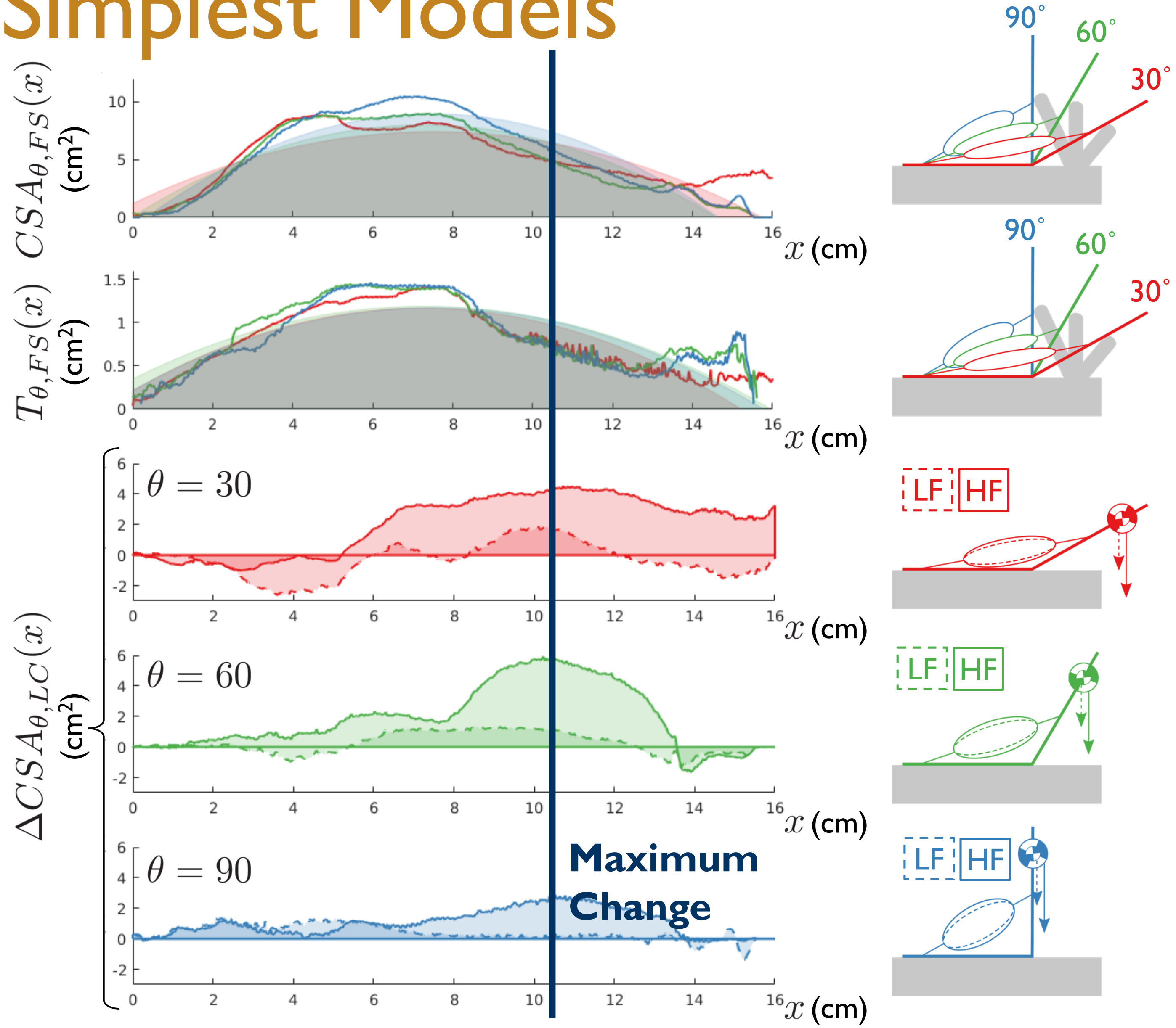

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