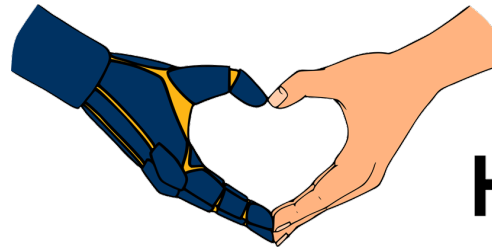


Human Musculoskeletal Dynamic Modeling: Current Research and Objectives

LAURA HALLOCK
RUZENA BAJCSY
CAEC SEMINAR
2017.01.22



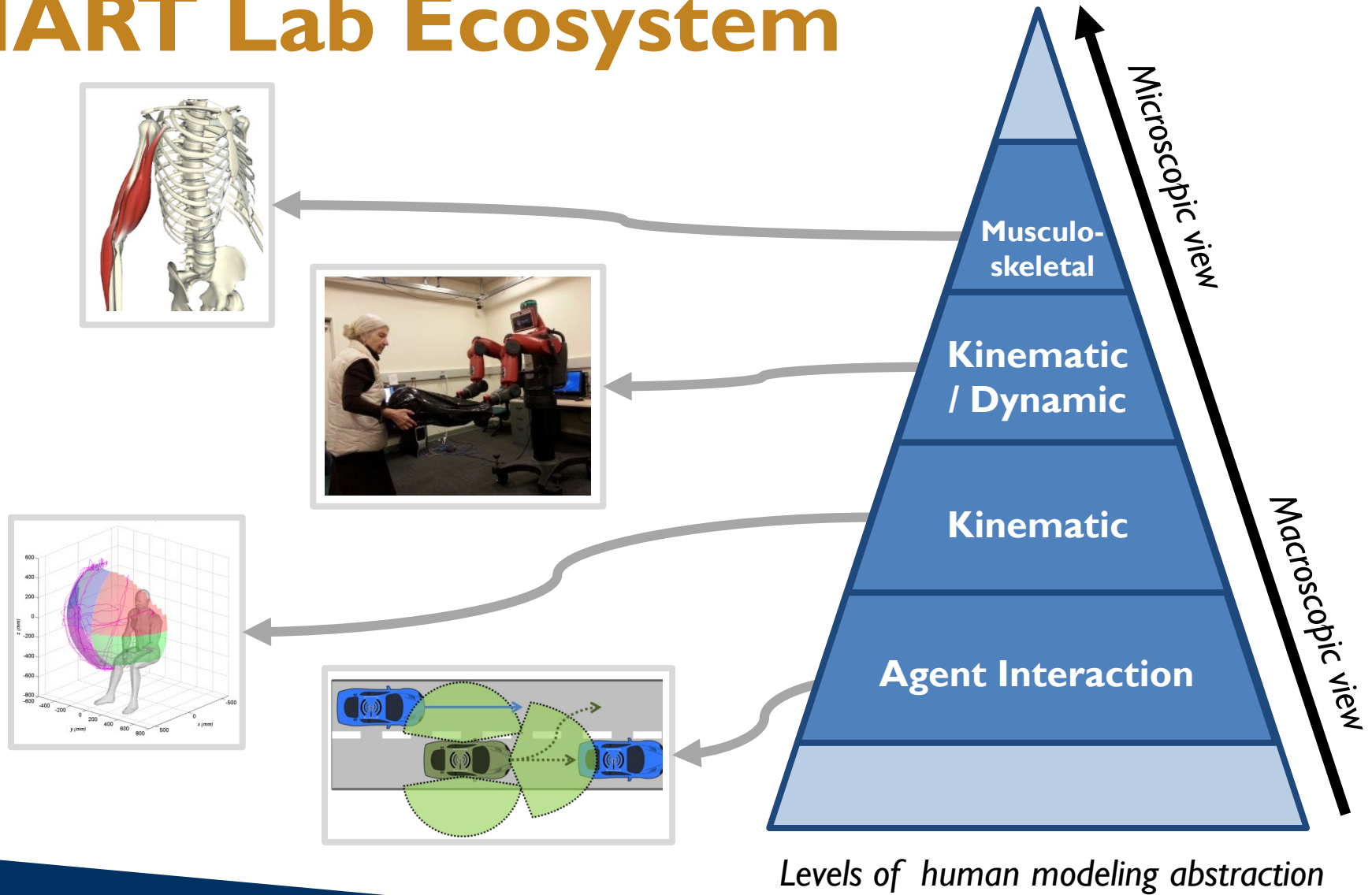
HART Lab

Human-Assistive Robotic Technologies

Human-Assistive Robotic Technologies (HART) Lab

OVERVIEW

HART Lab Ecosystem



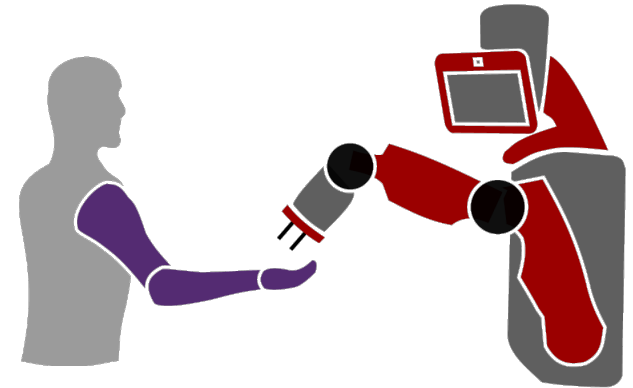
Why model musculoskeletal dynamics?

Human dynamical modeling is essential for many applications.

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



Gamma exoskeleton, HART
Lab 2016



Objectives & Approach

We seek to:

- **develop a dynamical modeling framework** of the human arm
- **understand the assumptions made** when simplifying these models

Objectives & Approach

We seek to:

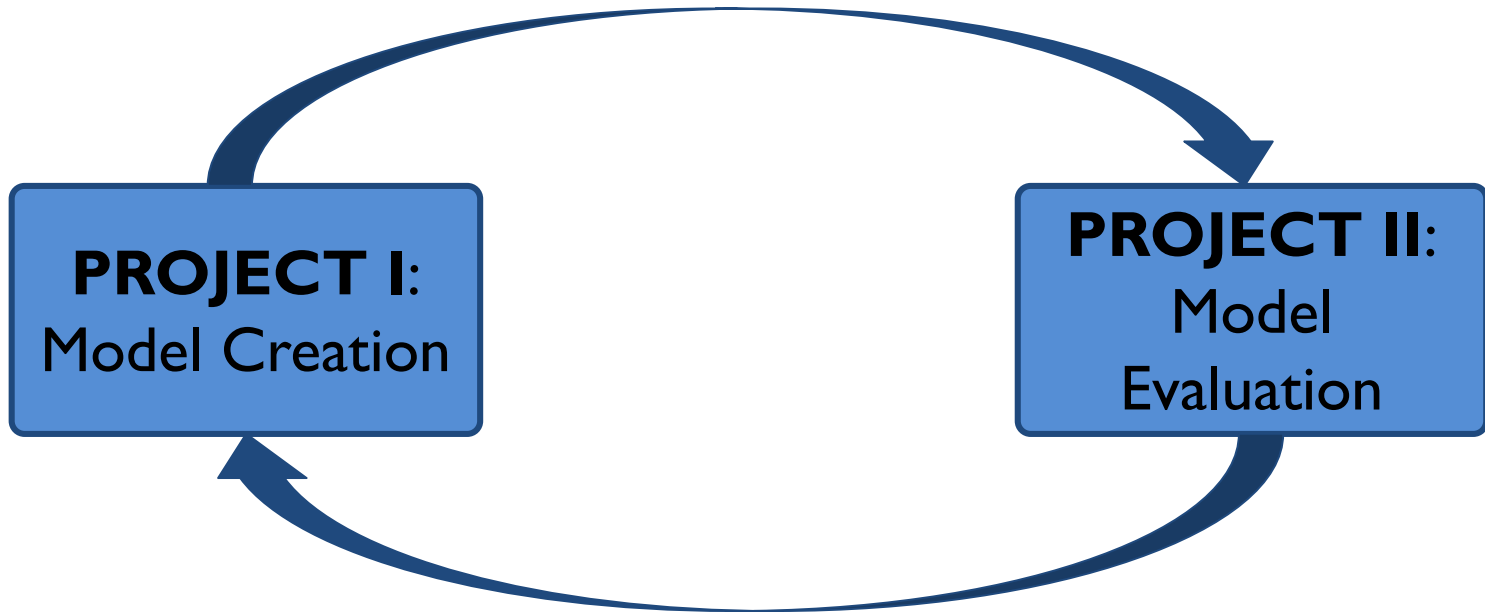
- **develop a dynamical modeling framework** of the human arm
- **understand the assumptions made** when simplifying these models

