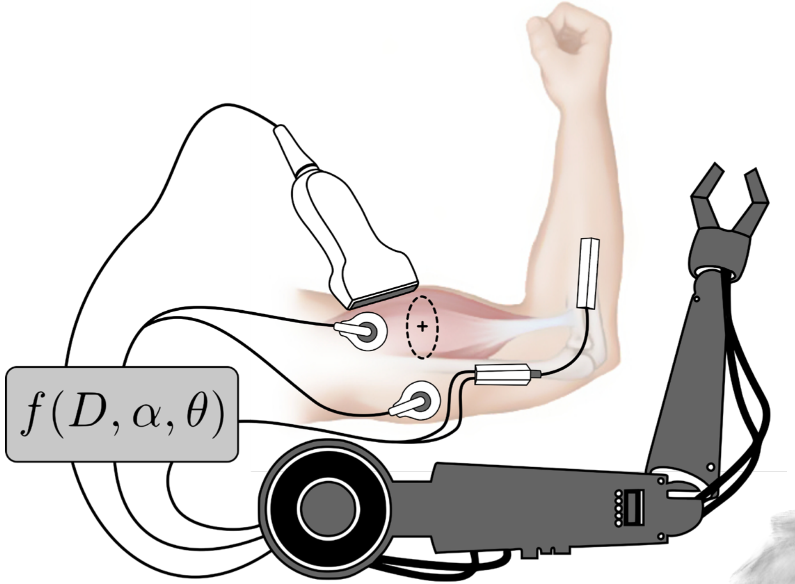
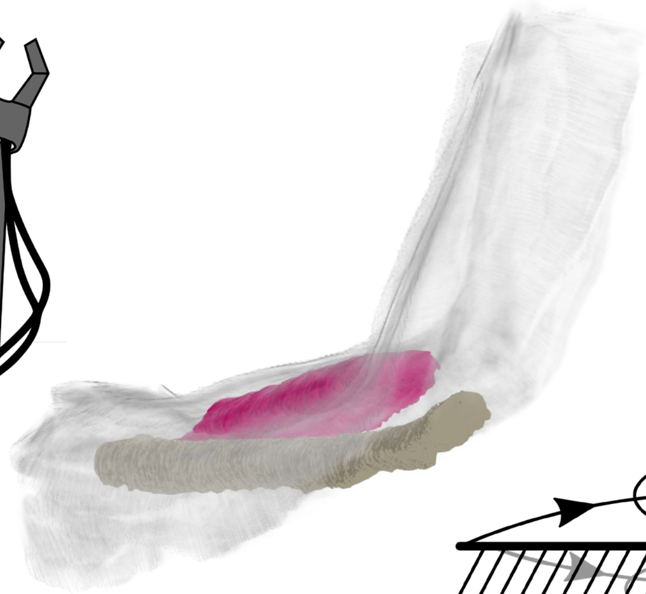
A systematic study of the muscle force–deformation relationship at the human elbow: Toward physiology-aware assistive device control and noninvasive muscle force sensing

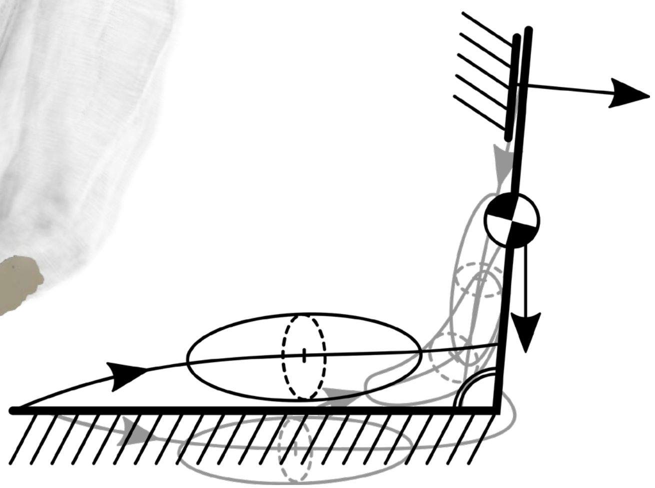
Laura Hallock

Dissertation Talk

2021.08.11







HART Lab
Human-Assistive Robotic Technologies

Berkeley
UNIVERSITY OF CALIFORNIA

Which hand would you prefer?

UW "Highly Biomimetic Anthropomorphic Robotic Hand"

Which hand would you prefer?