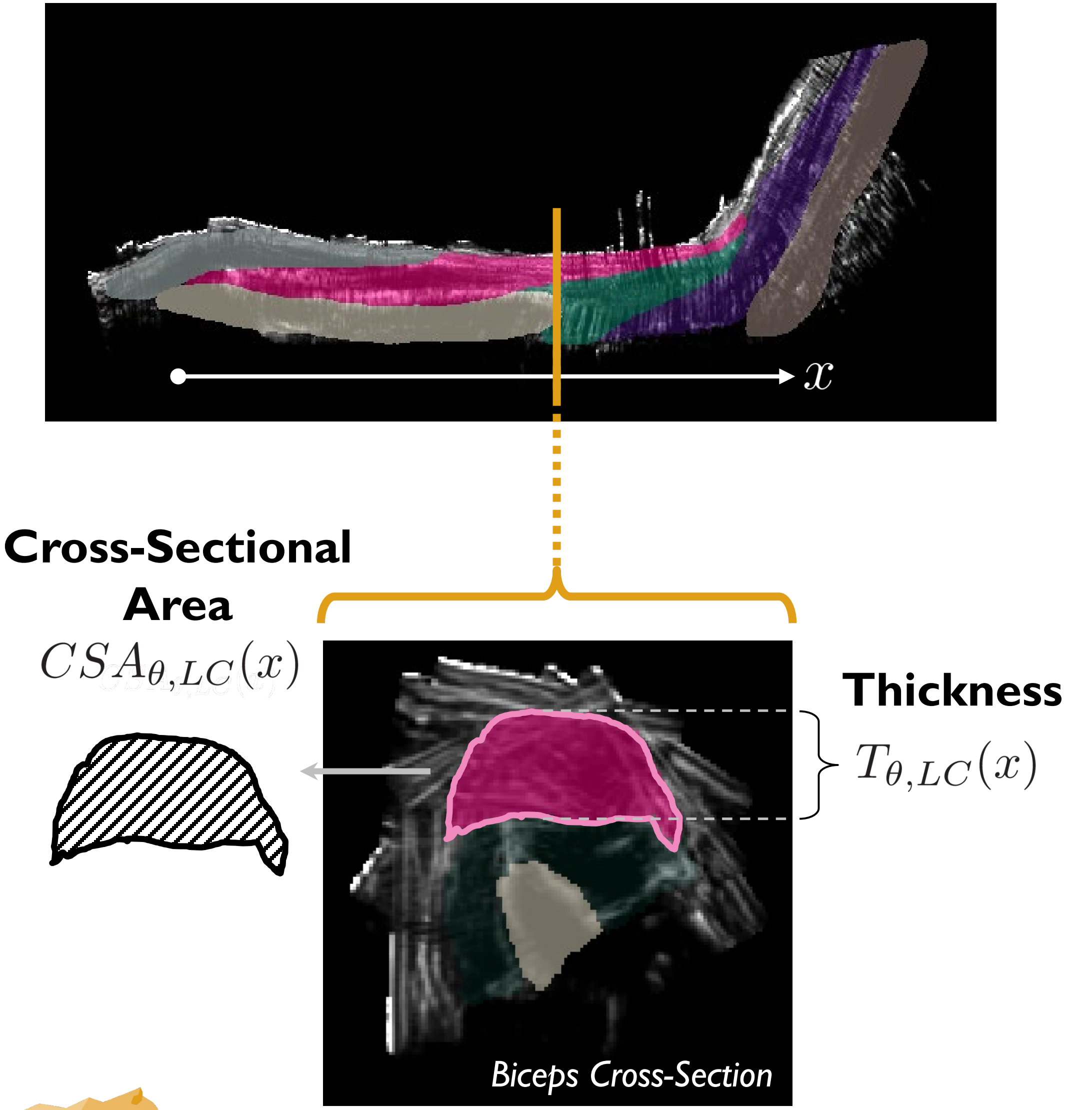
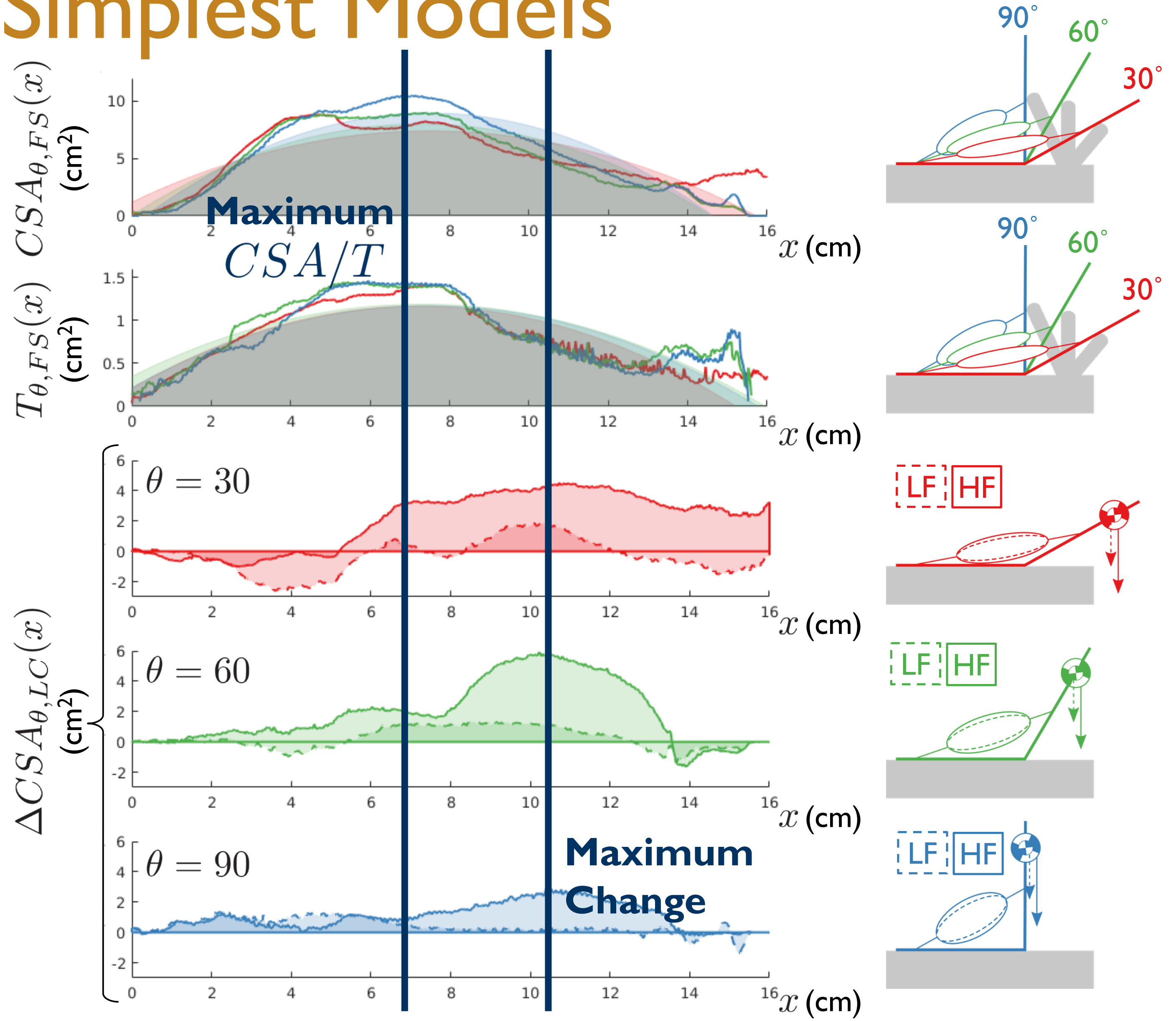
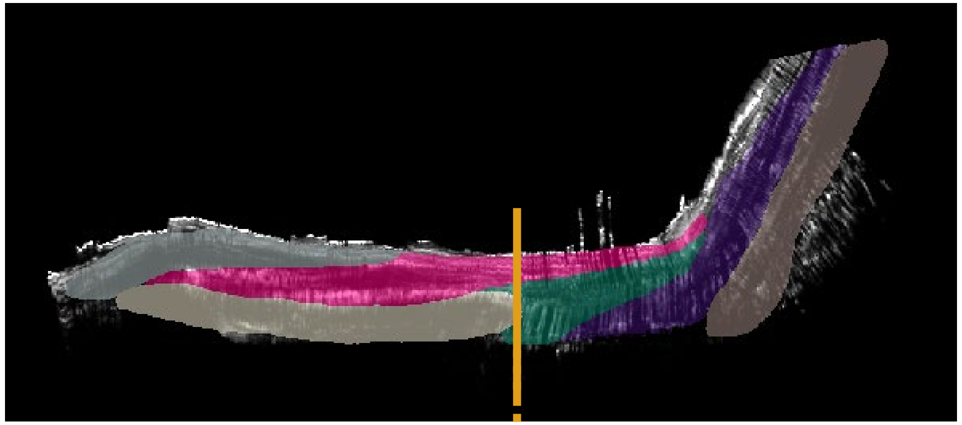