For clarity, we define:

- **Project I:** multi-sensor minimal modeling of the human arm (*UCB*)
- **Project II:** multi-subject MRI data analysis and dynamical simulation (*Stanford-UCB collaboration*)

Project I-II Interfacing

parameters that are of interest



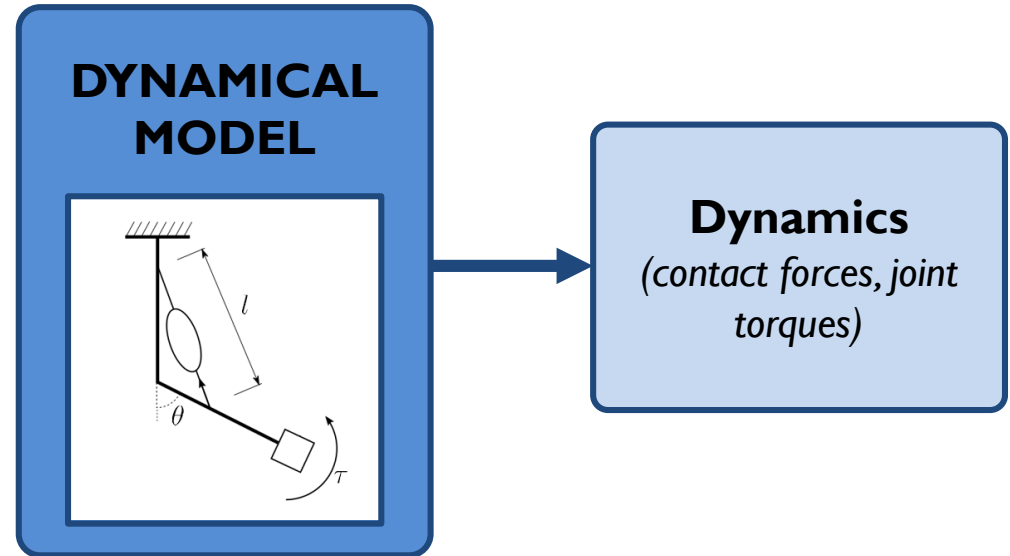
parameters that must be measured precisely

PROJECT I (*UCB*)

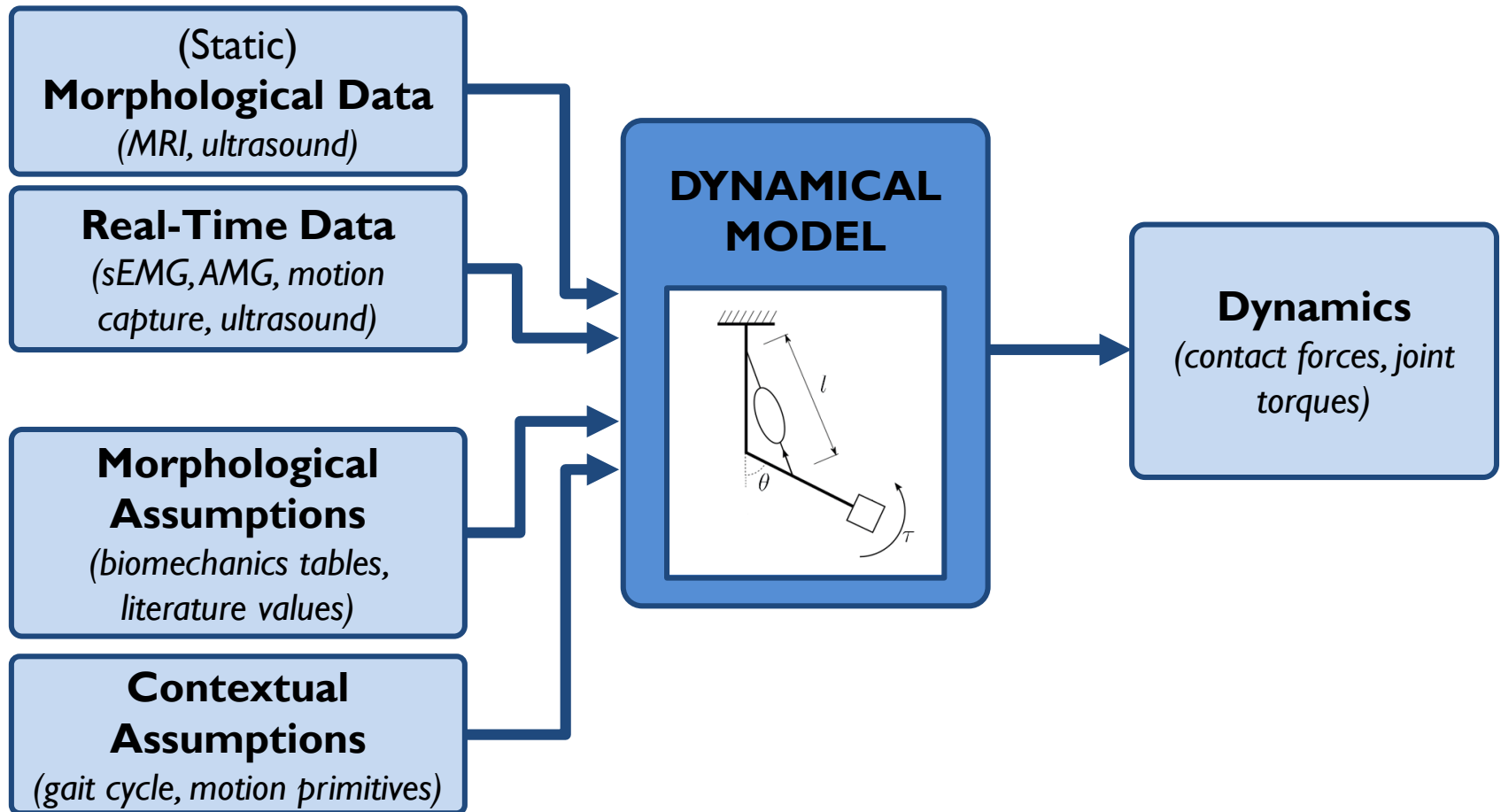
Multi-Sensor Minimal Modeling of the Human Arm

