Human Musculoskeletal Dynamics Modeling:

Toward Biomimetic Assistive Device Control

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IB 222
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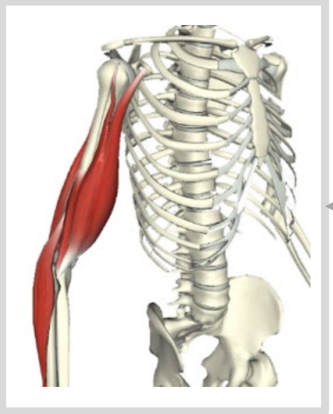
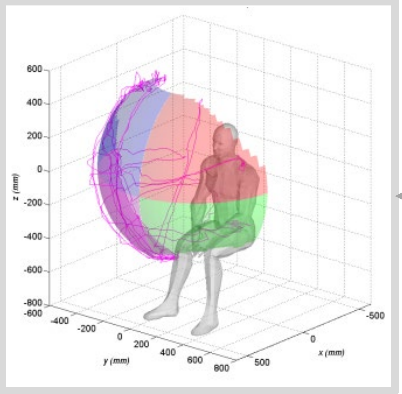
HART Lab
Human-Assistive Robotic Technologies

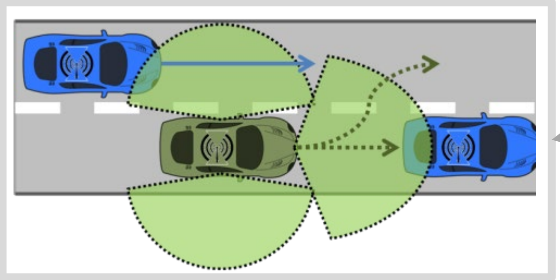
Human-Assistive Robotic Technologies (HART) Lab

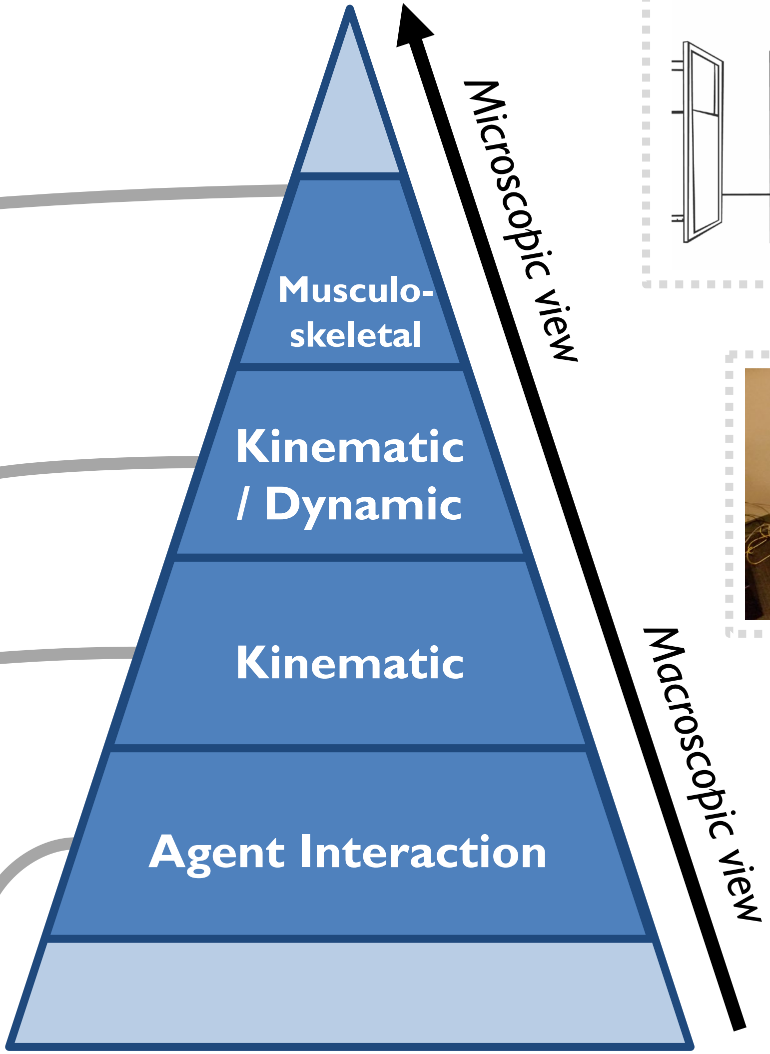
OVERVIEW

HART Lab Ecosystem

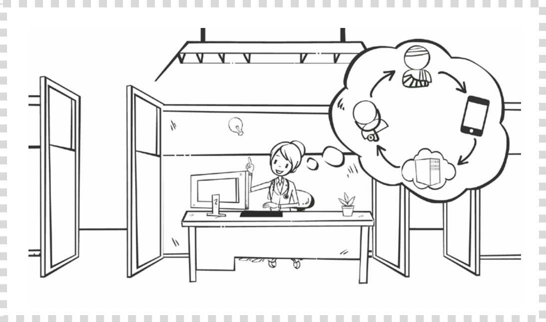








Levels of human modeling abstraction



People (Musculoskeletal Modeling)

UC Berkeley


R. Bajcsy


R. Matthew


L. Hallock


S. Seko


J. Zhang


A. Kato


A. Sy


S. Sharma


I. McDonald


D. Ho


Y. Tuo


L. Howard


S. Nair


P. Kiran

Stanford


O. Khatib

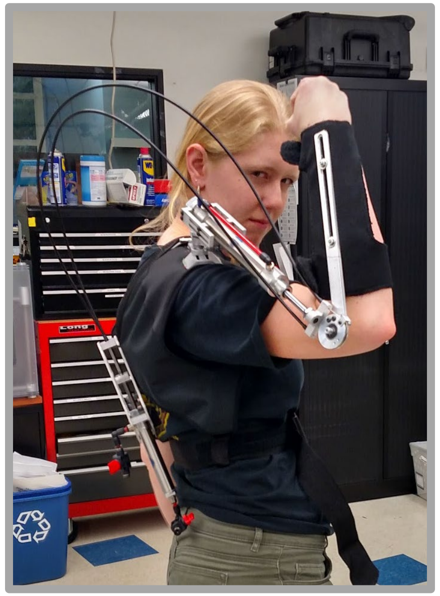

S. Menon


T. Migimatsu

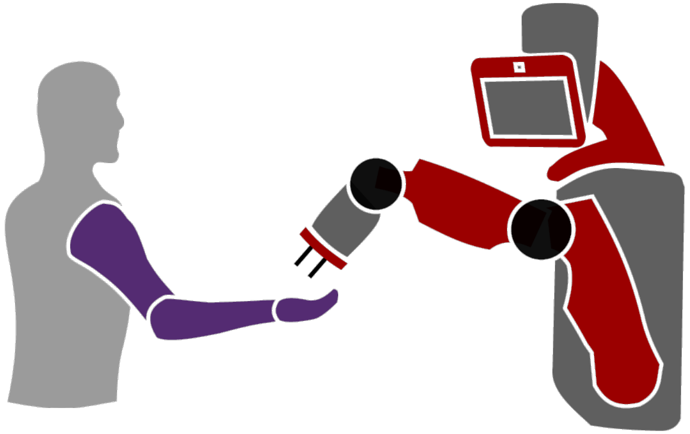
Why model musculoskeletal dynamics?

Human dynamics modeling is essential for many applications.

- understanding forces imperative in physical HRI
- non-physiological models cannot sufficiently predict dynamics



APEX Gamma exoskeleton, HART Lab 2016



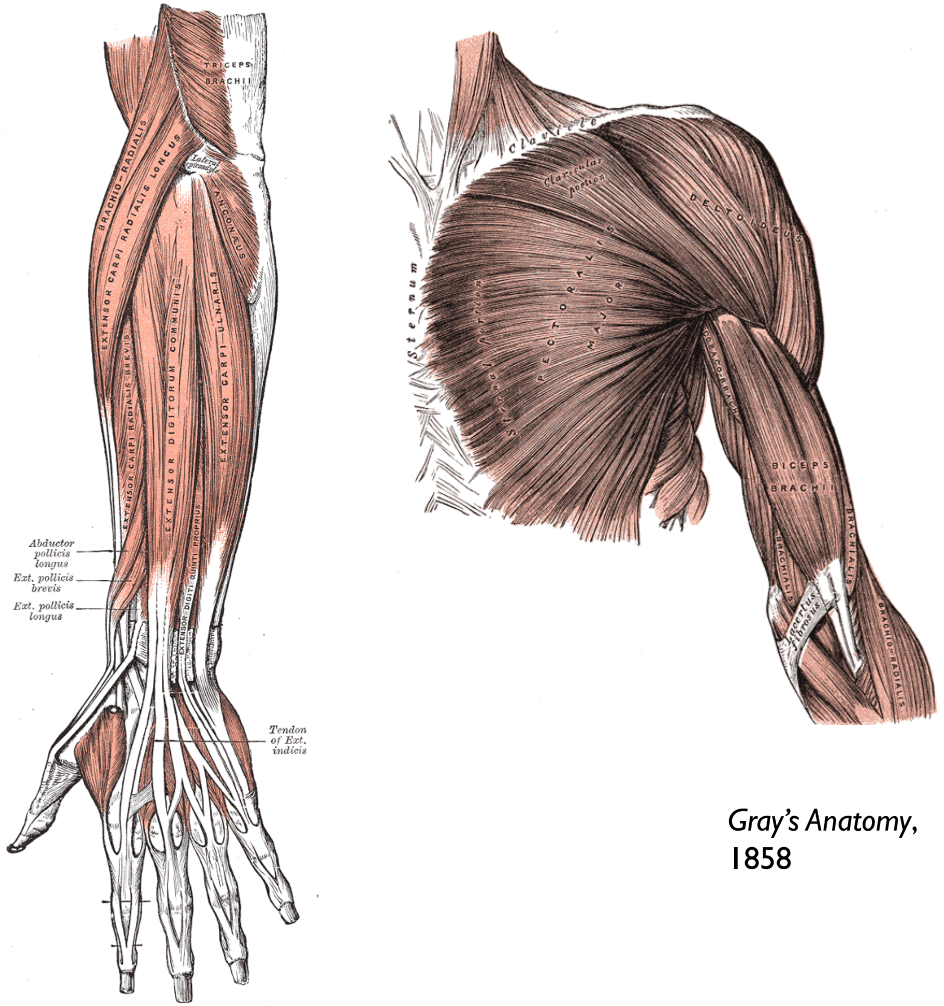
Why model musculoskeletal dynamics?

Human dynamics modeling is essential for many applications.

- understanding forces imperative in physical HRI
- non-physiological models cannot sufficiently predict dynamics

It's also difficult.

- complex dynamical system
- morphological variation
- limited sensing (esp. non-invasive)



Gray's Anatomy, 1858

Objective

We seek to develop models to predict human arm dynamics that

- have appropriate level of abstraction (**as simple as possible** while accommodating **dynamically- and medically-relevant pathologies**)
- are trainable/customizable using **non-invasive sensing** (MRI, ultrasound, EMG, AMG, etc.)
- can be used in assistive device control system using **non-invasive, wearable sensing** (EMG, AMG, *ultrasound*)

Approach

- **Project 0**: The Simplest Possible Dynamics Model
- **Project 1**: Geometric Models
  - **A**: Morphology Analysis via Multi-Subject MRI *(Stanford-UCB collaboration)*
  - **B**: Muscle Deformation Analysis via Ultrasound
- **Project 2**: Stress-Strain/Elasticity Models
  - **A**: Acoustic Myography (AMG)
  - **B**: cine DENSE MRI

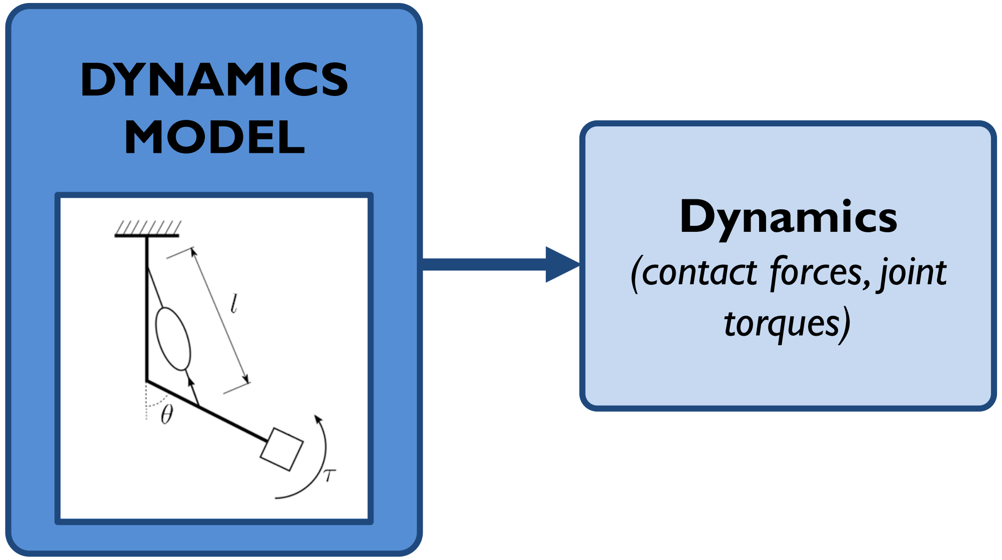
PROJECT 0

The Simplest Possible Dynamics Model:

Multi-Sensor "Minimal Modeling" of the Human Arm

Goal: Predictive Upper-Limb Model

- predicts contact forces / joint torques of interest
- accommodates musculoskeletal pathology
  - injury
  - disease (e.g., MD)
- individualized
- computationally tractable



Existing Human Dynamics Models

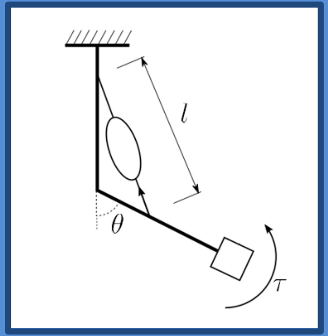
(Static)
Morphological Data
(MRI, ultrasound)

Real-Time Data
(sEMG, AMG, motion capture, ultrasound)

Morphological Assumptions
(biomechanics tables, literature values)

Contextual Assumptions
(gait cycle, motion primitives)

DYNAMICS MODEL



Dynamics
(contact forces, joint torques)

Our Objective

(Static)
Morphological Data
(MRI, ultrasound)