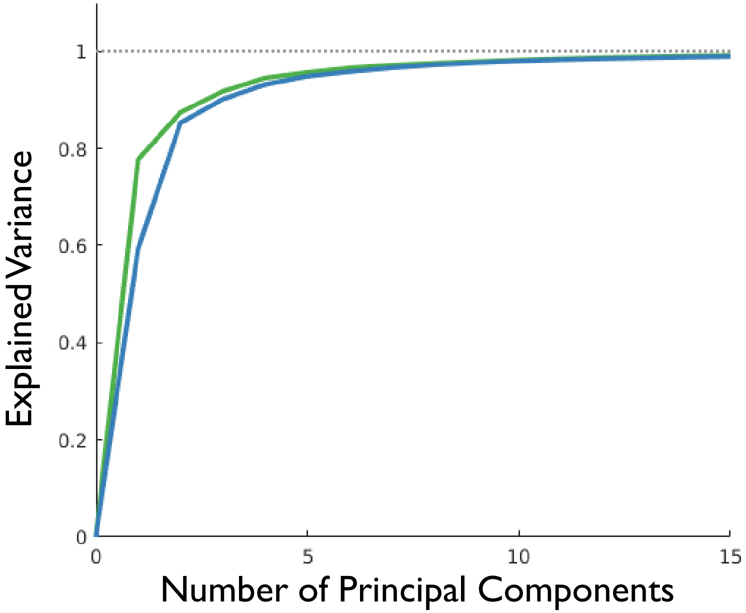
Preliminary Results: Statistical Shape Modeling