Goal: Predictive Upper-Limb Model

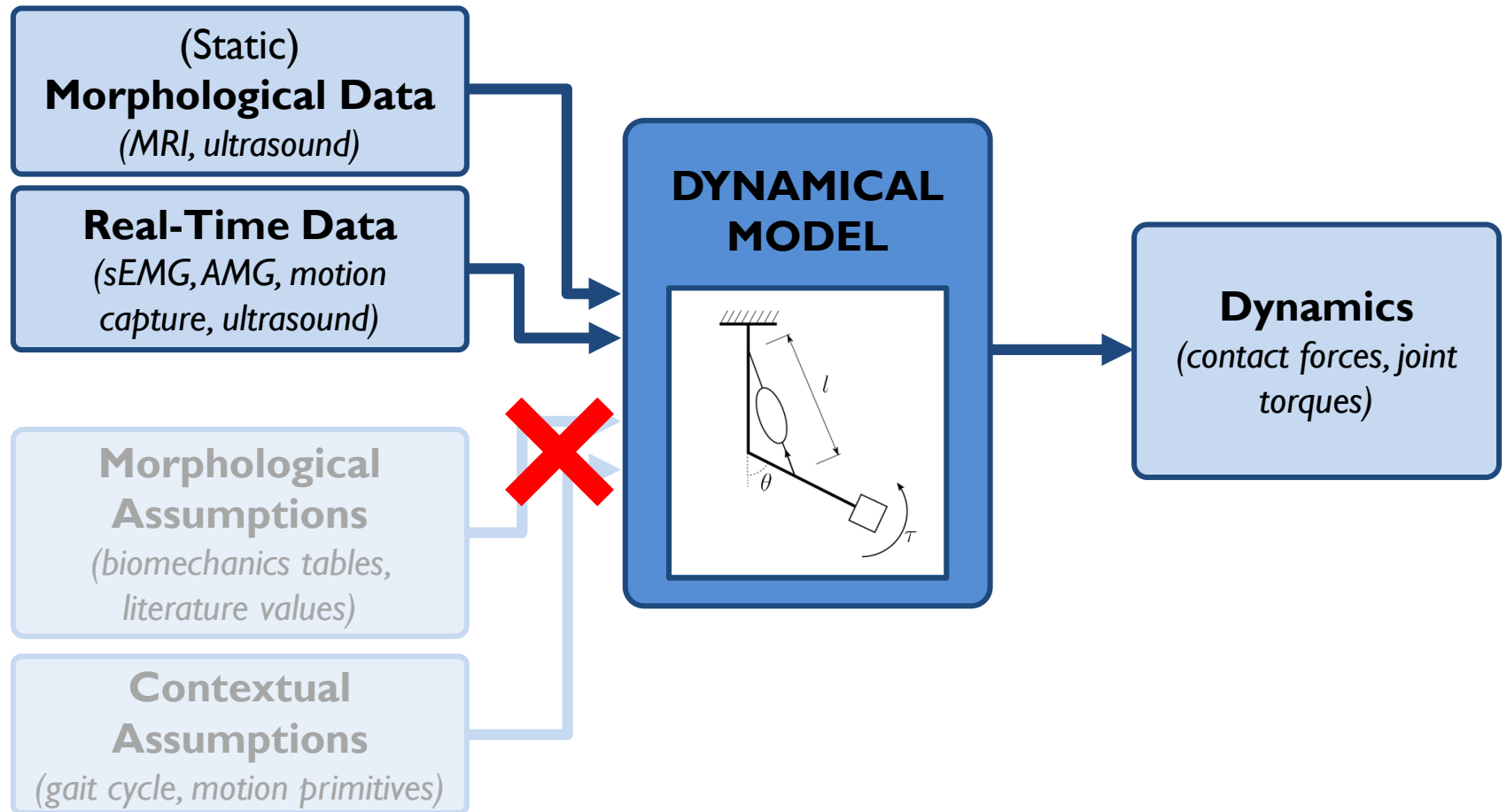
- predicts contact forces / joint torques of interest
- accommodates musculoskeletal pathology
 - injury
 - disease (e.g., MD)
- individualized
- computationally tractable



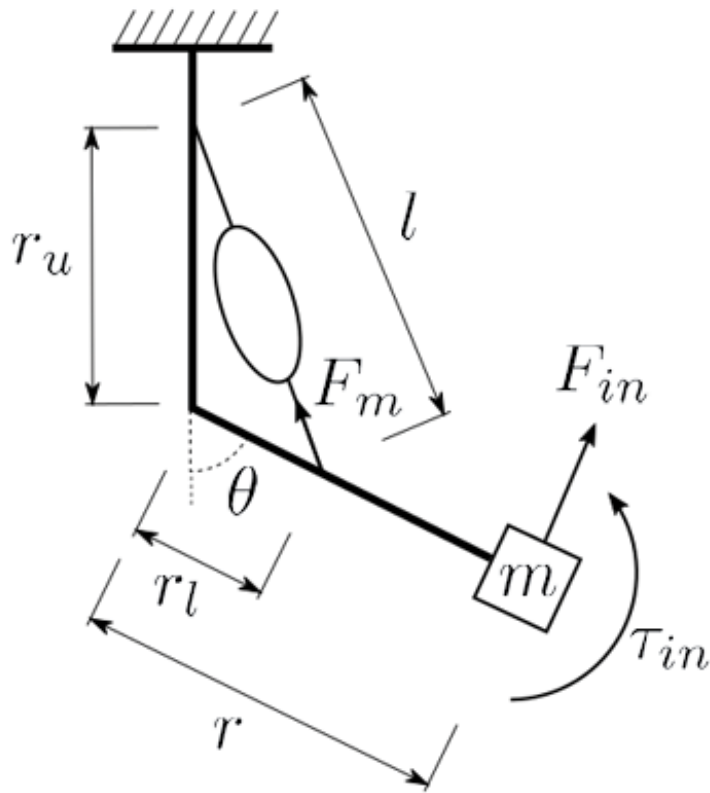
Existing Human Dynamical Models



Our Objective



Starting Point: Simplified Model



- single individual
- elbow joint (hinge)
- single aggregate “muscle”
- static
- **Inputs:**
 - \bar{a} normalized activation (sEMG)
 - θ joint angle (motion capture)
- **Outputs:**
 - τ elbow torque

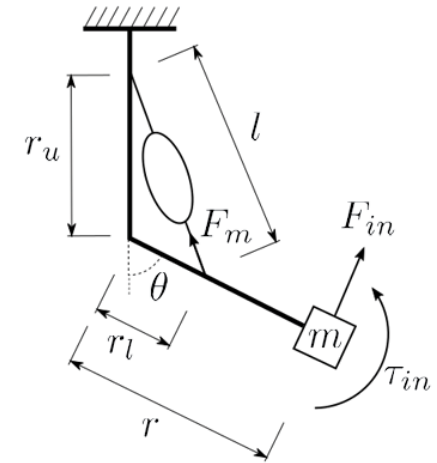
Starting Point: Simplified Model

Assuming muscle force-length relation

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

and normalized muscle activation and length

$$\bar{a} = \frac{a}{a_{max}} \quad \bar{l} = \frac{l}{l_{opt}}$$



the dynamics relation of each (\bar{a}, τ, θ) pair is described by

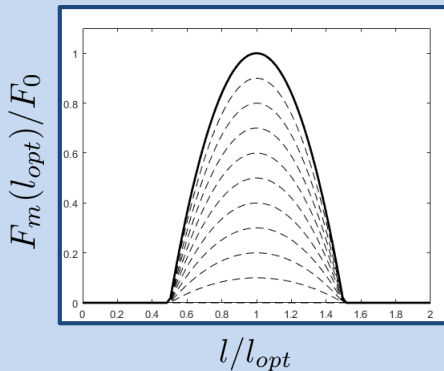
$$\begin{bmatrix} \tau_{in,1} + rF_{in,1} - \frac{1}{2}mg \sin \theta_1 r \\ \vdots \\ \tau_{in,n} + rF_{in,n} - \frac{1}{2}mg \sin \theta_n r \end{bmatrix} = \underbrace{\begin{bmatrix} \tau_1 \\ \vdots \\ \tau_n \end{bmatrix}}_T = F_0 r_l r_u \underbrace{\begin{bmatrix} \frac{l_1}{l_{opt}^2} \sin \theta_1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

Simplified Model Validation

Can we expect to learn muscle force-length relation from the data we have?

Hypothesize Approximate System

- Set morphological parameters to approximate biceps
- Assume force-length curve:

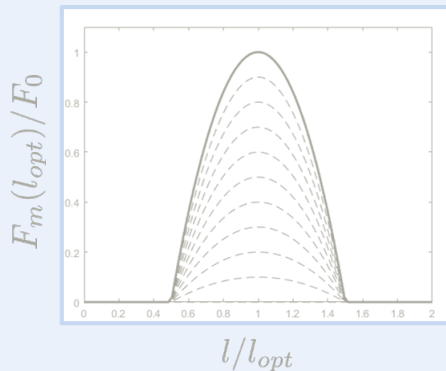


Simplified Model Validation

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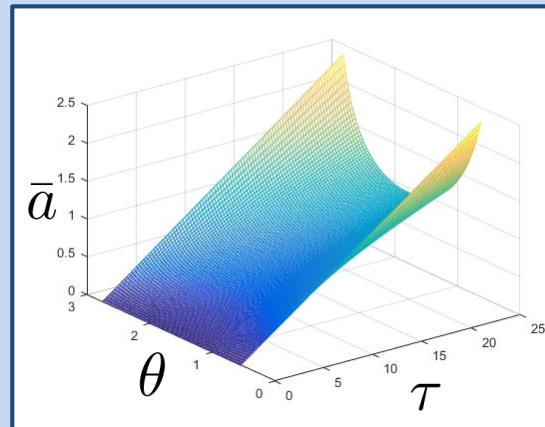
Hypothesize Approximate System

- Set morphological parameters to approximate biceps
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Generate Synthetic Data

Based on hypothesized system, generate (\bar{a}, τ, θ) pairs:

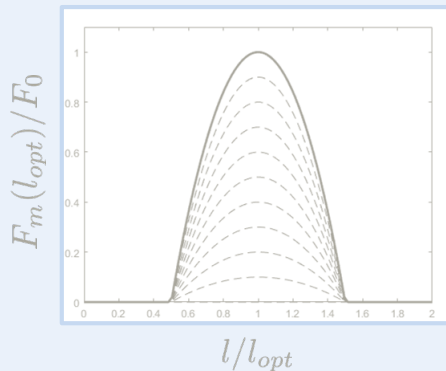


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Can we expect to learn muscle force-length relation from the data we have?