Real-Time Data
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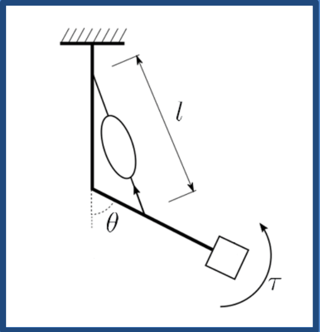
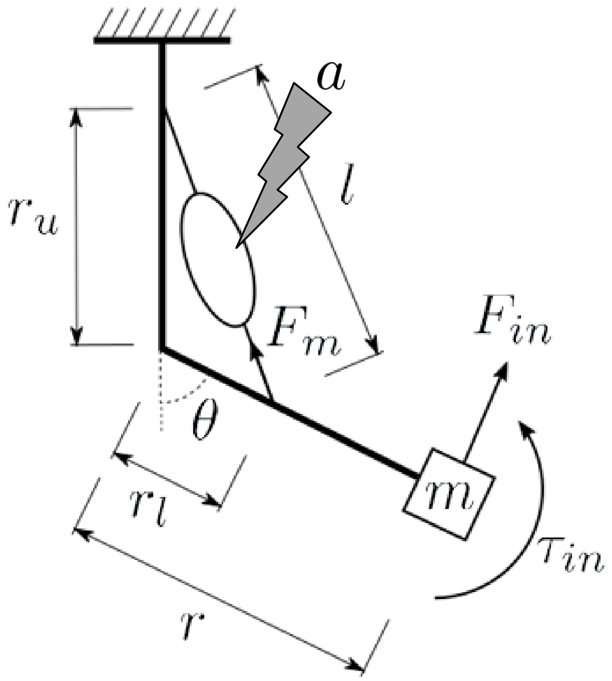
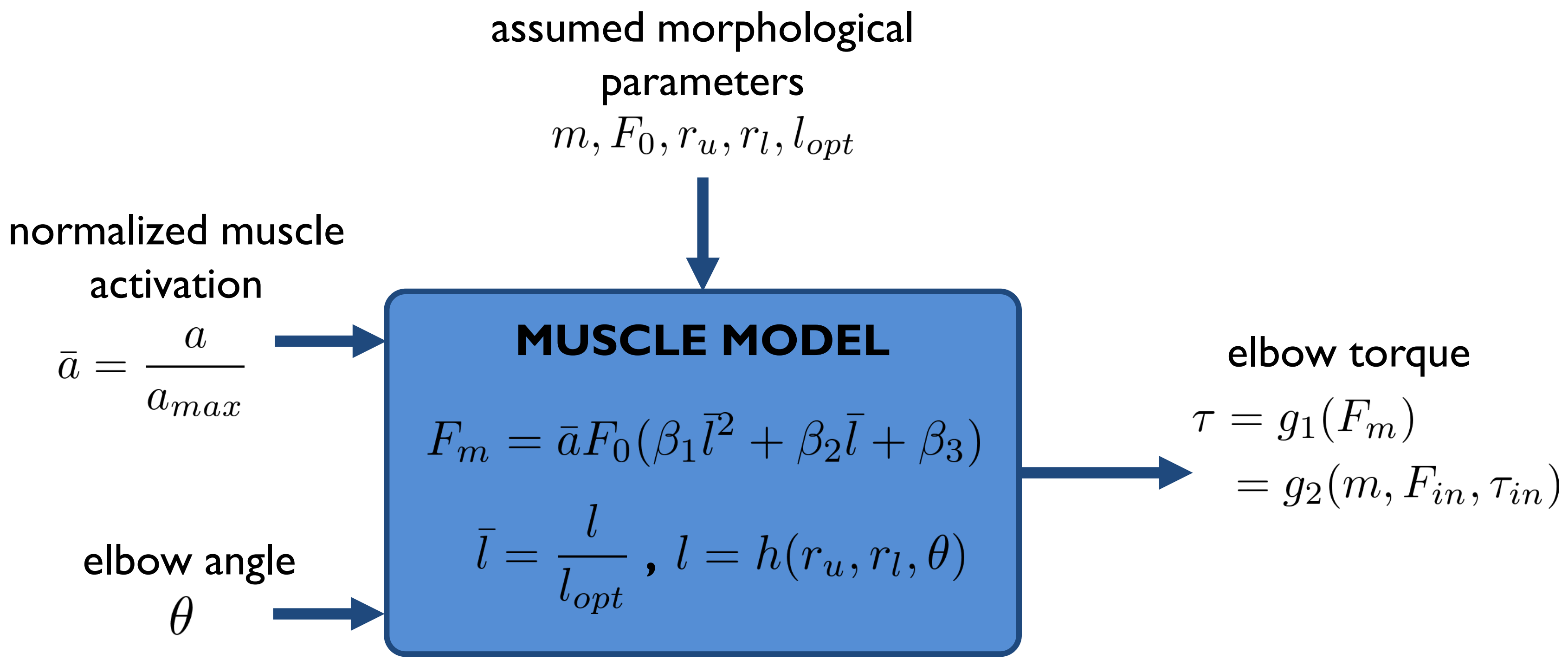


Dynamics
(contact forces, joint torques)

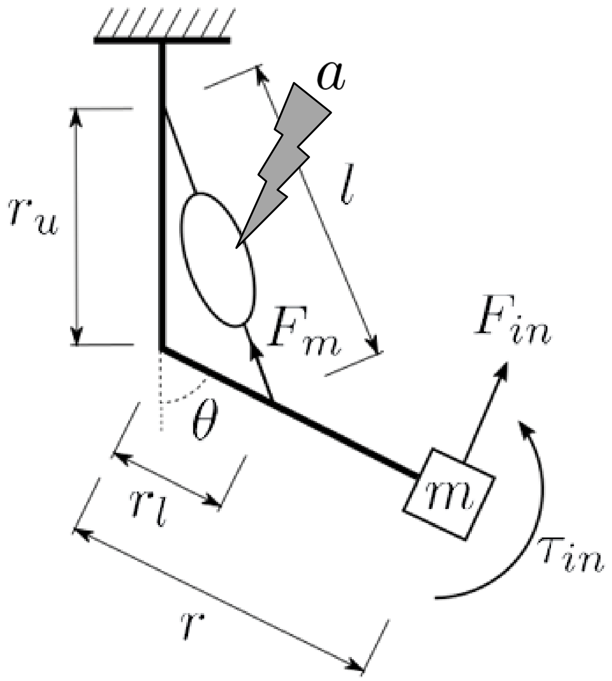
Starting Point: Simplified Model





- single individual
- elbow joint (hinge)
- single aggregate "muscle"
- static

Starting Point: Simplified Model



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assumed morphological parameters
$m, F_0, r_u, r_l, l_{opt}$

normalized muscle activation
$\bar{a} = \frac{a}{a_{max}}$

elbow angle
θ

MUSCLE MODEL

$$F_m = \bar{a}F_0(\beta_1 \bar{l}^2 + \beta_2 \bar{l} + \beta_3)$$

$$\bar{l} = \frac{l}{l_{opt}}, \; l = h(r_u, r_l, \theta)$$

elbow torque
$$\tau = g_1(F_m) = g_2(m, F_{in}, \tau_{in})$$

If we measure $(\bar{a}, \tau, \theta)$, can we infer $B = \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 \end{bmatrix}^\top$?

Starting Point: Simplified Model

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By examining many discrete coordinate pairs $(\bar{a}, \tau, \theta)$, we can write the system dynamics as

$$\begin{bmatrix} \tau_{in,1} + rF_{in,1} - \frac{1}{2}mg\sin\theta_1 r \\ \vdots \\ \tau_{in,n} + rF_{in,n} - \frac{1}{2}mg\sin\theta_n r \end{bmatrix} = \underbrace{\begin{bmatrix} \tau_1 \\ \vdots \\ \tau_n \end{bmatrix}}_{T} = \underbrace{F_0 r_l r_u \begin{bmatrix} \frac{l_1}{l_{opt}^2}\sin\theta_1\bar{a}_1 & \frac{1}{l_{opt}}\sin\theta_1\bar{a}_1 & \frac{1}{l_1}\sin\theta_1\bar{a}_1 \\ \vdots & \vdots & \vdots \\ \frac{l_n}{l_{opt}^2}\sin\theta_n\bar{a}_n & \frac{1}{l_{opt}}\sin\theta_n\bar{a}_n & \frac{1}{l_n}\sin\theta\bar{a}_n \end{bmatrix}}_{W} \underbrace{\begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix}}_{B}$$

which admits linear least-squares optimization

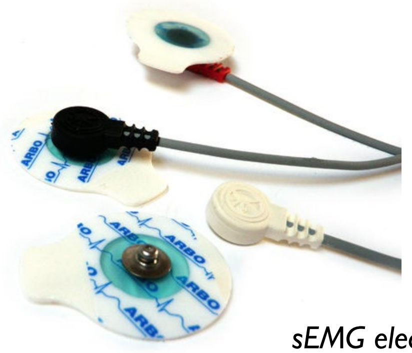
$$\min_B \|T - WB\|_2^2$$

to allow the fitting of B from experimental data.

Activation ($\bar{a}$) Measures: sEMG and AMG

sEMG (surface electromyography)

- sensitive, noisy
- aggregate
- based on neurological signals (*neurological disorder* → *poor signal*)
- well-explored
- industry standard



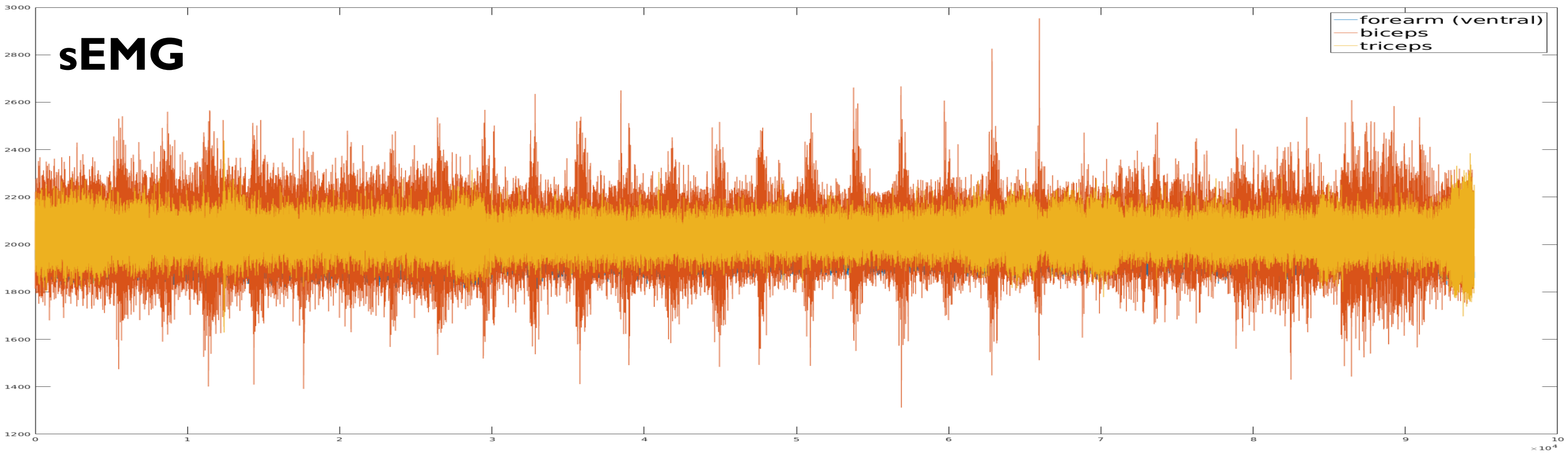
sEMG electrodes

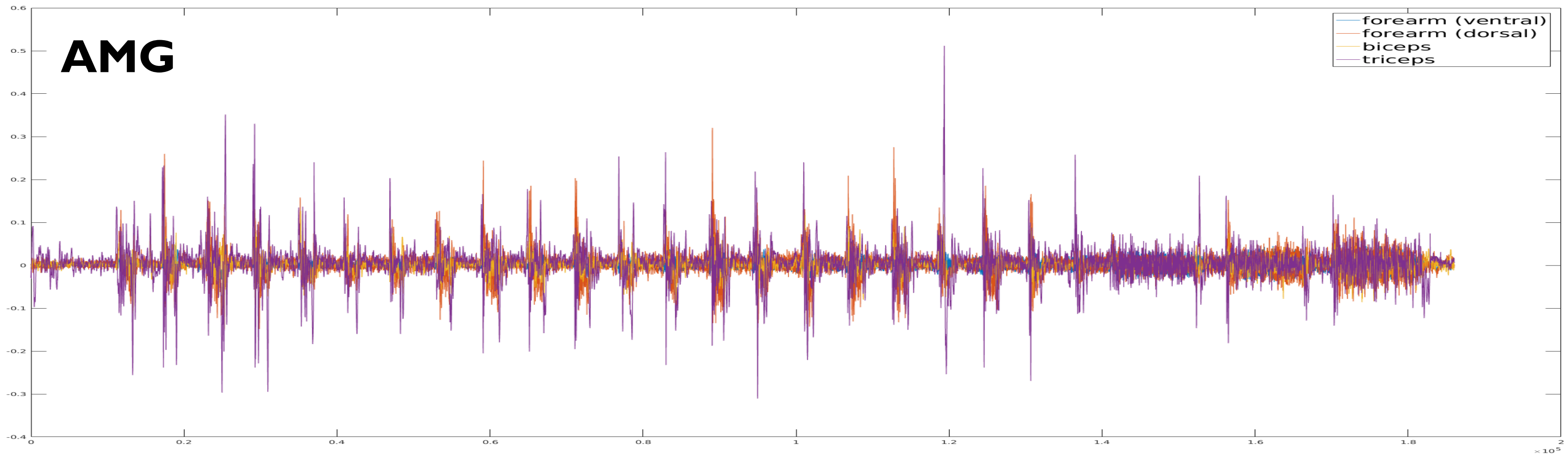
AMG (acoustic myography)

- improved SNR
- aggregate
- based on physiological signals
- novel

CURO

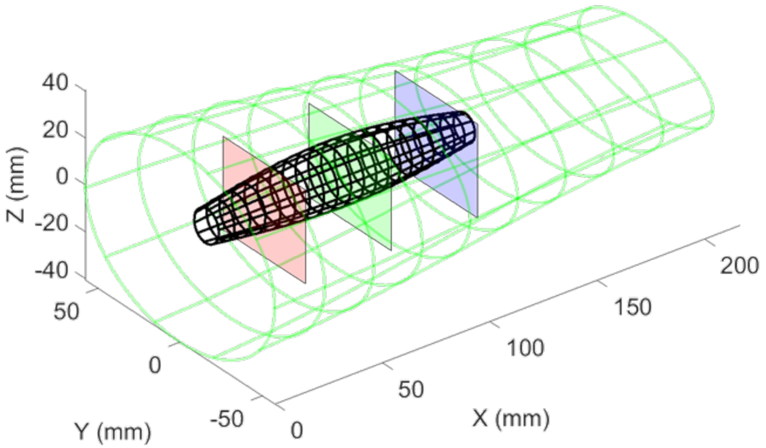
Sample Activation Data





Activation ($\bar{a}$) Measures: Ultrasound

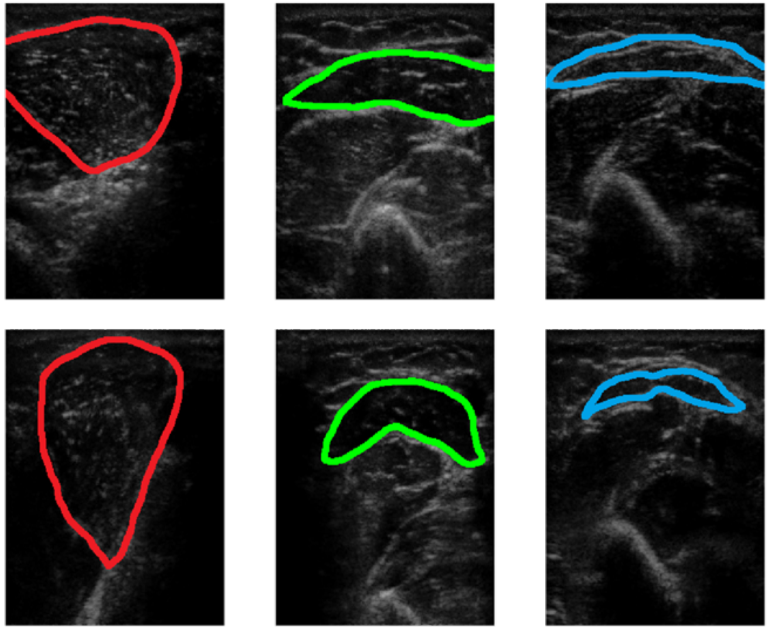
3D View

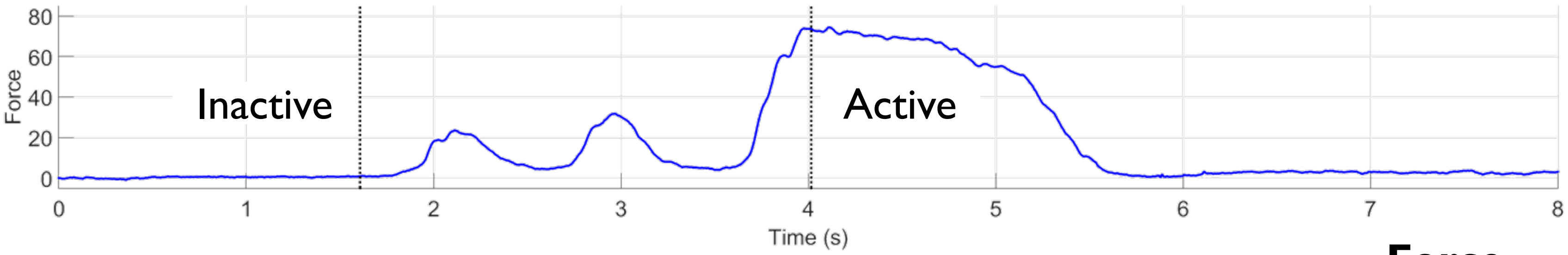


Muscle Cross-Section

Inactive

Active





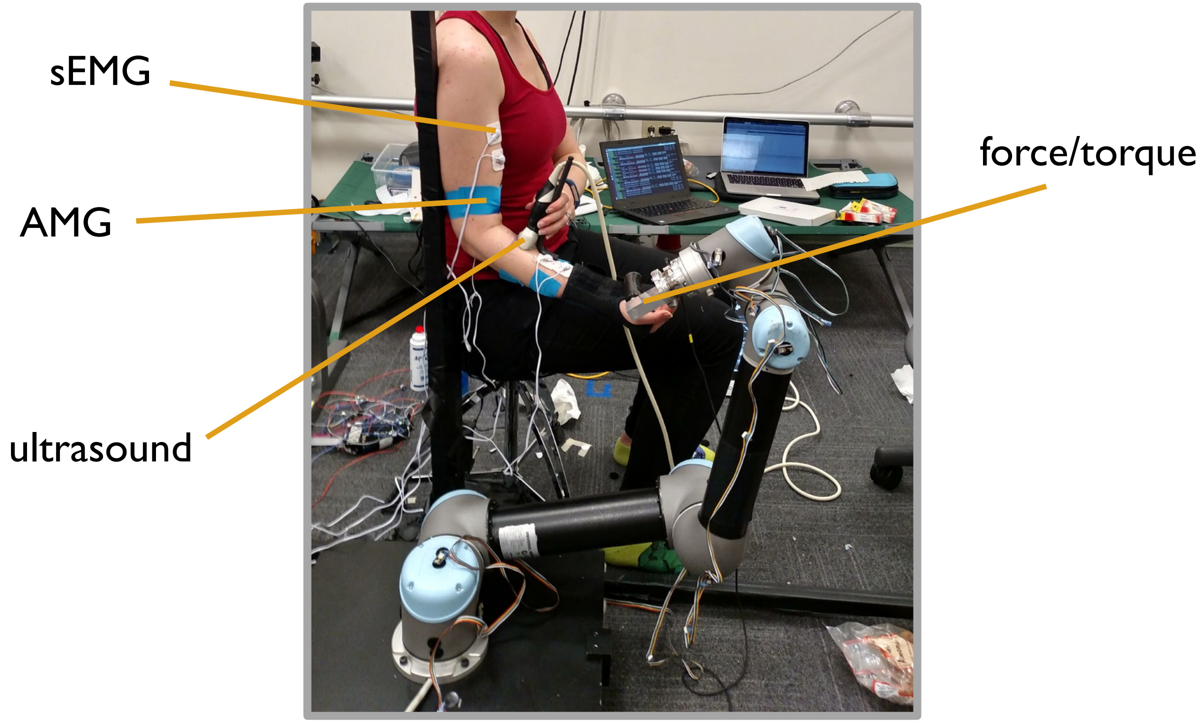
Force

Experimental Setup

~230 $(\bar{a}, \tau, \theta)$ data points

- $\bar{a}$ via single-channel (biceps)
  - sEMG
  - AMG
  - ultrasound
- τ via F/T sensor (mounted to UR5 robot)
- θ calculated from images (13 waypoints)