SHAPE DECOMPOSITION :

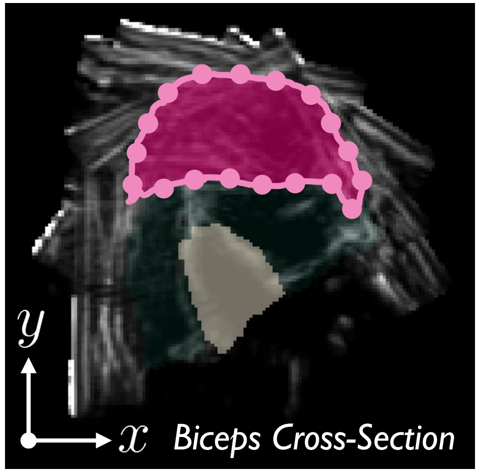
$$S = \underbrace{\overbrace{\bar{S}}^{\text{mean shape}} + \overbrace{P}^{}}_{} \overbrace{b}^{\text{weight vector}}$$

mean shape: $\bar{S}$; weight vector: b; eigenvectors of covariance: P



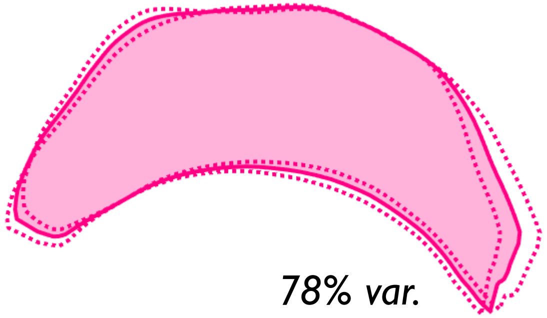
Shape

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

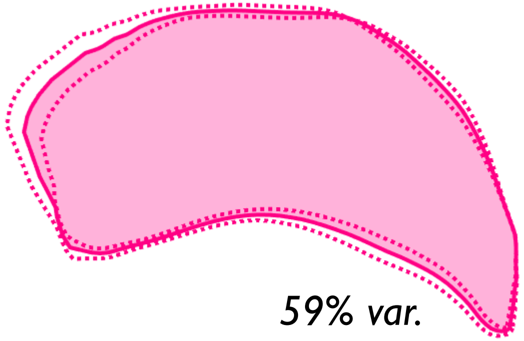


First Shape Modes

No Force, Vary Angle



30° Angle, Vary Force



Current / Future Work: Big Questions

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- **Basic**: Can these muscle force measures be used to **build better models of neuromuscular contraction dynamics** and **better interpret {EMG, fMRI, EEG, etc.} signals**?

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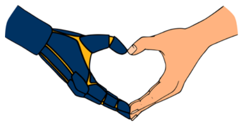

Download the full data set at
hart.berkeley.edu/datasets

Papers

Y. Nozik*, L.A. Hallock*, D. Ho, S. Mandava, C. Mitchell, T. H. Li, and R. Bajcsy, "OpenArm 2.0: Automated Segmentation of 3D Tissue Structures for Multi-Subject Study of Muscle Deformation Dynamics." *International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2019. *equal contribution

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)

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