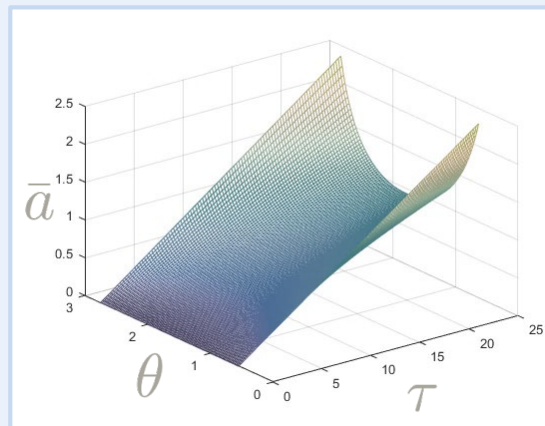
Hypothesize Approximate System

- Set morphological parameters to approximate biceps
- Assume force-length curve:



Generate Synthetic Data

Based on hypothesized system, generate (\bar{a}, τ, θ) pairs:



Add Noise + Recover System Function via Least Squares

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

SNR (dB)	cond(W)	$\sum_{i=1}^3 \frac{ \beta_i - \beta_i^{fit} }{ \beta_i }$
100	591.0	0
10	624.2	0.0248
1	619.1	0.0472
1e-2	625.7	0.0309
1e-64	622.3	0.0341

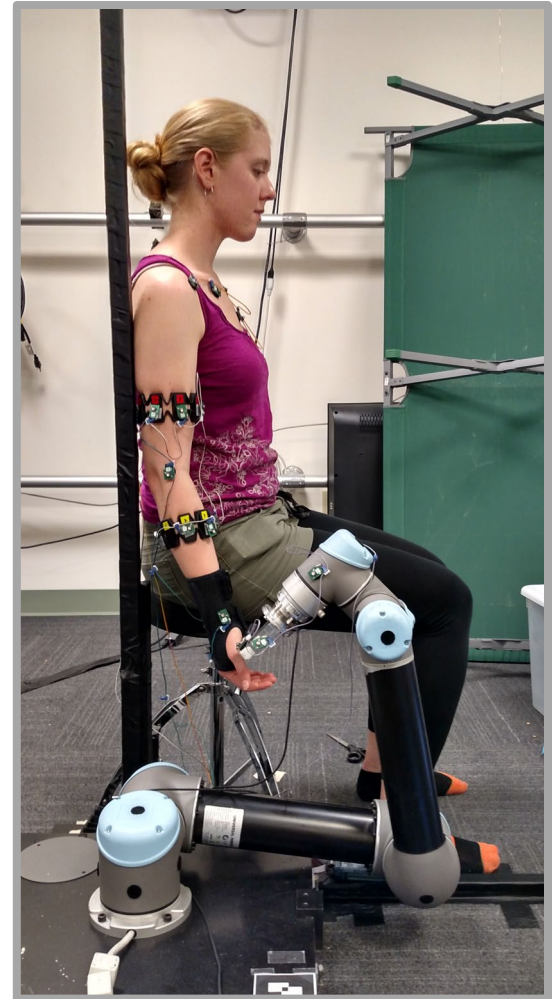
To verify system's validity:

- condition number of W
- numerical computation of base parameters

Experimental Setup

~400 (\bar{a} , τ , θ) data points

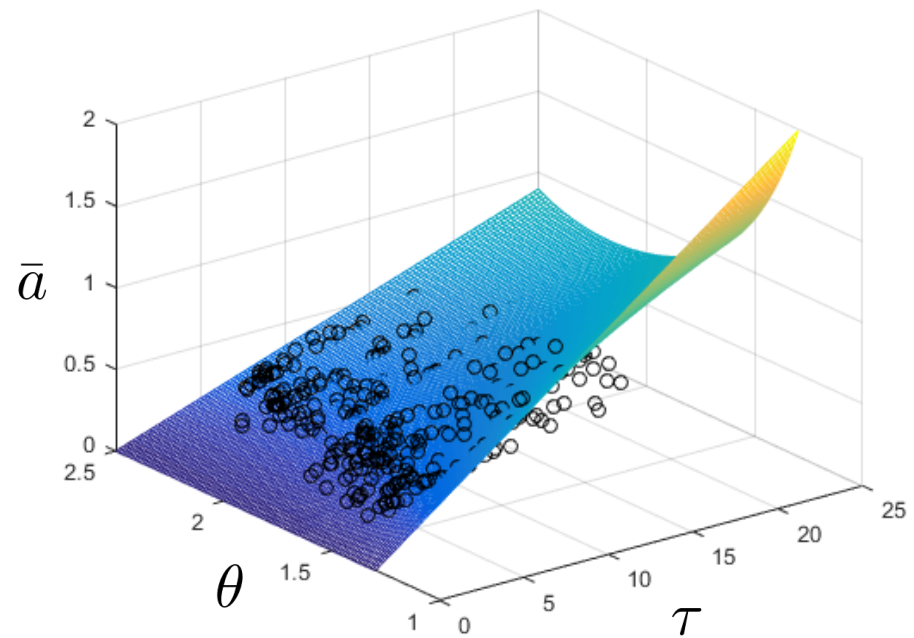
- \bar{a} via single-channel sEMG (Myo on upper arm)
- τ via F/T sensor (mounted to UR5 robot)
- θ calculated from images (15 waypoints)



Preliminary Results

The generated (\bar{a}, τ, θ) **surface is qualitatively reasonable** and fits the data well, and the predicted **force-length relation is biologically reasonable**.

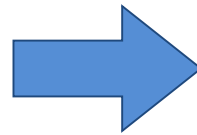
$$\begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} = \begin{bmatrix} -8.3685 \\ 10.3654 \\ -1.0560 \end{bmatrix}$$



Future Work: sEMG → AMG

sEMG

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



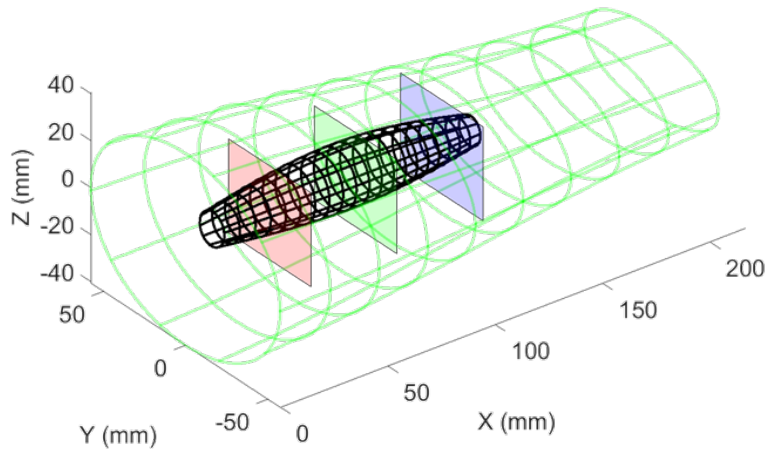
AMG (acoustic myography)