50% training, 50% testing (randomly assigned)



Data collection, HART Lab 2017

Preliminary Results: sEMG vs. AMG

Using both sEMG and AMG:

- **predicted force** using fitted B is reasonable (~5-10% mean error over test set)

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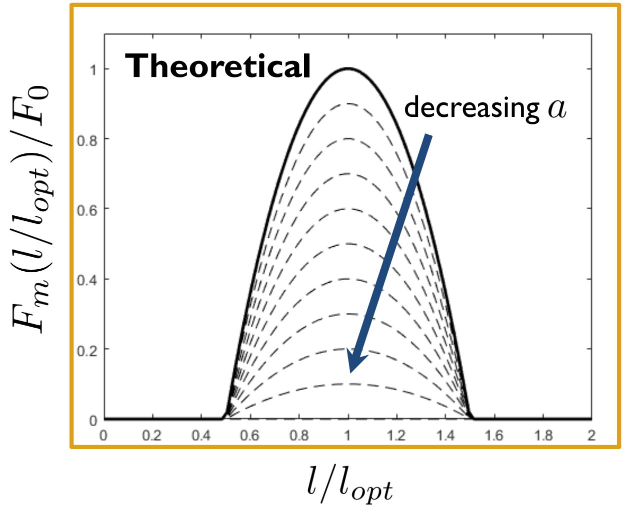
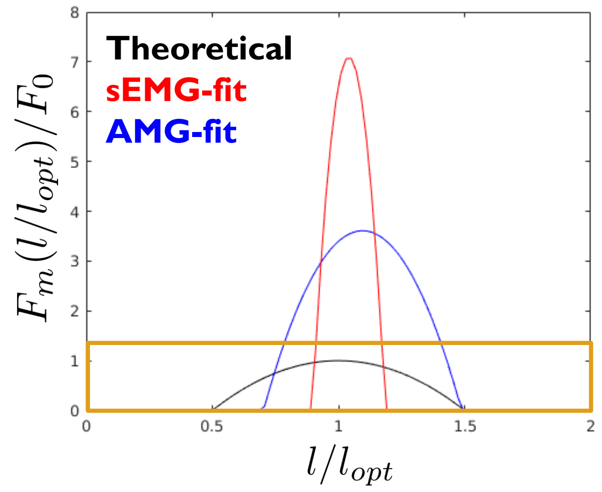
- **predicted force** using fitted B is reasonable (~5-10% mean error over test set)

- predicted **force-length relation** is biologically reasonable but differs across sensors
  - max force at reasonable location → l_{opt} accurate
  - normalization unreasonable → F_0 inaccurate
  - more investigation into other parameters needed

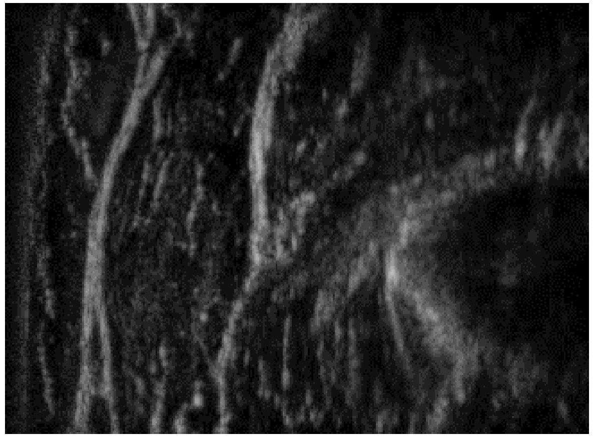




Preliminary Results: Ultrasound

WP 1
(25°)
(extended)

WP 5
(69°)



WP 13
(117°)
(flexed)

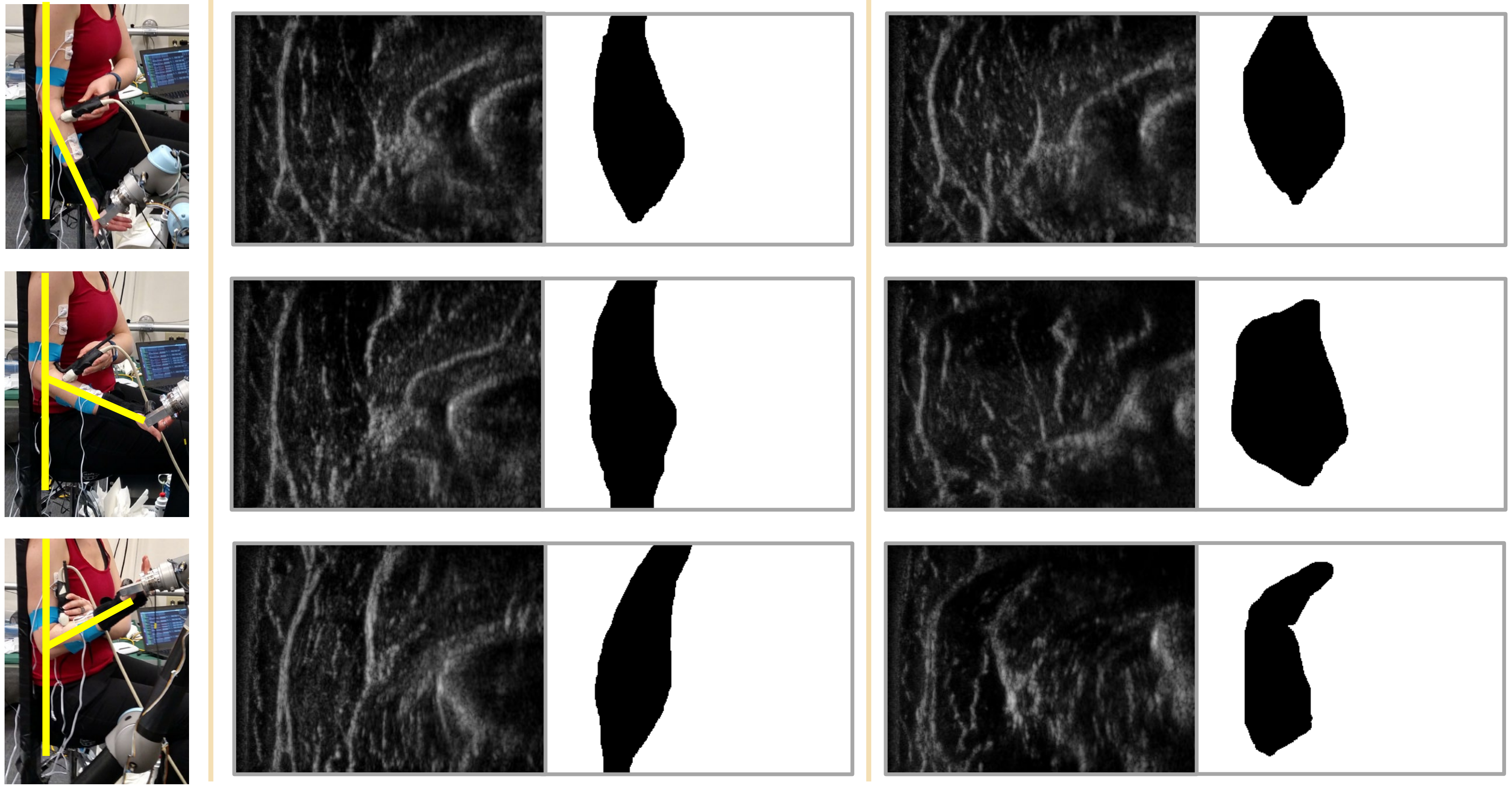
Preliminary Results: Ultrasound

No Force | **Max Force**

WP 1 (25°)

WP 5 (69°)

WP 13 (117°)



Refined Approach: "Sensor-Driven" Modeling

Key ideas moving forward:

- use **an abstraction** for each sensing modality **that generates reliable results**, even at the expense of detail (e.g., sEMG as binary signal)
- determine **which parameters/signals are most critical** to measure correctly, and focus on those
- use **optimization/control techniques** to use signals effectively (e.g., hybrid systems)
- increase model complexity **without overfitting**

Limitations

The obvious: The model is vastly over-simplified and is not obviously more useful than other single-DoF rigid body models.

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The less obvious: To effectively extend these models, we need a much more sophisticated understanding of the sensor physics.

- **Option 1**: geometric models (MRI, ultrasound)
  - – no ready "wearable" signal sources
  - \+ highly localized
  - – more computationally intensive?
- **Option 2**: stress-strain/elasticity models (AMG, cine DENSE)
  - \+ AMG as "wearable" signal source
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Project 1

Project 2

PROJECT 1

Geometric Models:

Muscle Morphology and Deformation Analysis

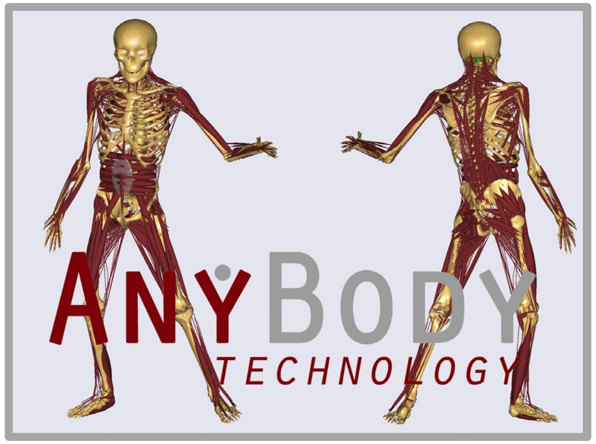
PROJECT 1A *(Stanford-UCB collaboration)*

Morphology Analysis via Multi-Subject MRI

Motivation

There exist **frameworks for human dynamical modeling** . . .

- OpenSim / AnyBody
- task-specific models
- our own models



Motivation

There exist **frameworks for human dynamical modeling** . . .

- OpenSim / AnyBody
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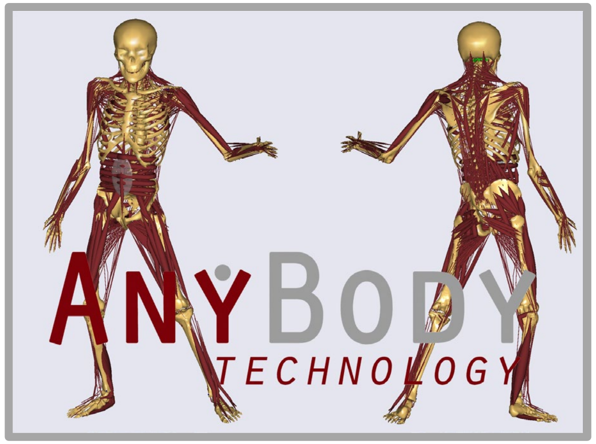
. . . but there do not exist frameworks that tell us **how good these models are**.



Goal: Quantify Model Accuracy

We seek to examine

- the morphological variation across subjects,
- existing frameworks' ability to account for this variation, and
- the impact of this variation on dynamical model prediction accuracy

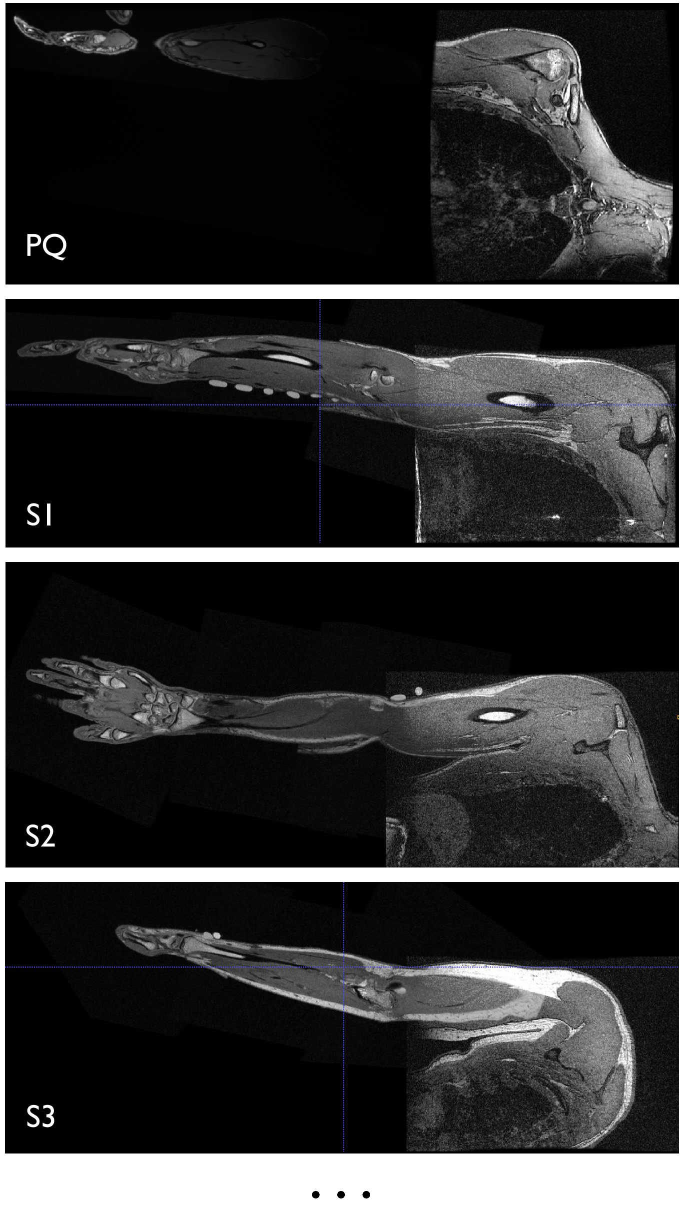
(specifically, for the human arm).