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



Future Work: sEMG \rightarrow Ultrasound

3D View

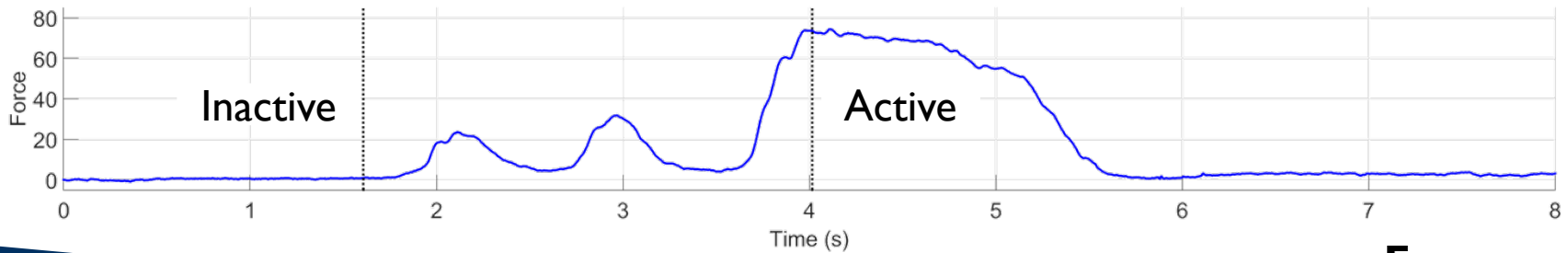


Muscle Cross-Section

Inactive



Active



Force

Future Work: Model Improvements

- **Extract morphological parameters** from
 - MRI (bone volumes, muscle volumes, muscle attachment points)
 - ultrasound (PCSA, tendon length)
- Maintain “minimal modeling” framework while **increasing complexity**
 - multiple muscles
 - dynamic conditions (Hill model)

PROJECT II (*Stanford-UCB collaboration*)

Multi-Subject MRI Data Analysis and Dynamical Simulation

Motivation

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

- OpenSim / AnyBody
- task-specific models
- our project I model

Motivation

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

- OpenSim / AnyBody
- task-specific models
- our project I model

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

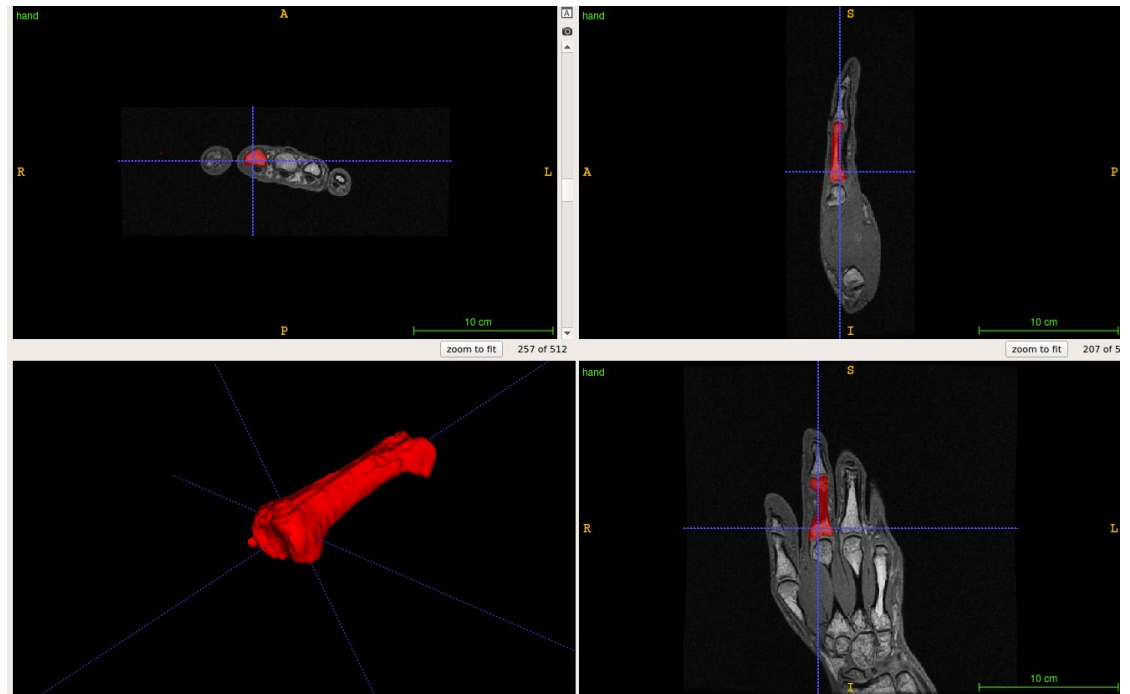
Goal: Quantify Model Accuracy

We seek to examine

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

Dataset: Upper-Limb MRI Scans

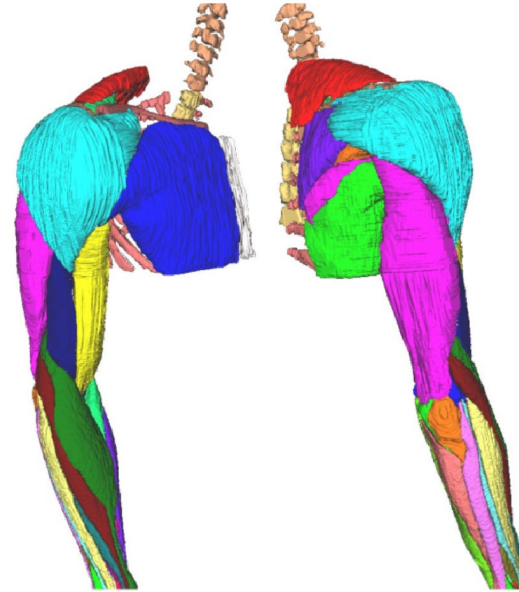
- 8-10 subjects, full arm (hand through torso)
- vary in
 - age
 - health
 - height/weight
 - gender



Hand MRI, intermediate phalanx manually segmented, Berkeley 2016

Approach

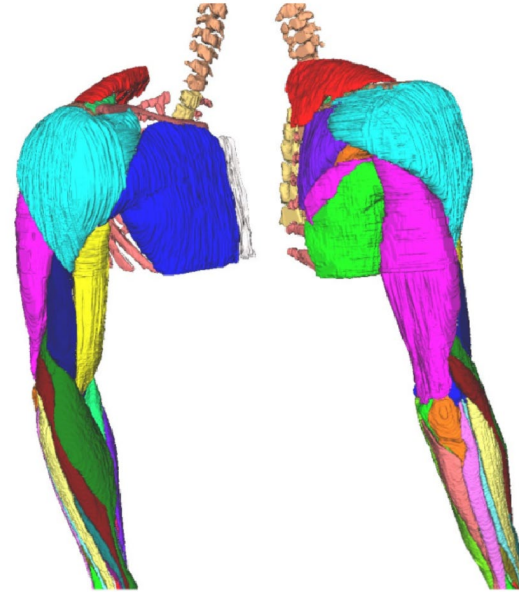
- **extract** parameters of interest
 - bone/muscle volumes
 - bone/muscle length
 - muscle-bone attachment points



*Segmented muscle data,
Stanford 2016*

Approach

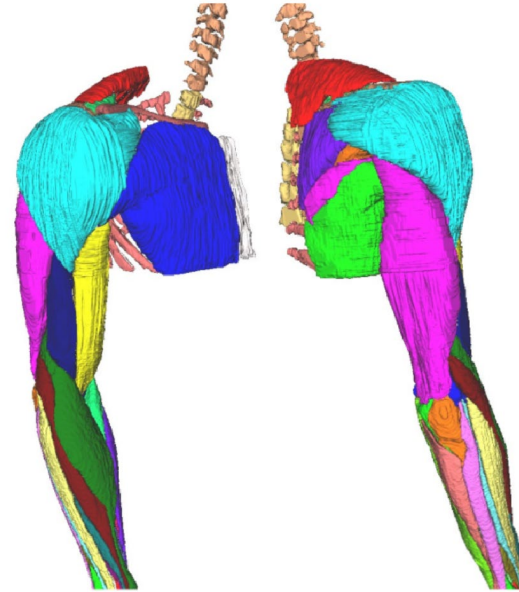
- **extract** parameters of interest
 - bone/muscle volumes
 - bone/muscle length
 - muscle-bone attachment points
- **compare** parameters
 - across subjects
 - across perturbed subjects
 - with best canonical model approximation (e.g., OpenSim)



*Segmented muscle data,
Stanford 2016*

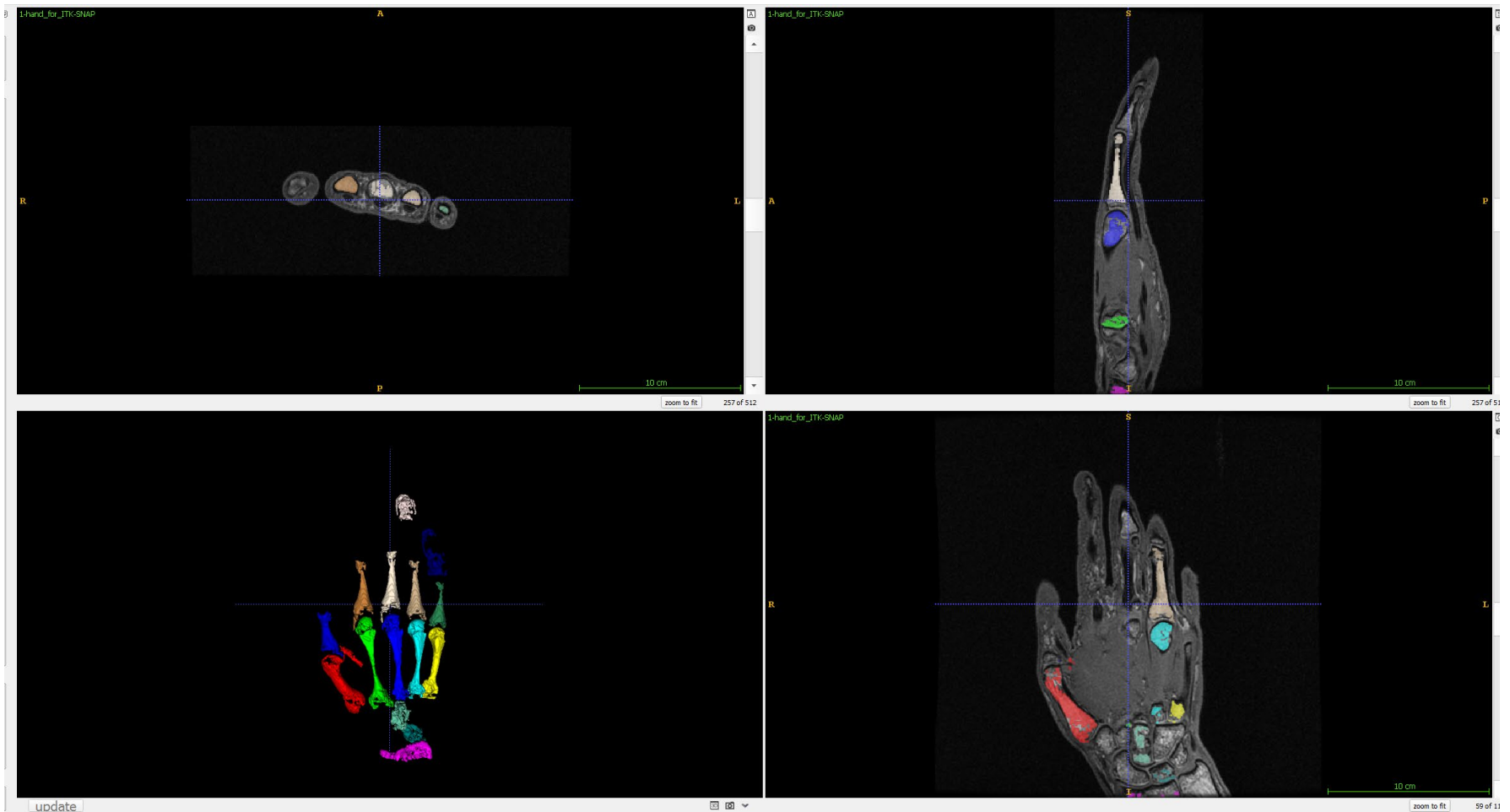
Approach

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

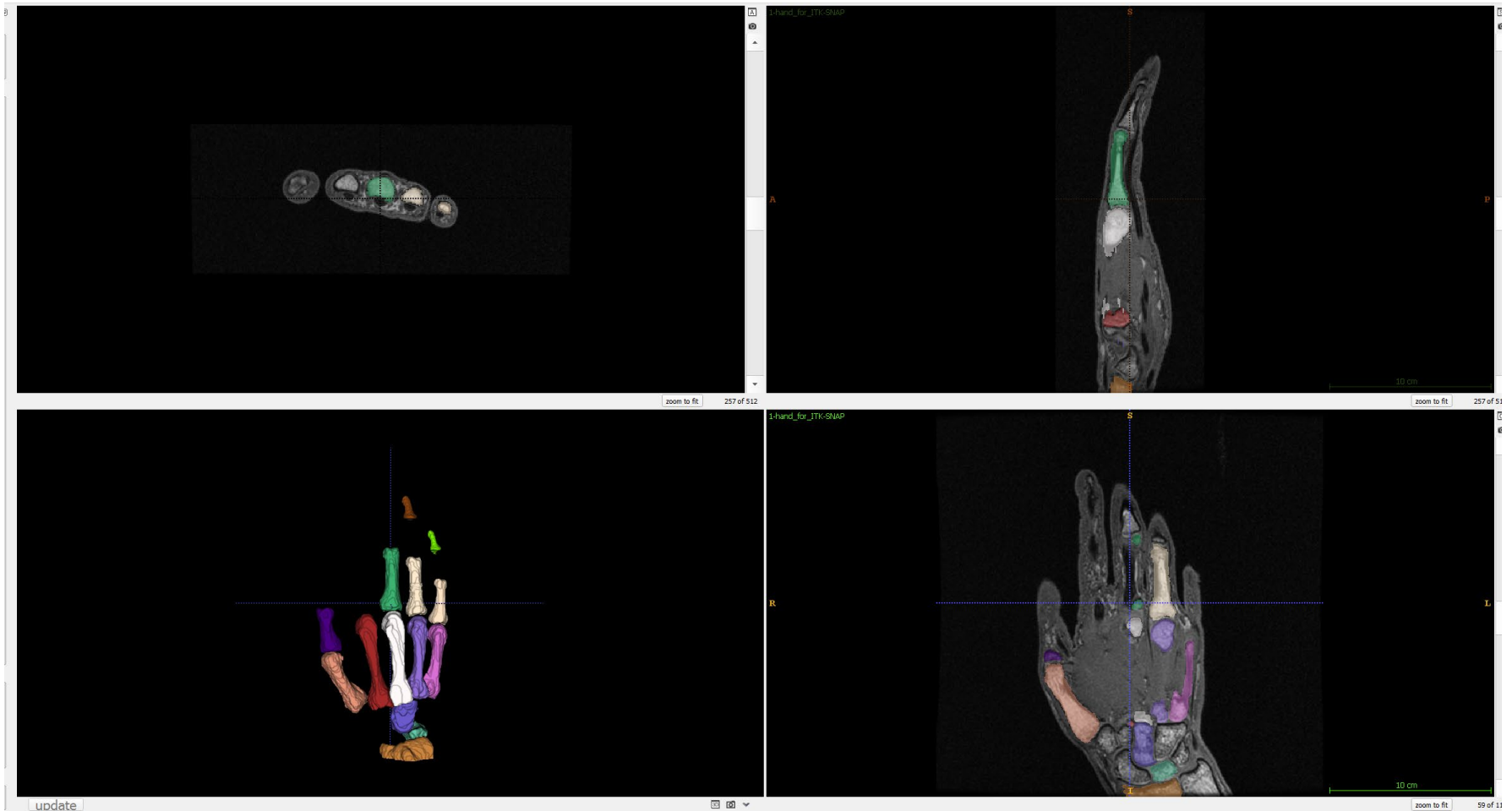


*Segmented muscle data,
Stanford 2016*

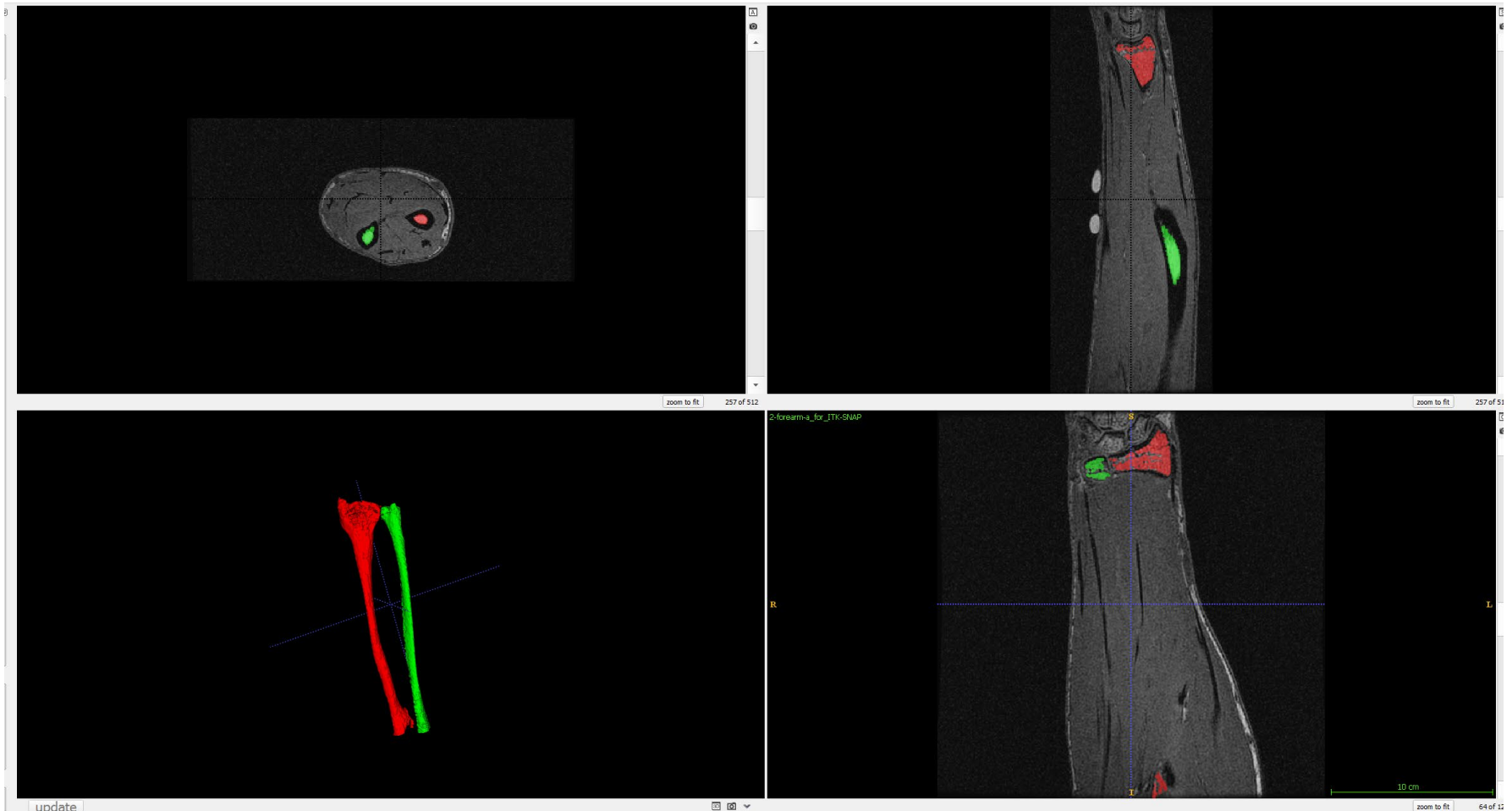
Preliminary Results: Hand/Auto



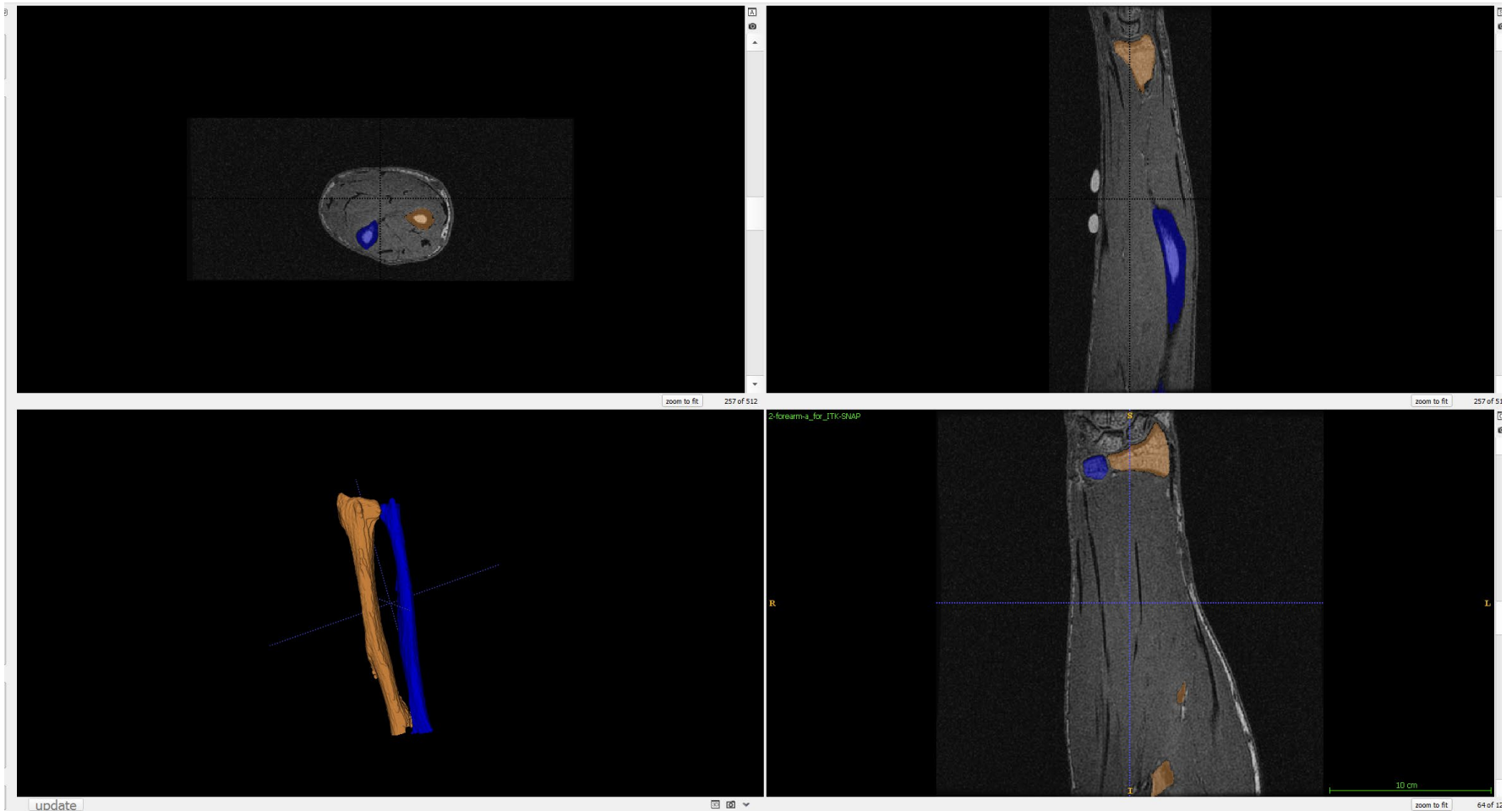
Preliminary Results: Hand/Manual



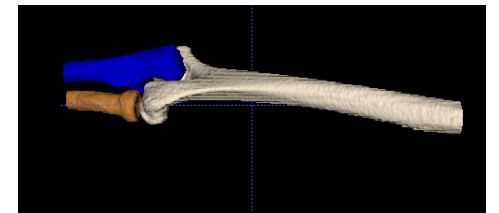
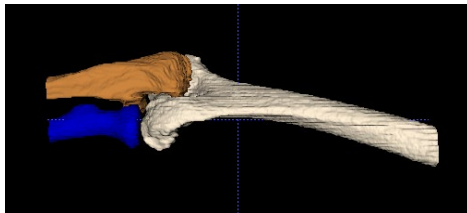
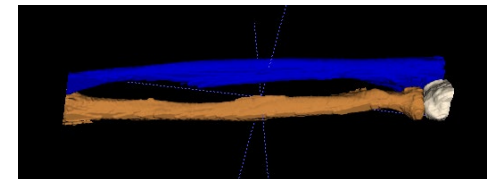
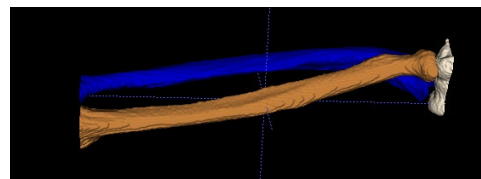
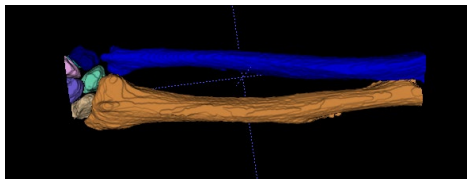
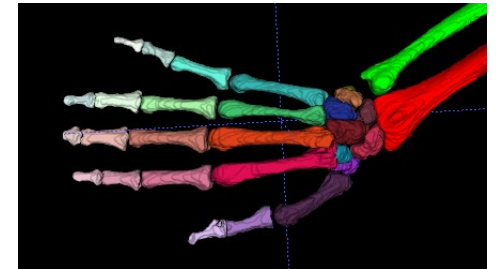