Dataset: Upper-Limb MRI Scans

- **~10 subjects**, full arm (hand through torso)

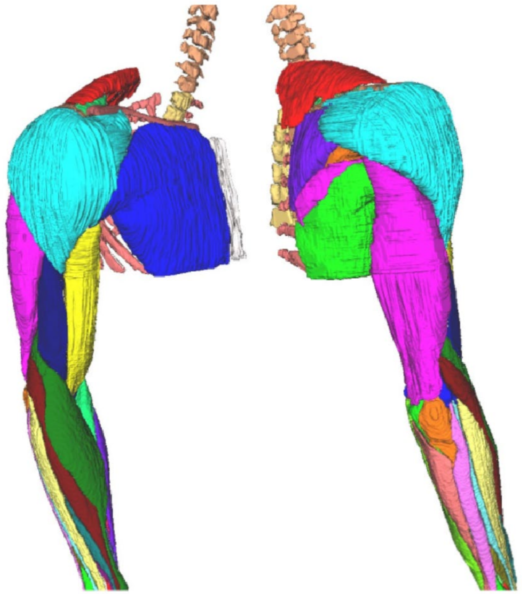
- vary in
  - age
  - health
  - height/weight
  - gender

- **4 separate scans** taken to improve contrast where possible, then stitched together in post-processing
  - hand, forearm, elbow (“bird cage” coil)
  - shoulder (no additional coil)



Approach

- **extract** parameters of interest
  - bone/muscle volumes
  - bone/muscle length
  - muscle-bone attachment points



Segmented muscle data, Stanford 2016

Approach

- **extract** parameters of interest
  - bone/muscle volumes
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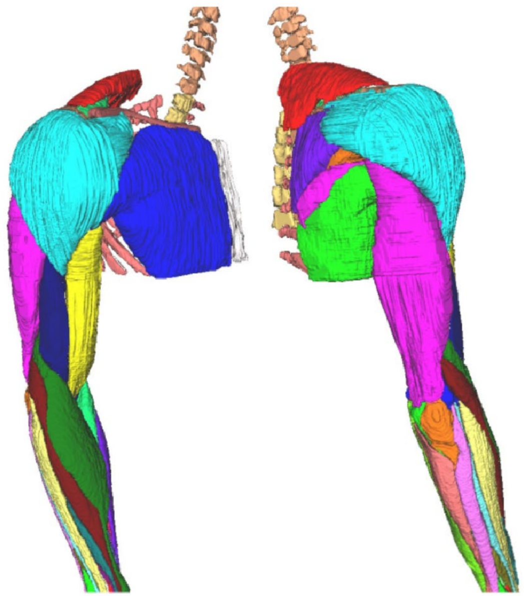
- **compare** parameters
  - across subjects
  - across perturbed subjects
  - with best canonical model approximation (e.g., OpenSim)



Segmented muscle data,
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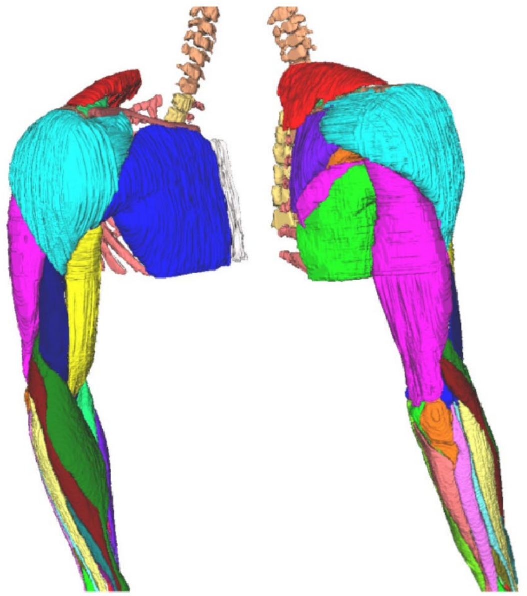
- **compare** parameters
  - across subjects
  - across perturbed subjects
  - with best canonical model approximation (e.g., OpenSim)
- **evaluate** each parameter's impact on predicted dynamics (contact forces, joint torques) using Stanford's SCL



Segmented muscle data,
Stanford 2016

Approach: Bone Segmentation

Arm bones of 4 subjects segmented using

- **MSER** (implemented in MATLAB) *(small — e.g., hand — bones)*
- **active contours** (built into itk-SNAP) *(larger bones)*
- **manual coloring** in itk-SNAP *(poor contrast — e.g., shoulder — bones)*
- **manual cleanup** *(required on ALL bones)*

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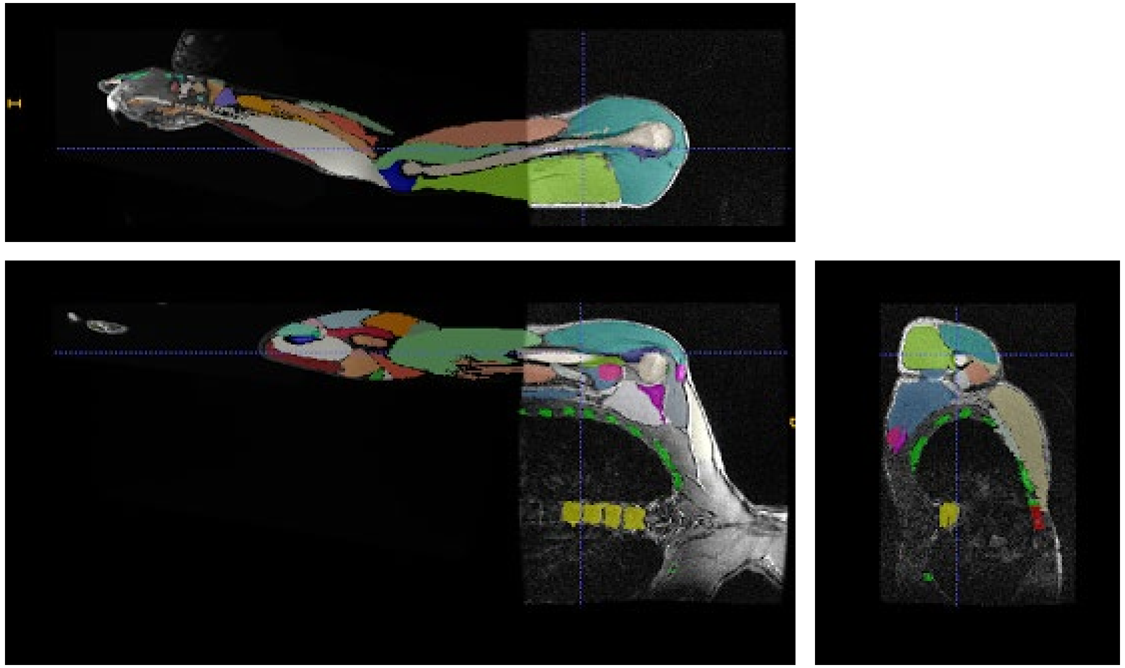
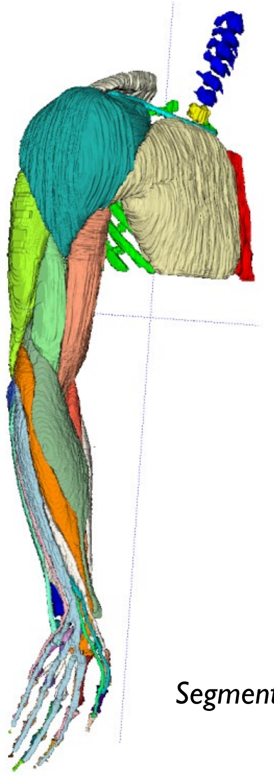
extensive manual cleanup required!

Approach: Muscle Segmentation

Muscle segmentation presents further challenges:

- manual segmentation **prohibitively time-intensive** (*multiple months for single subject by Stanford collaborators*)



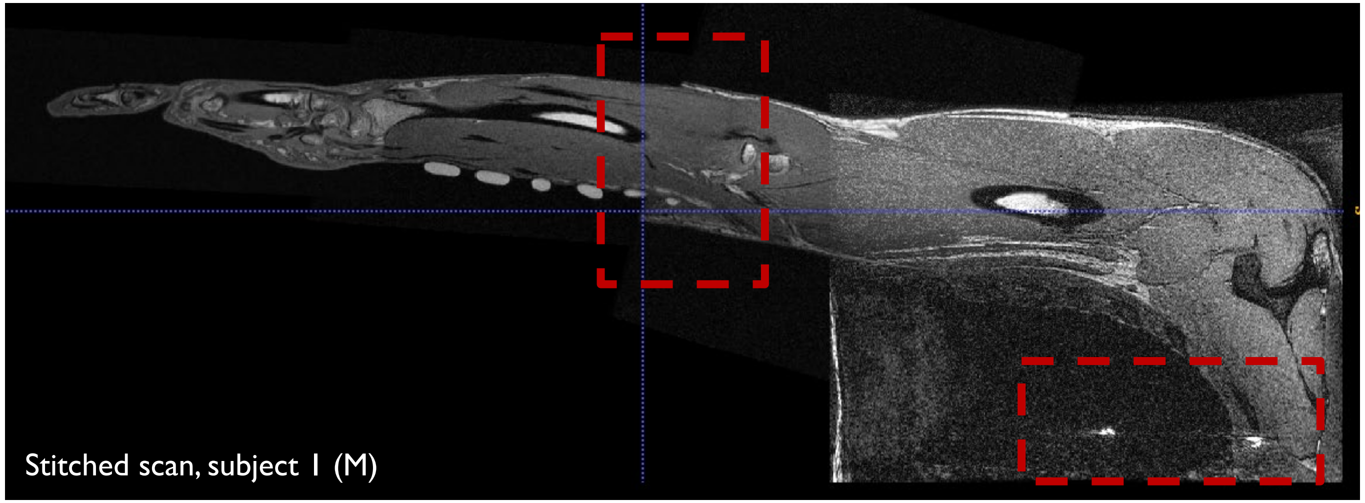


Segmented muscle data,
Stanford 2016

Approach: Muscle Segmentation

Muscle segmentation presents further challenges:

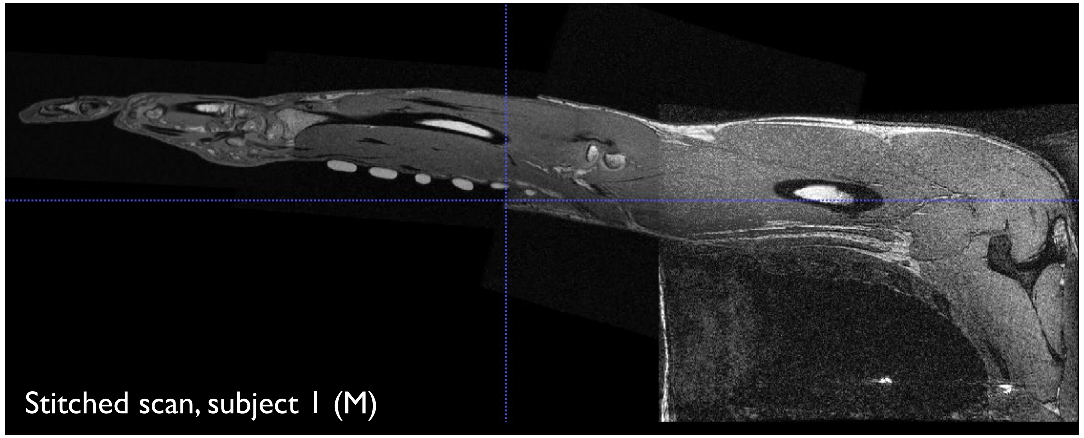
- manual segmentation **prohibitively time-intensive**
- **poorly suited** to generic blob/edge detection
  - large inter- and intra-subject contrast variation
  - muscle fascia hard to observe, even for humans
  - artifacts (stitching, motion, etc.)



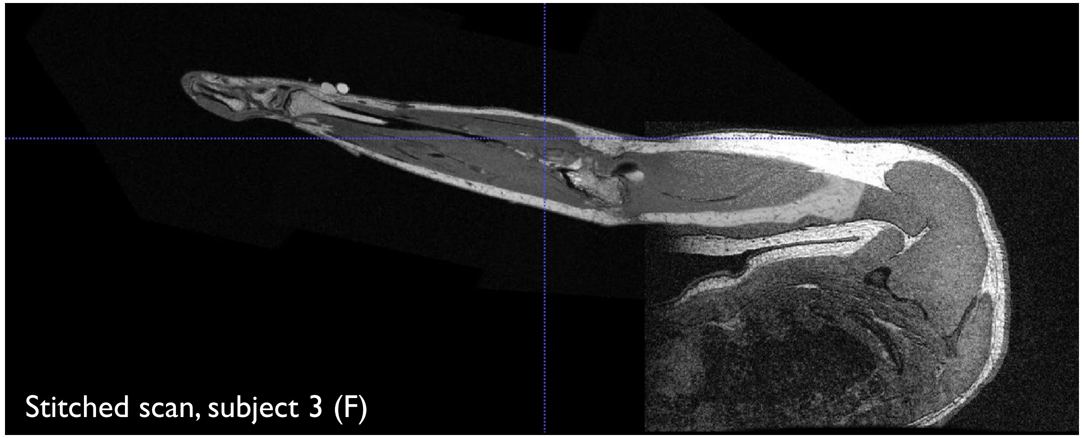
Approach: Muscle Segmentation

Muscle segmentation presents further challenges:

- manual segmentation **prohibitively time-intensive**
- **poorly suited** to generic blob/edge detection
- **significant non-affine variation** predicted across subjects
  - joint angles (likely need to match segments and stick them back together)
  - overall morphology



Stitched scan, subject 1 (M)



Stitched scan, subject 3 (F)

Approach: Muscle Segmentation

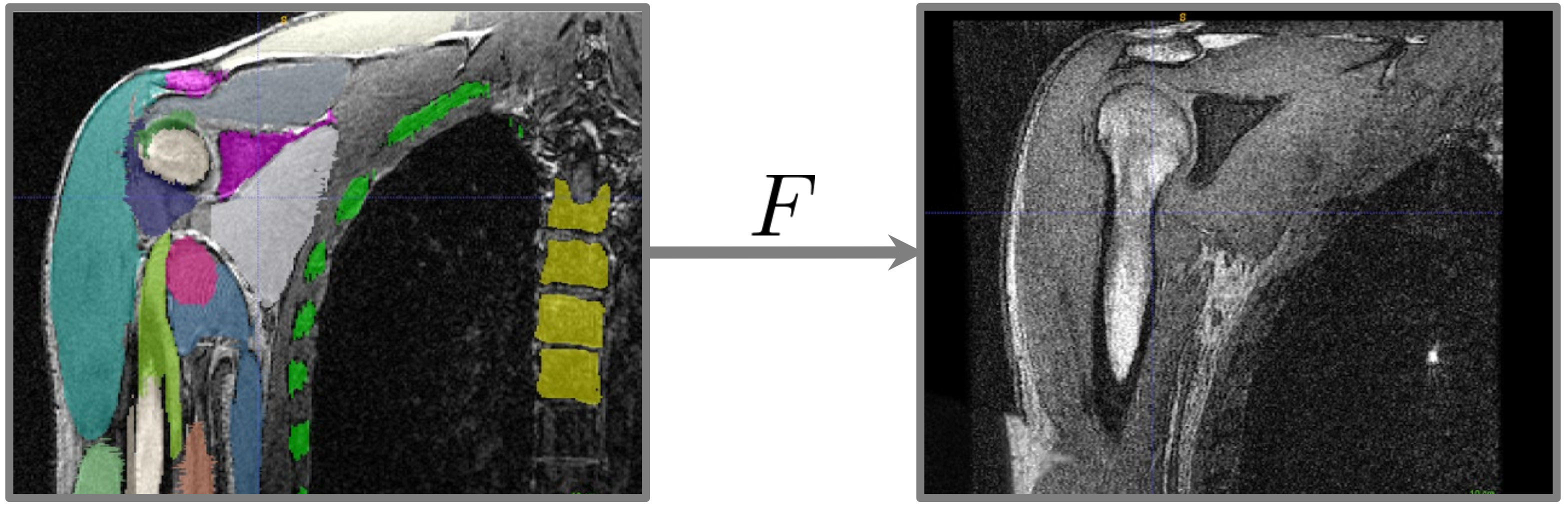
Muscle segmentation presents further challenges:

- manual segmentation **prohibitively time-intensive**
- **poorly suited** to generic blob/edge detection
- **significant non-affine variation**

→ Instead of segmenting from scratch, map segmented muscles from one subject to another!

Approach: Muscle Segmentation

Goal: Find best transformation $F : R \to T$



(segmented) reference subject
R

target subject
T

Approach: Muscle Segmentation

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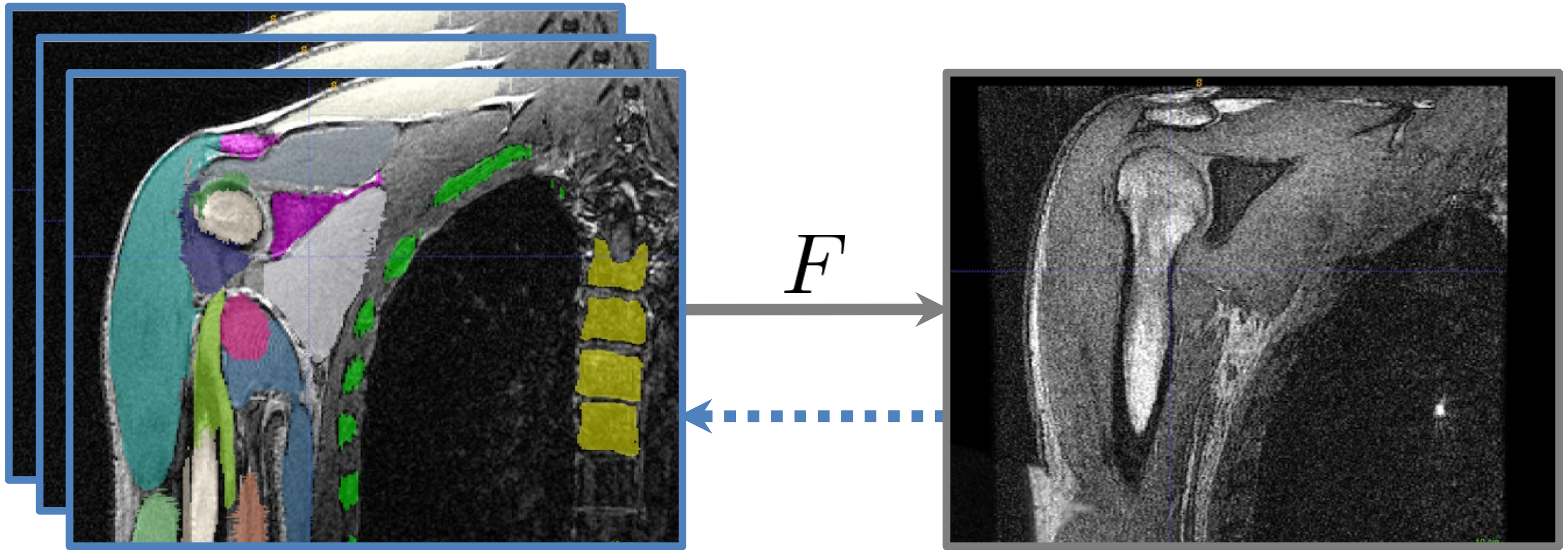


(segmented) reference subject atlas

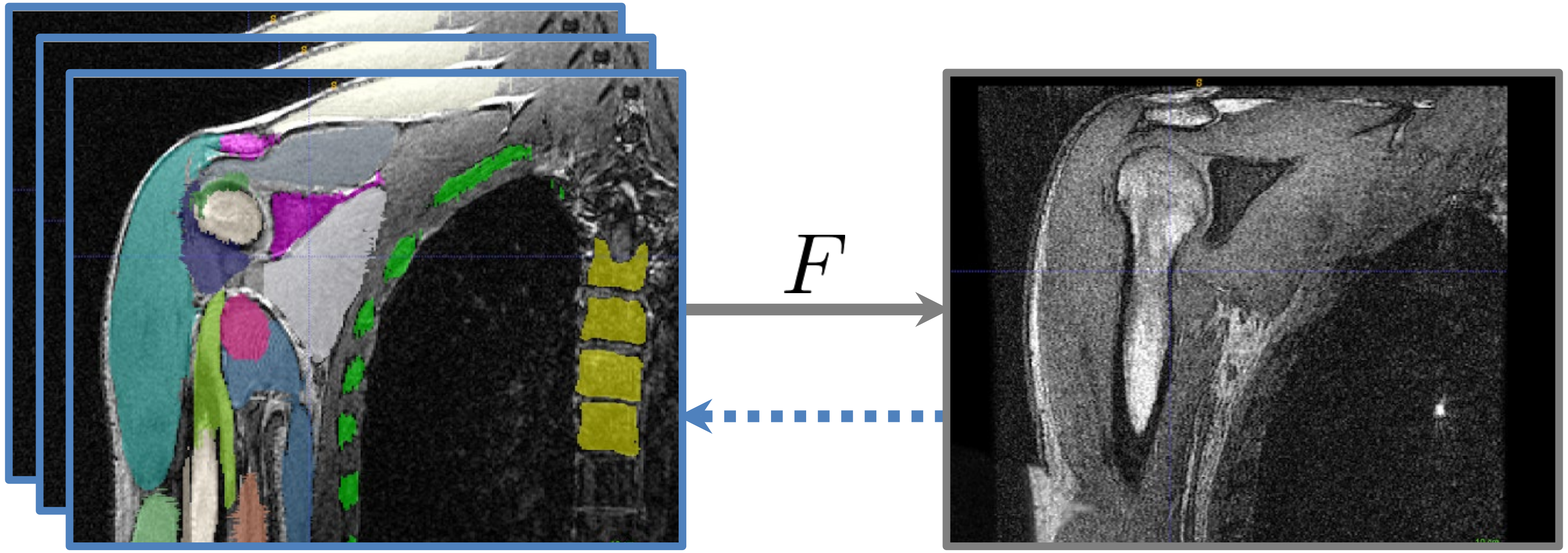
$R \in \mathbf{R}$

target subject

T

Approach: Muscle Segmentation

Goal: Find best transformation $F : R \rightarrow T$



(segmented) reference subject atlas
$R \in \mathbf{R}$

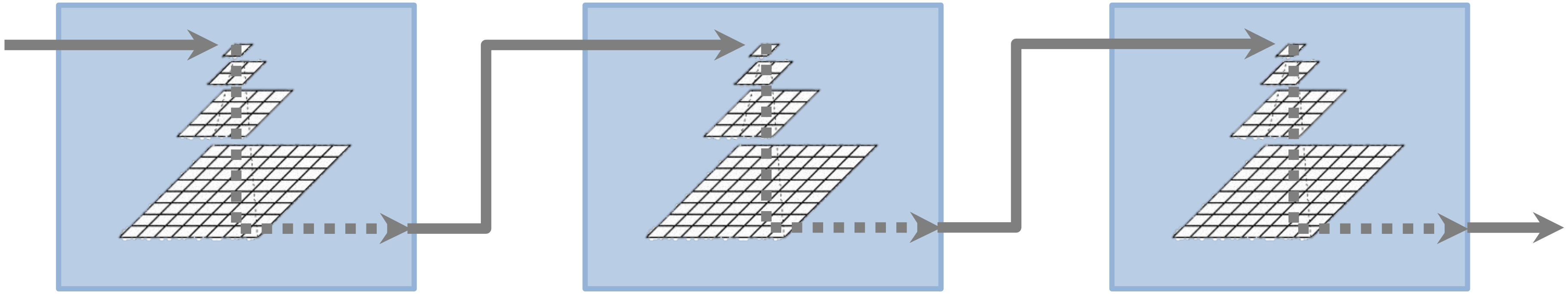
target subject
T

→ This is a canonical **MRI registration problem** (use same F on raw scans and muscles), so we can explore existing libraries!

Approach: Registration Pipeline (Elastix)

Most promising results thus far obtained via:

- **intensity-based** registration
- **multi-resolution image pyramids**: registered lower-resolution image initializes that of next highest resolution
- **weighted combination of transform types**: lower-DOF transform results initialize higher-DOF transform

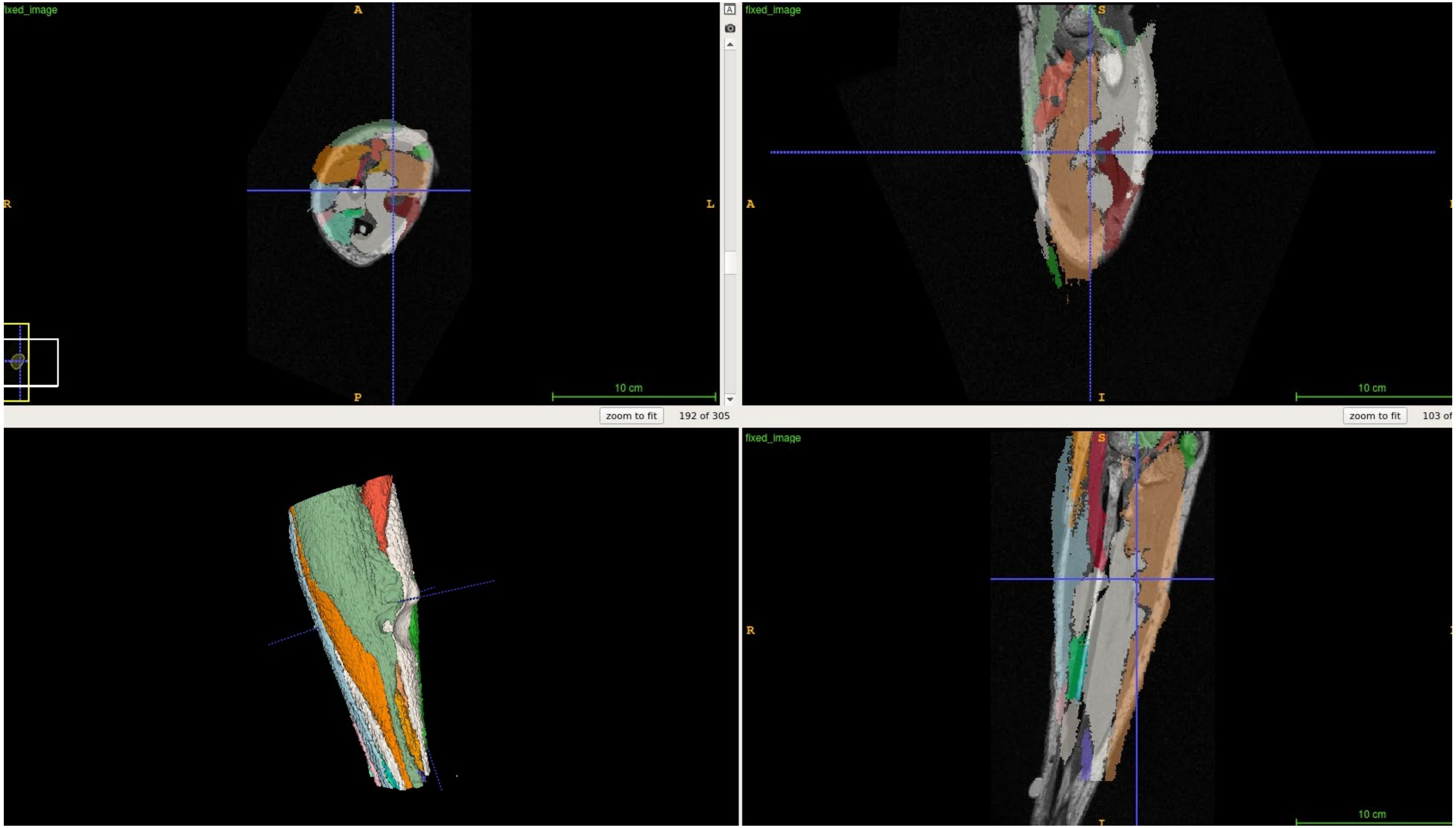


translation + rotation (Euler)

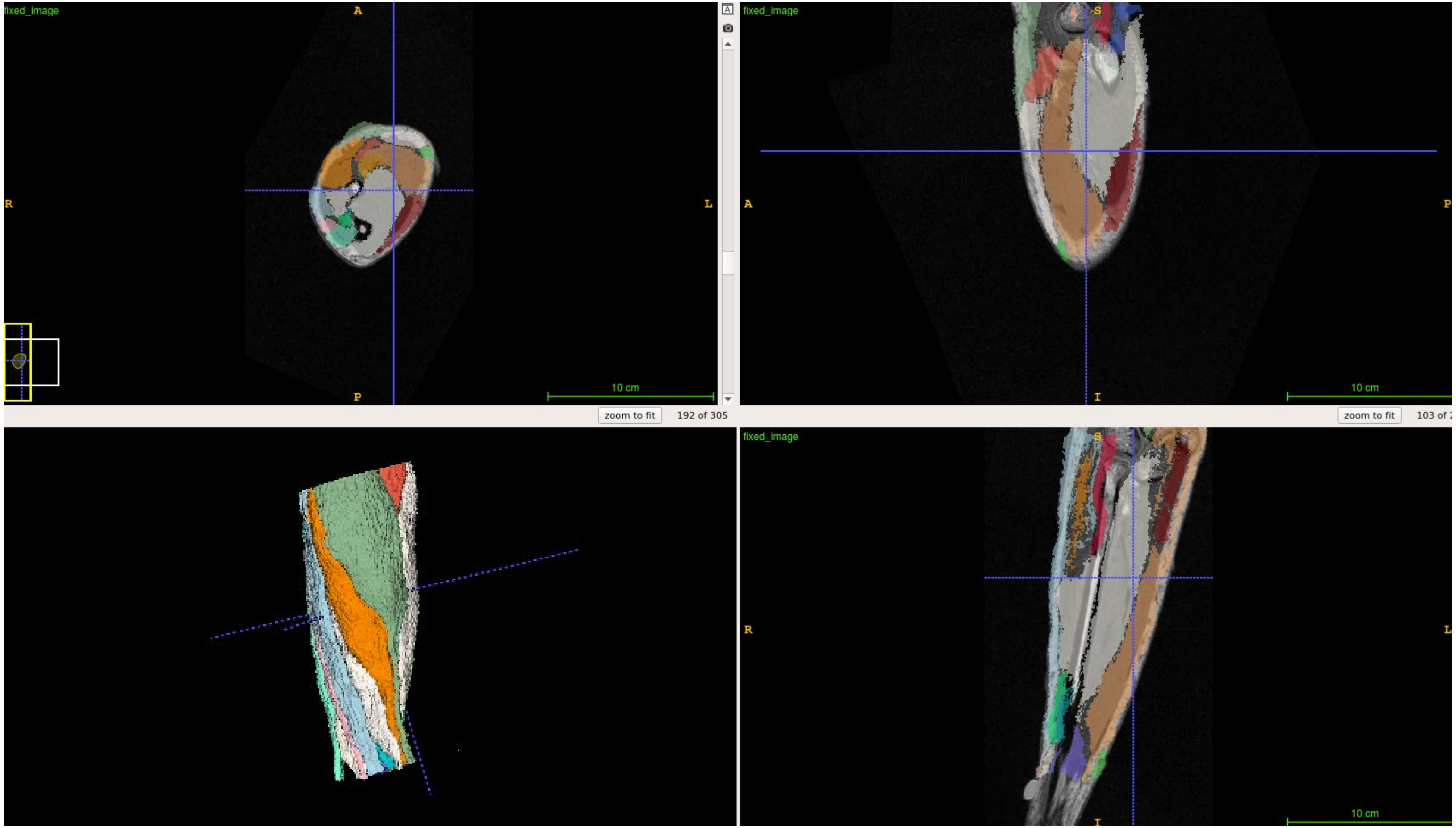
affine transformation

free-form deformation (FFD) *(b-spline parameterized)*

Preliminary Results: Muscle Mapping (*sim. only*)



Preliminary Results: Muscle Mapping *(bending pen.)*

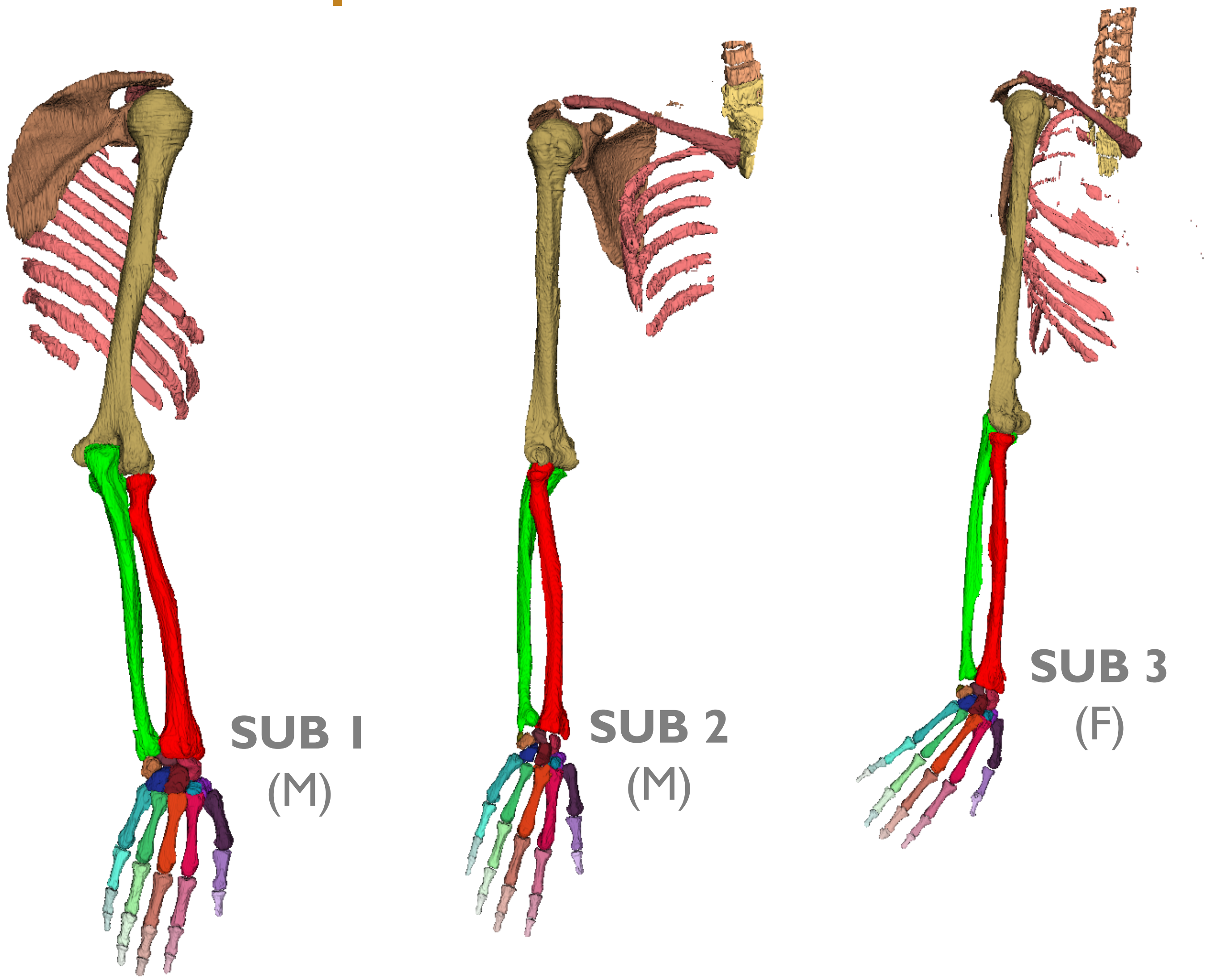


Preliminary Results: Muscle Mapping *(ground truth)*

. . . we're working on it.