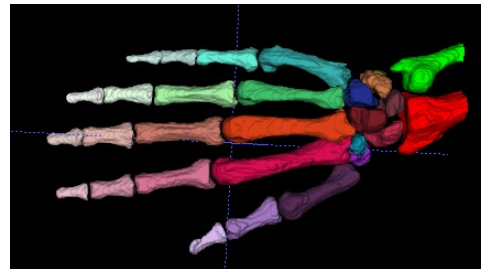
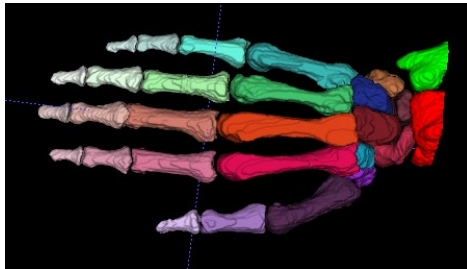
Preliminary Results: Forearm/Auto



Preliminary Results: Forearm/Manual



Preliminary Results: Comparison



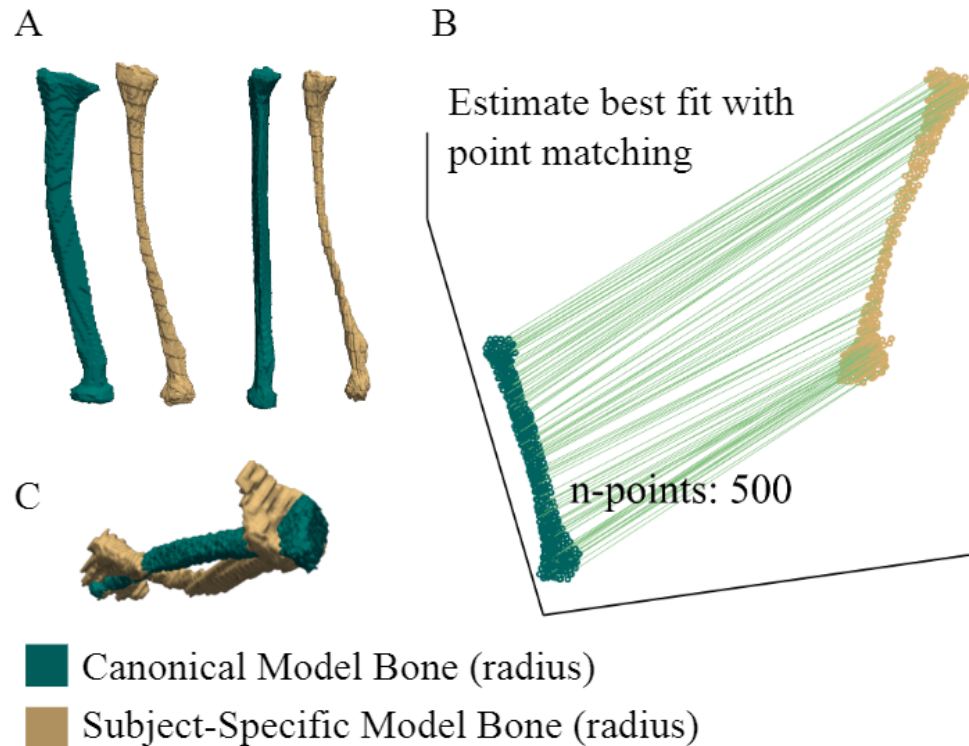
SUBJECT 1

SUBJECT 2

SUBJECT 3

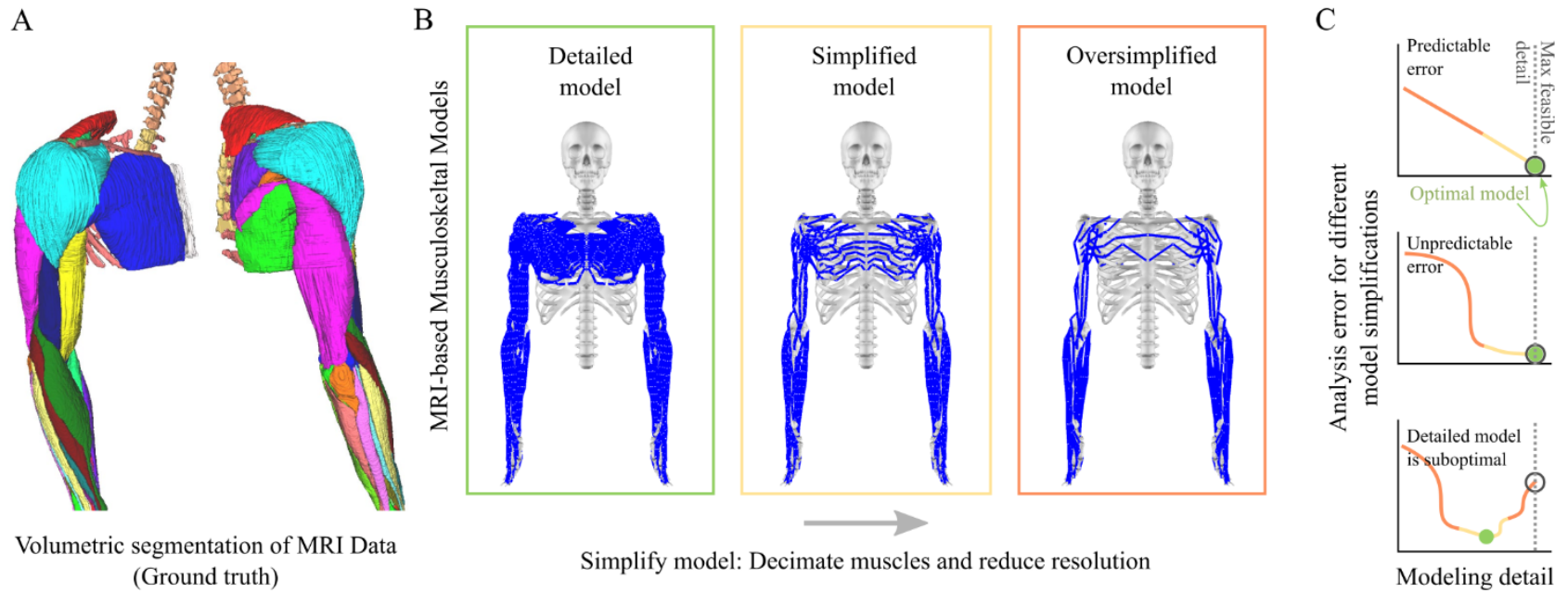
Preliminary segmentation results **show significant morphological variation across subjects** that cannot be modeled in existing frameworks.

Preliminary Results: Comparison



MRI vs. canonical, Stanford 2016

Preliminary Results: Simulation



Model resolution comparison, Stanford 2016

PROJECT I & II

CONCLUSIONS

Conclusions

By investigating both

- multi-sensor modeling of a single subject, and
- large-scale morphological modeling of many subjects,

we seek to generate a modeling framework that **surpasses existing models in predictive accuracy** while **remaining useful in a wide range of applications.**

People (Musculoskeletal Modeling)

UC Berkeley



R. Bajcsy



L. Hallock



R. Matthew



S. Seko



A. Sy



S. Sharma



J. Zhang

Stanford Collaborators



O. Khatib



S. Menon

Sponsors

SIEMENS

Berkeley

Artificial Intelligence Research Laboratory



Papers

Conference Papers

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.