Preliminary Results: Comparison

Preliminary bone segmentation results show **significant morphological variation across subjects** that cannot be modeled in existing frameworks.



Preliminary Results: Comparison

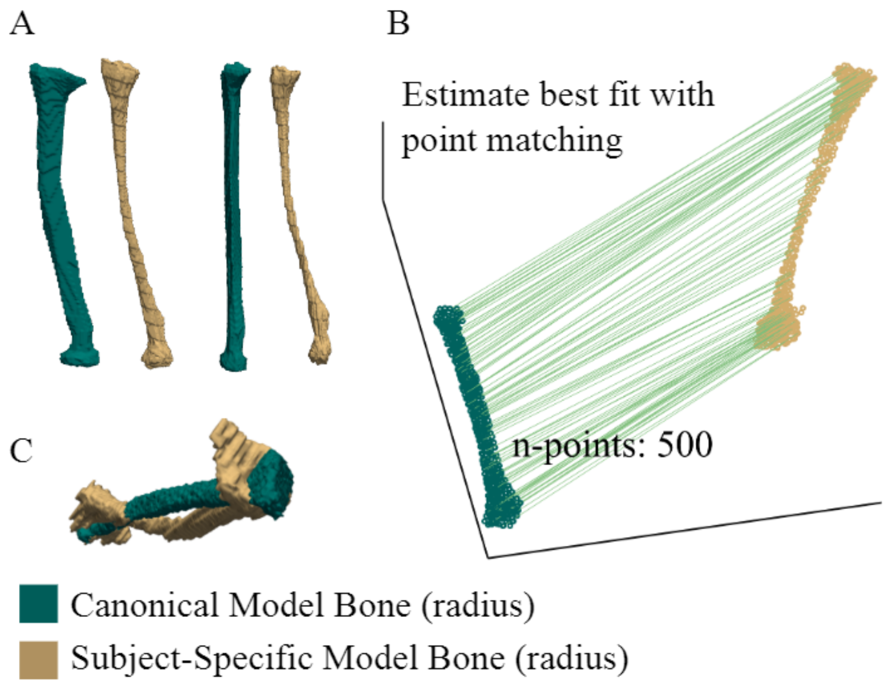
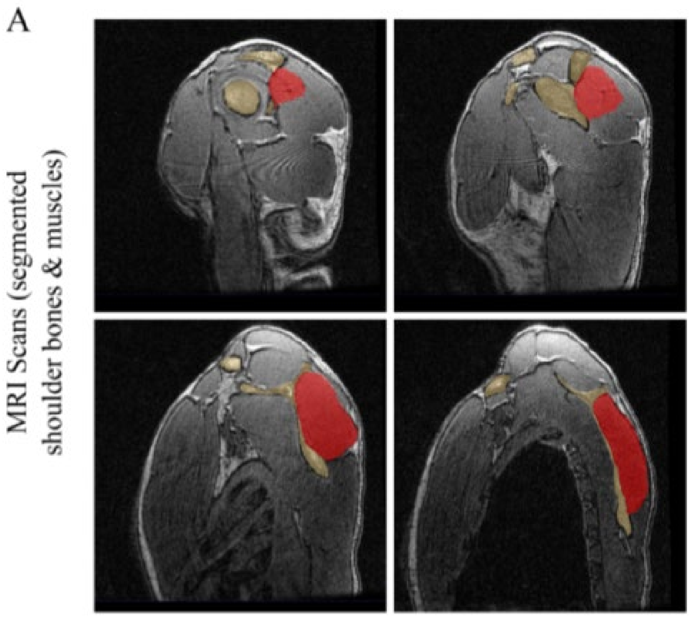


Fig. 5. **Model Scaling Errors. A.** A canonical model's radius bone side-by-side with an MRI-based subject-specific model's radius bone. The subject-specific model is accurate to < 1mm, and considered to be ground truth. **B.** We scaled the canonical model to the subject's radius with an affine transformation that optimized the distance between five hundred corresponding points between the two bones. **C.** The scaled canonical model was unable to match the geometry of the subject-specific model. Moreover, affine fits can be expected to be substantially worse when ground truth is unavailable.

MRI vs. canonical, Stanford 2016

Preliminary Results: Simulation



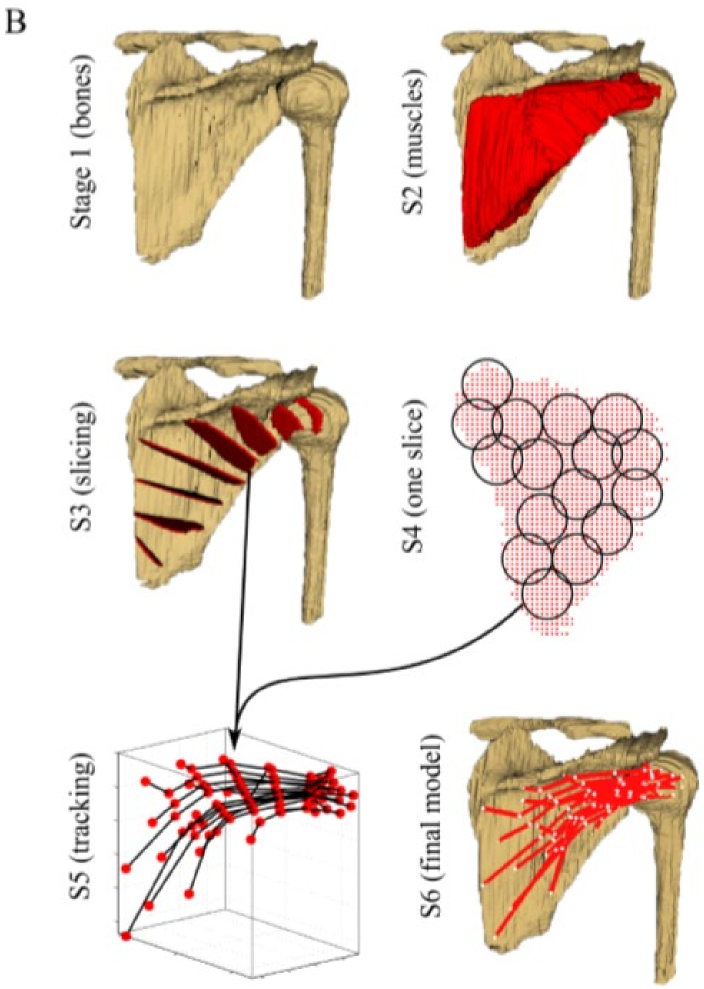


Fig. 3. **Model Generation. A.** MRI-based musculoskeletal models were obtained by segmenting high-resolution anatomical scans. Exemplar sagittal cross-sections for the shoulder are shown, matching the volumetric reconstruction below. **B.** The model generation pipeline consists of six stages. Stages 1 and 2 involved extracting three dimensional volumes for bones and muscles. Stage 3 involved slicing muscles normal to their direction of force. Stage 4 involved packing fiber-group actuator cross-sections into the muscle slices. Stage 5 involved associating actuator intersection circles across slices. And, finally, stage 6 involved connecting actuators to create piece-wise muscle approximations. Stages 3 and 4 may be parameterized to create families of models.

Dynamics model generation, Stanford 2016

Preliminary Results: Simulation

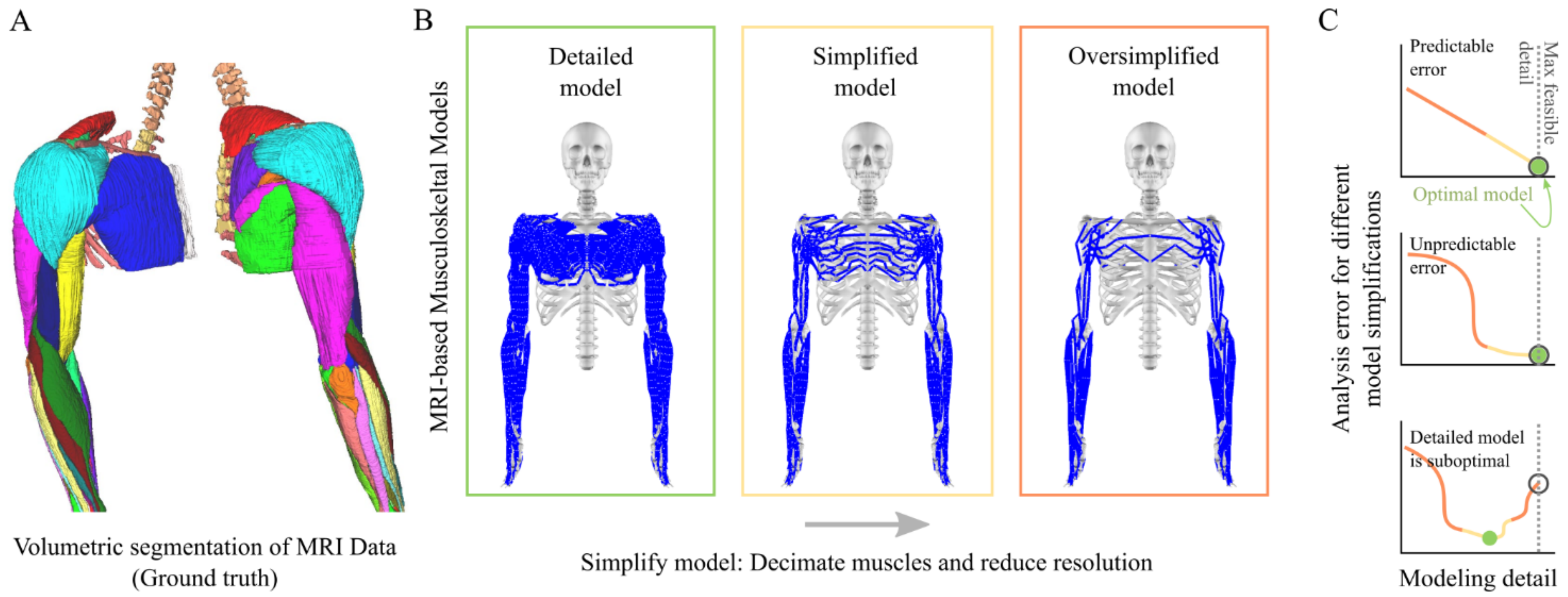


Fig. 2. **Comparing Model Accuracy and Analysis Error. A.** Volumetric rendering of bones and muscles extracted from a subject's anatomical MRI data. **B.** A family of models generated from the volumetric data. Skeletons are identical. The muscle model on the left very accurately captures muscle volumes (2.5mm radius and 2cm length fiber-group segments). The other two models are parametrically decimated by reducing the number of fiber groups per unit area, without dropping muscles. The musculature in the lower arm is better preserved since the muscles are more numerous and thinner, and thus lose less detail. **C.** Analyzing a family of MRI-based models with varying accuracy provides insights into the level of detail required for a given biomechanical analysis. A family of models with varying detail can help identify and avoid the model simplifications (or improvements) that increase errors. Ideal models have predictable errors.

Model resolution comparison, Stanford 2016

Limitations

There are lots of great things about our dynamics model . . .

- arbitrarily detailed
- well-conditioned
- trackable in real time
- easily parameterizable
- lends insight into parameters of importance through sensitivity analysis

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- arbitrarily detailed
- well-conditioned
- trackable in real time
- easily parameterizable
- lends insight into parameters of importance through sensitivity analysis

. . . but we **still can't validate how good it is**, since all of our data is static.

PROJECT 1B

Muscle Deformation Analysis via Ultrasound

Key Questions

- Can we differentiate muscle deformation associated with **kinematic configuration** from deformation associated with **force output**?
- If we account for pure configuration-associated deformation, can we infer a **clean relationship between force and deformation** that can be used as a control signal?

Key Questions

- Can we differentiate muscle deformation associated with **kinematic configuration** from deformation associated with **force output**?
- If we account for pure configuration-associated deformation, can we infer a **clean relationship between force and deformation** that can be used as a control signal?

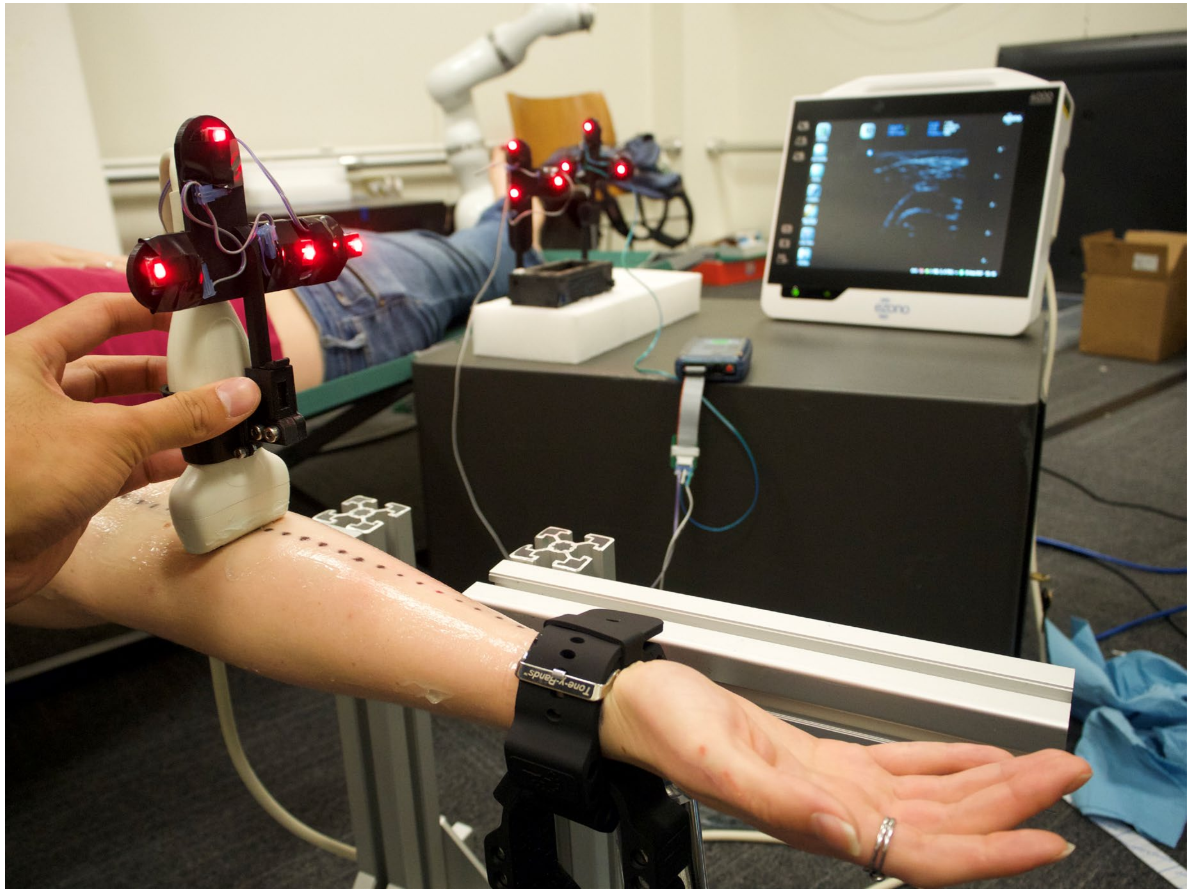
To answer these questions, we need a **factorial set of muscle scans** to compare across both joint positions and loading conditions.

Approach

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

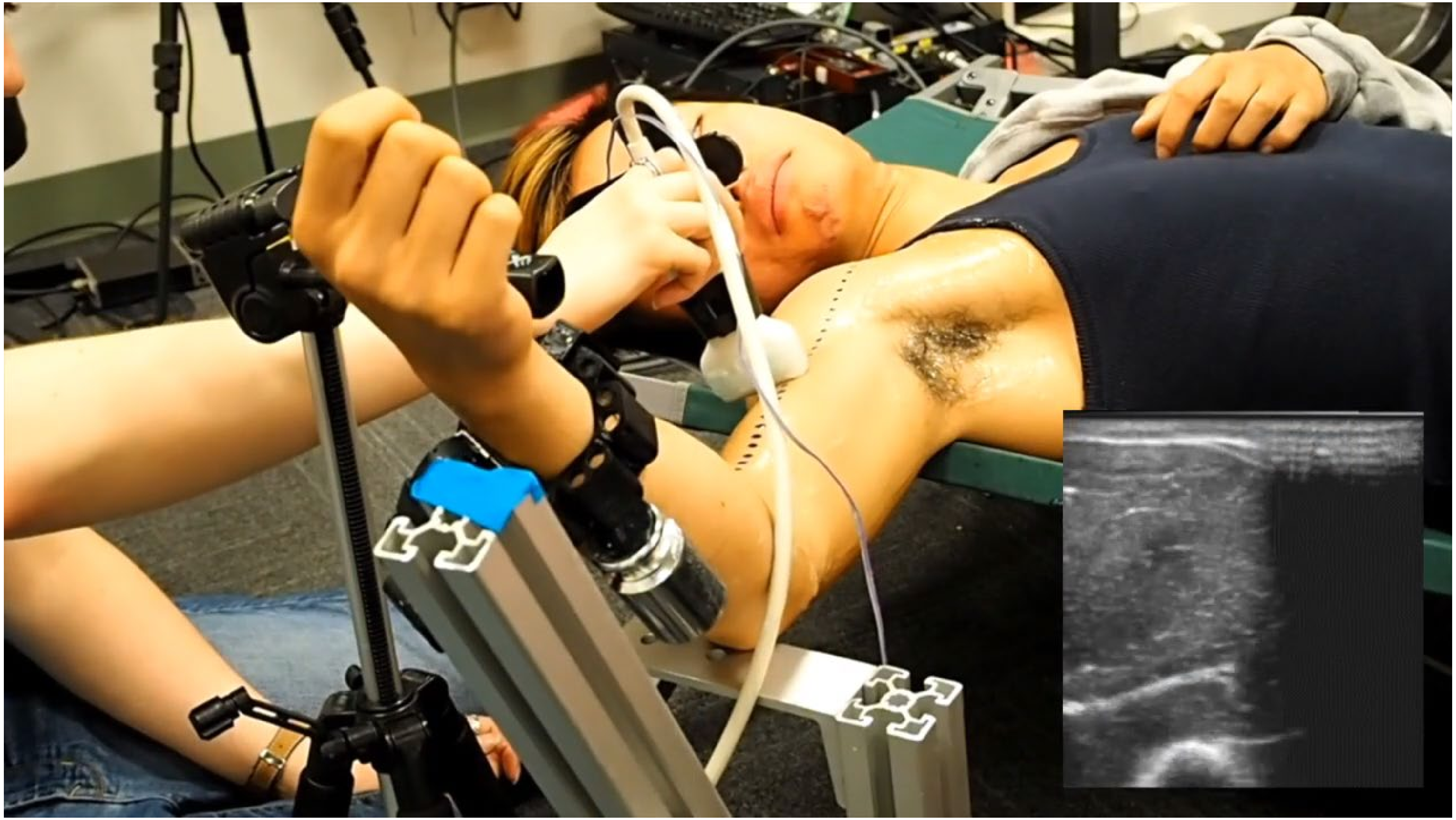
Data set:

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

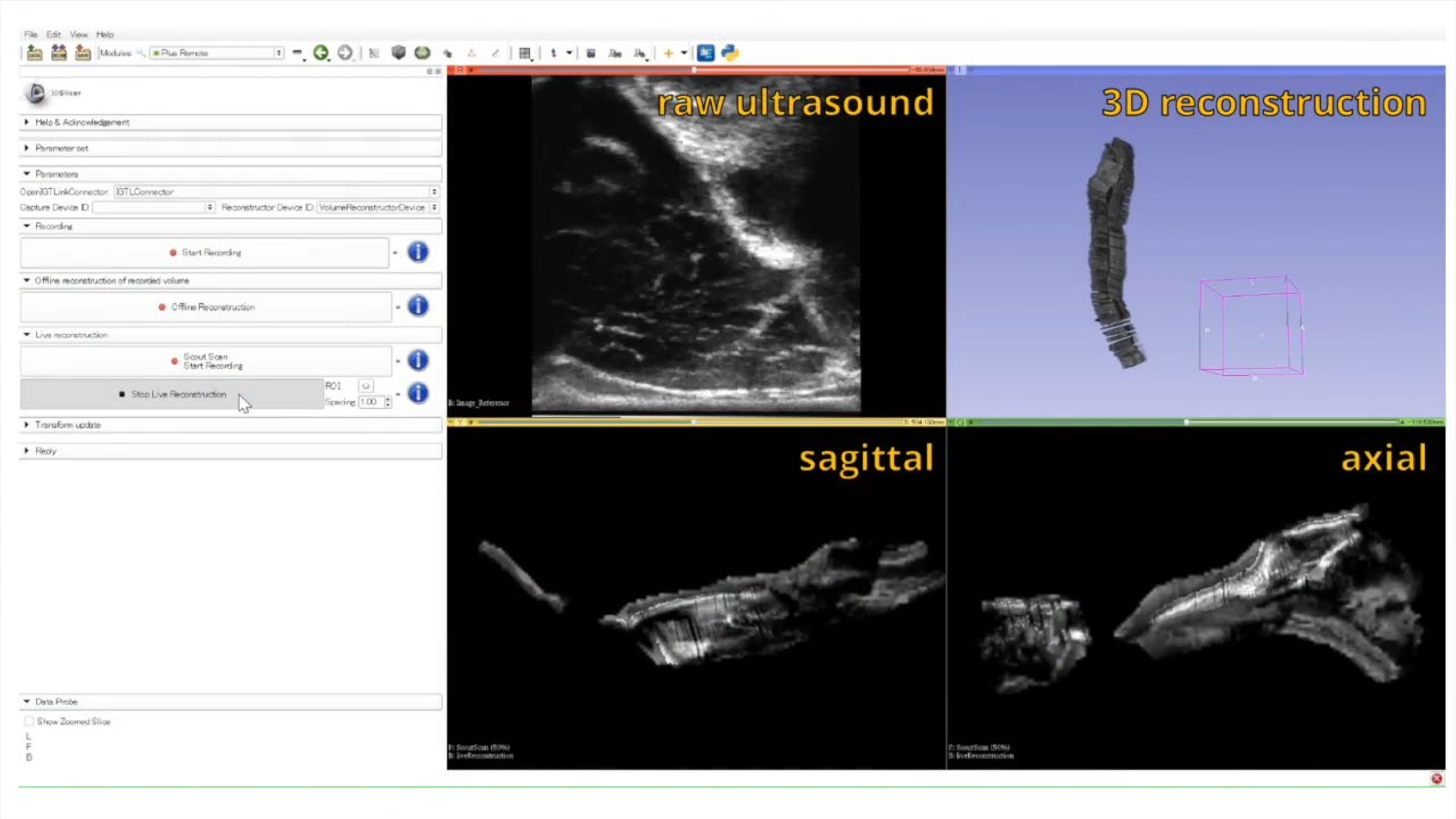


Ultrasound volumetric data collection, HART Lab 2017

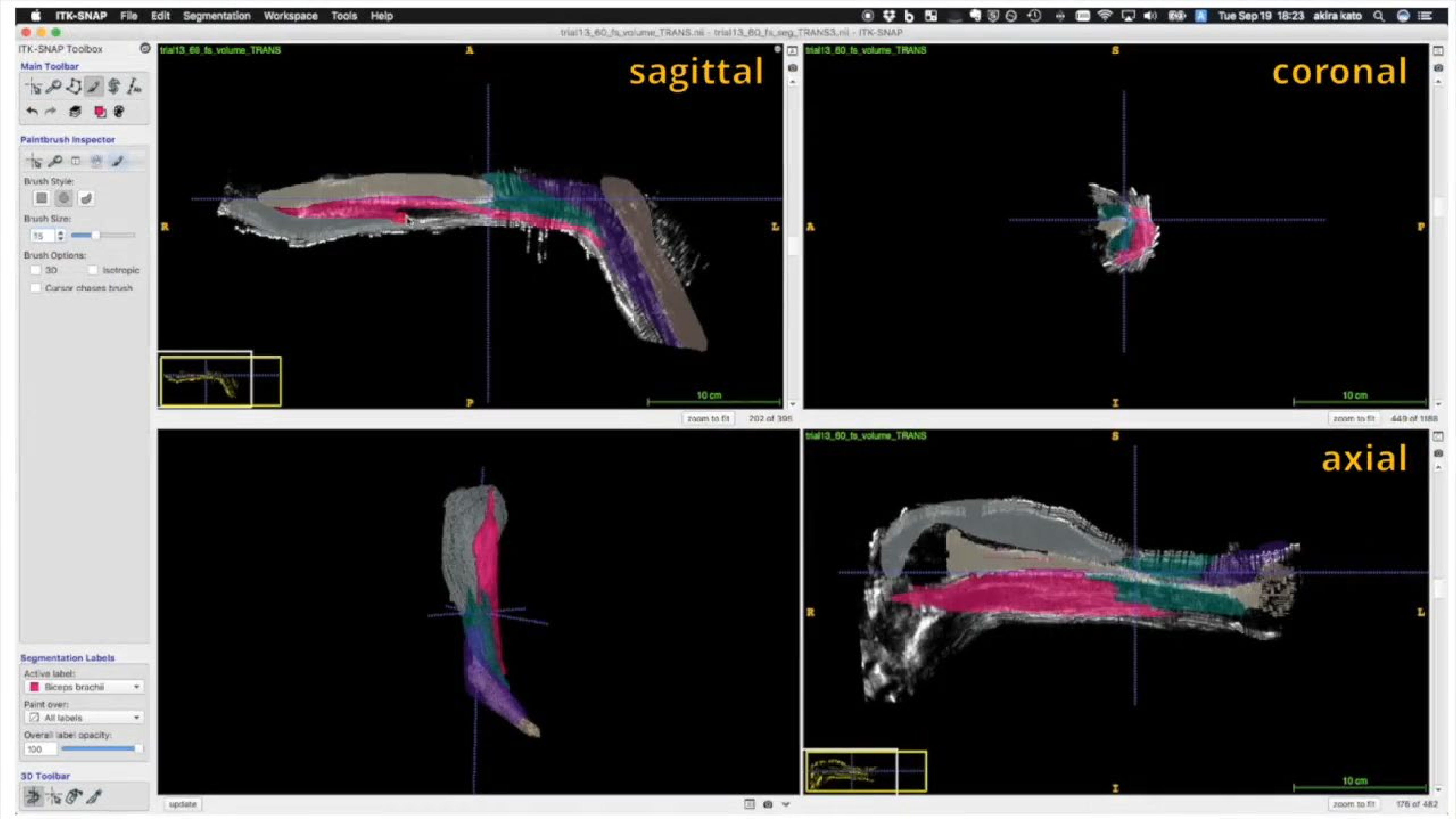
Data Collection and Processing



Data Collection and Processing: PLUS/3DSlicer

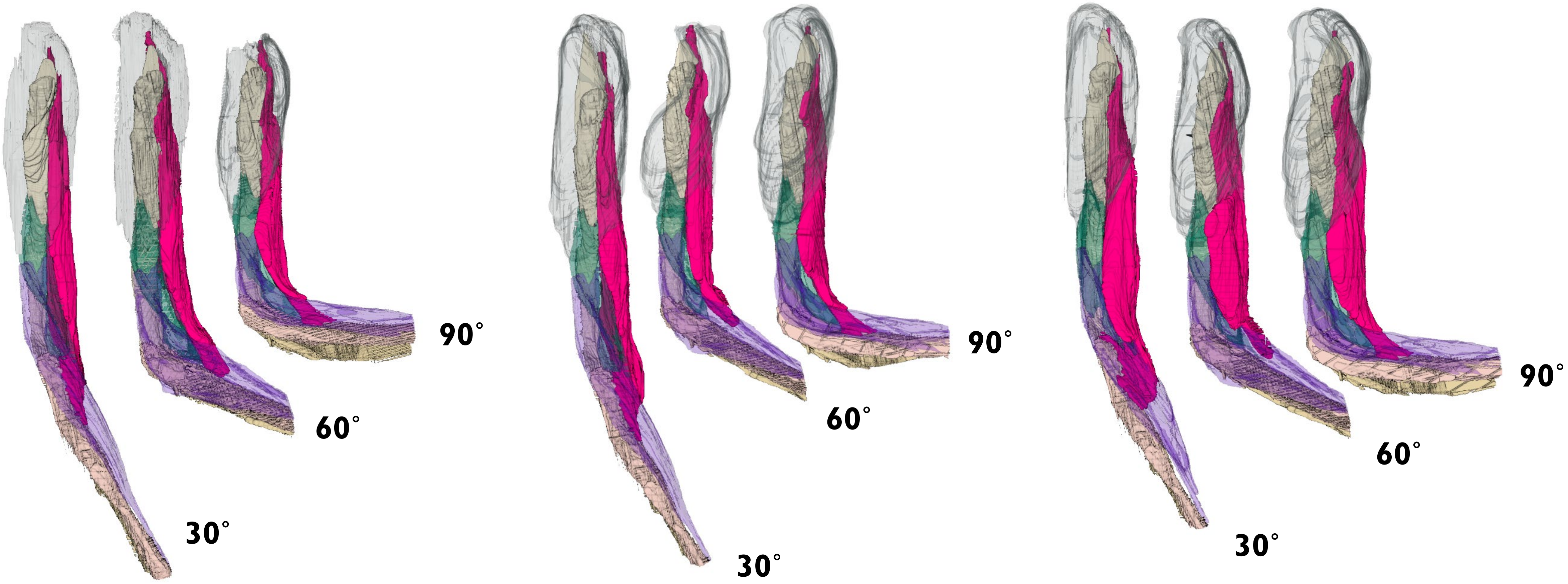


Data Collection and Processing: ITK-SNAP

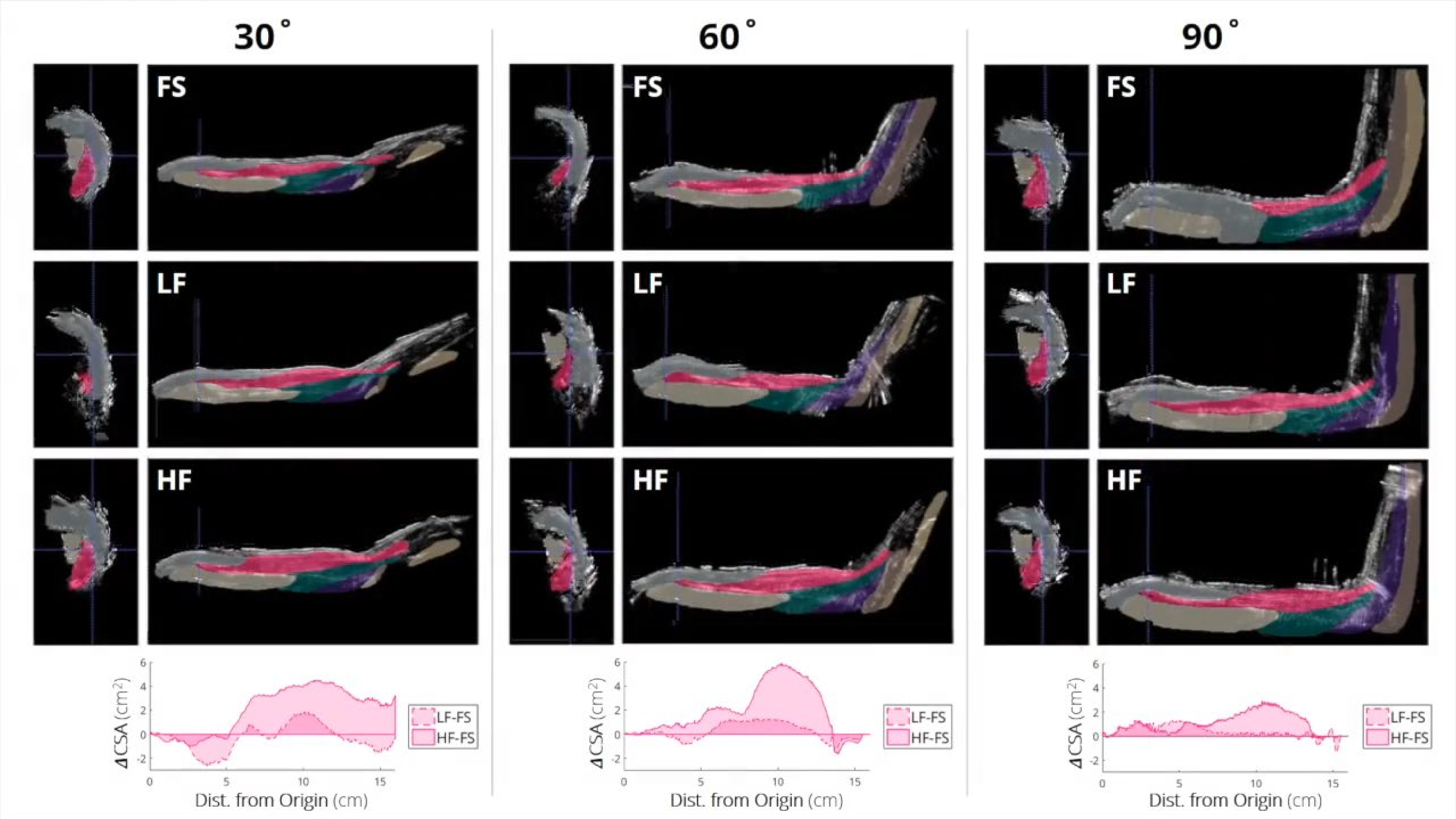


Preliminary Results

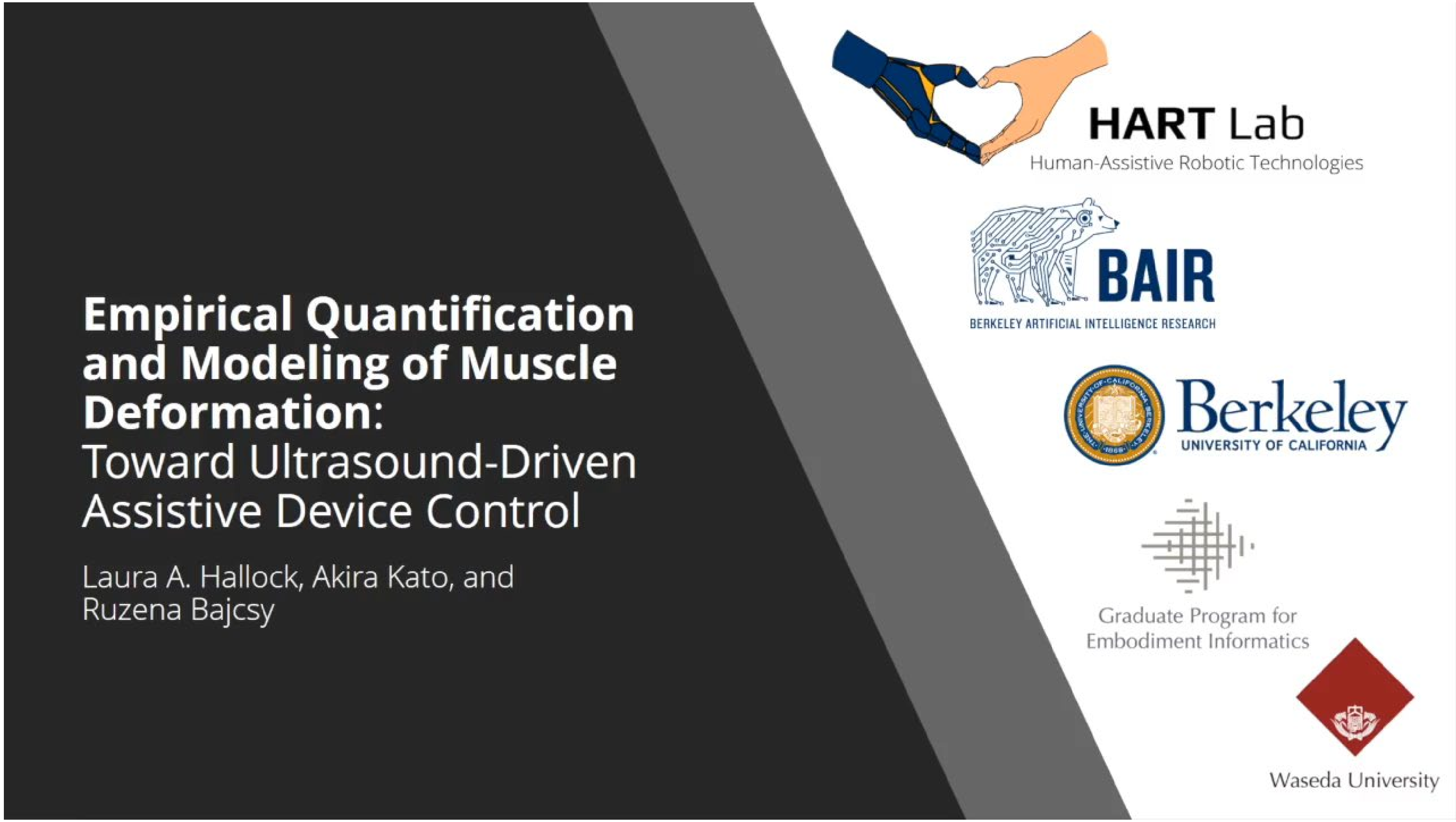
FS ("Fully Supported")	**LF** ("Low Force")	**HF** ("High Force")



Preliminary Results



Preliminary Results



ICRA 2018

Next Steps

- Impose and validate one or more **deformation models**:
  - cross-sectional area (CSA) changes
  - volume changes
  - superquadric models
  - shape models
  - FEM

- Refine experimental procedures to allow **clean comparison of force conditions across angles**

- Speed up / automate **segmentation pipeline**

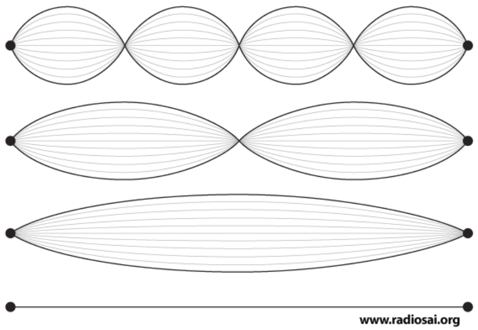
PROJECT 2

Stress-Strain/Elasticity Models:
AMG and cine DENSE MRI

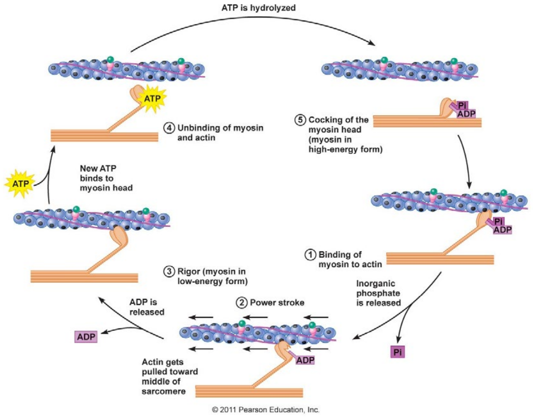
COMING SOON

Capabilities: AMG

"vibrating string" theory



"cross-bridge cycling" theory



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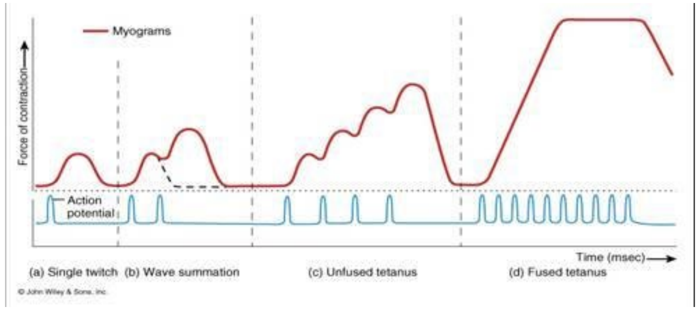
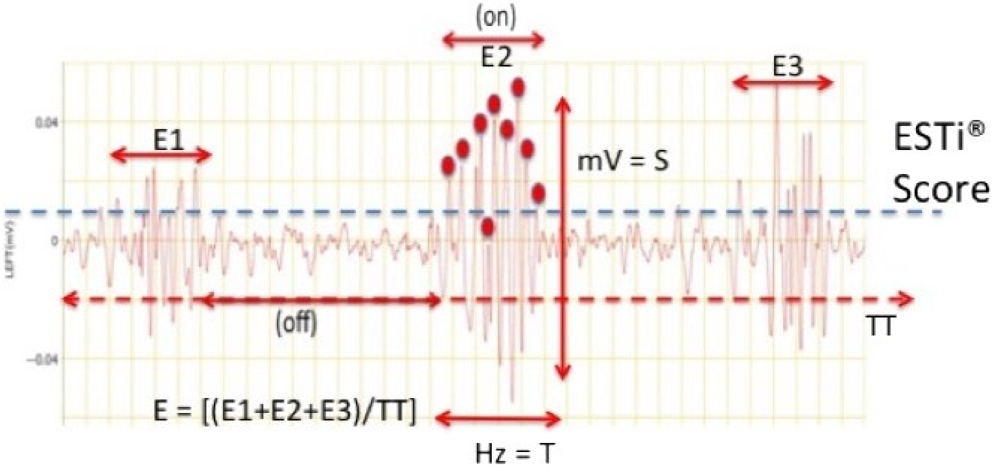
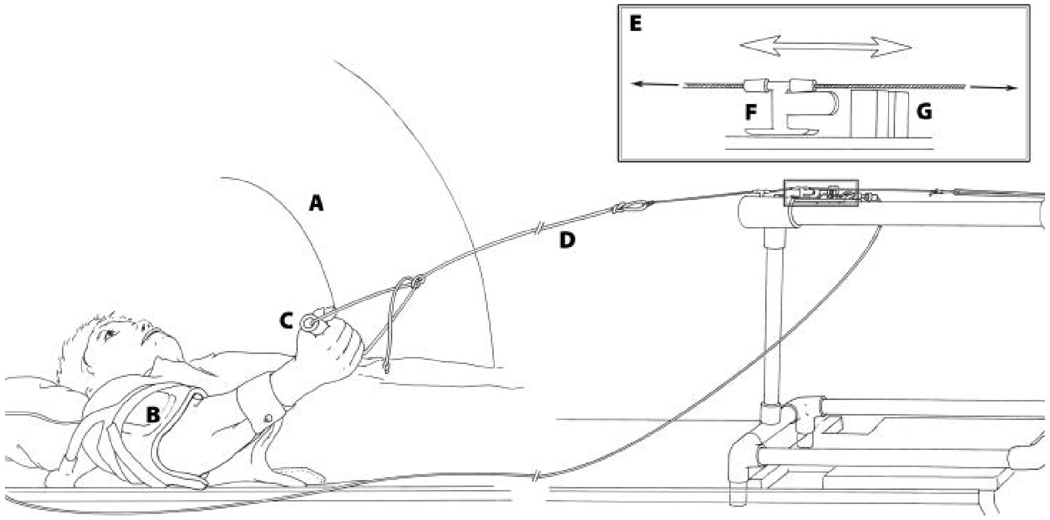


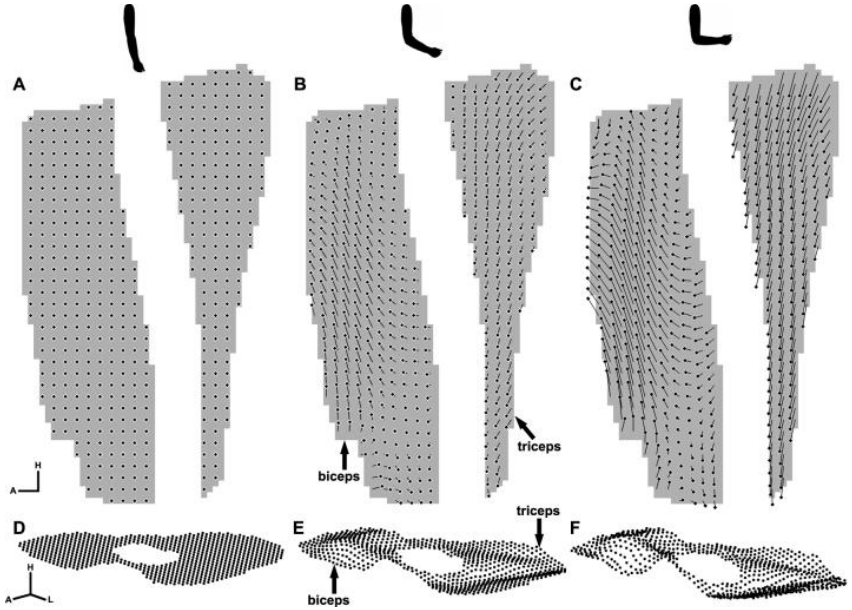
"unfused motor unit" theory

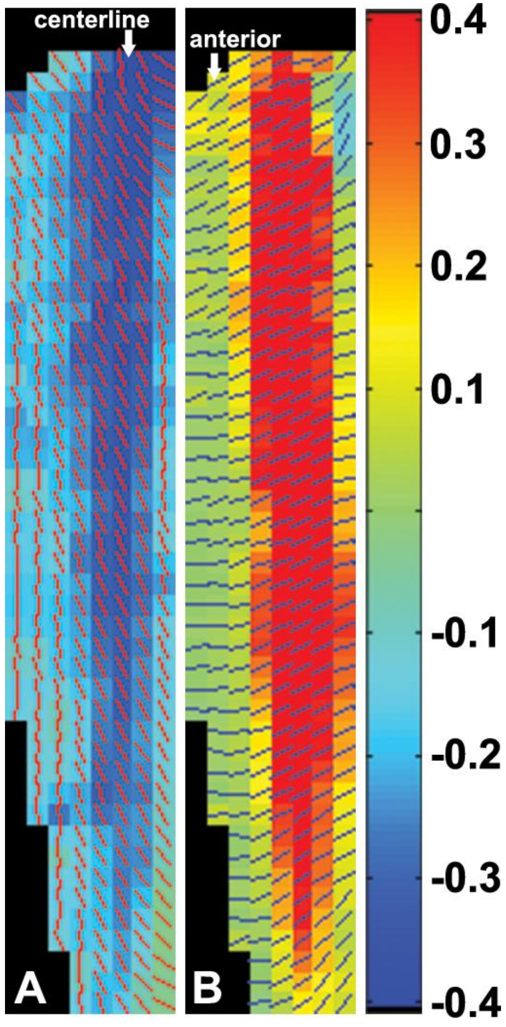


ESTi® Score evaluation, Harrison 2017

Capabilities: cine DENSE MRI







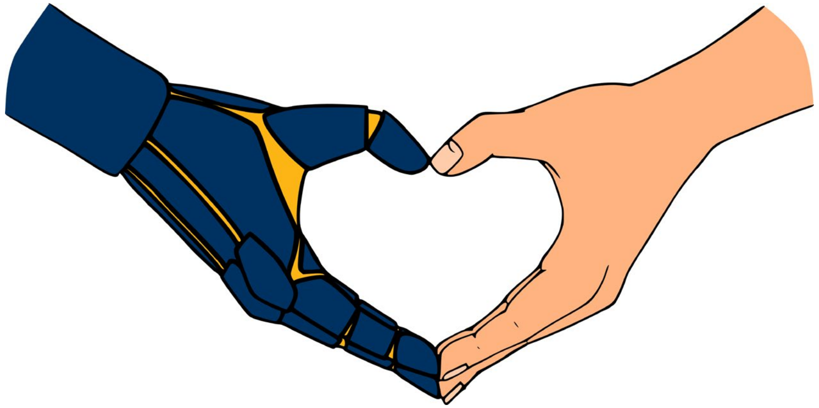
Experimental setup, displacement fields of the biceps and triceps, first and second principal strains of the biceps, Zhong 2008

PROJECT 1 & 2

CONCLUSIONS

Conclusions

By investigating both geometric and strain-based models of the human arm, we seek to generate a modeling framework that **surpasses existing models in predictive accuracy** while remaining **computationally tractable** and **useful in a wide range of applications**.



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hart.berkeley.edu

Papers

Conference 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. (under review)

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)

S. Menon, T. Migimatsu, and O. Khatib. "A Parameterized Family of Anatomically Accurate Human Upper-Body Musculoskeletal Models for Dynamic Simulation & Control." *IEEE RAS International Conference on Humanoid Robots*, 2016.

Technical Reports

L.A. Hallock, R.P. Matthew, S. Seko, and R. Bajcsy. (2016) "Sensor-Driven Musculoskeletal Dynamic Modeling." UC Berkeley EECS, Tech. Rep. UCB/EECS-2016-66.

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PROJECT 1 & 2

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