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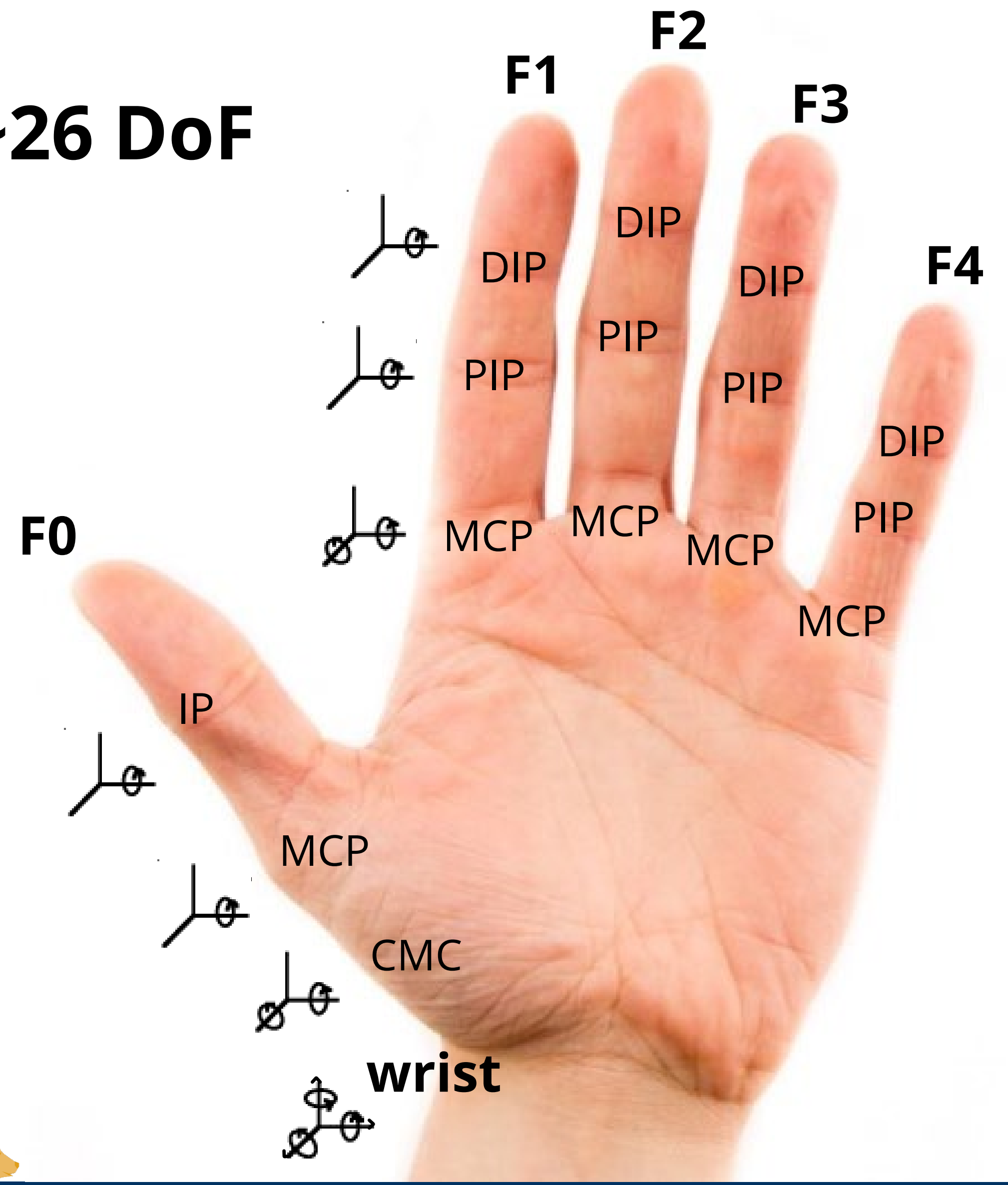
Which hand would you prefer?

~26 DoF

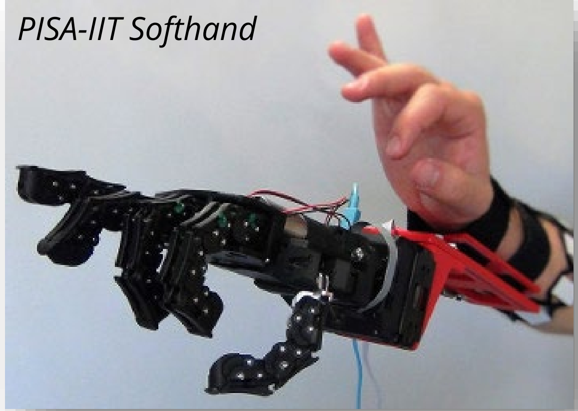


1 DoF

UW "Highly Biomimetic Anthropomorphic Robotic Hand"

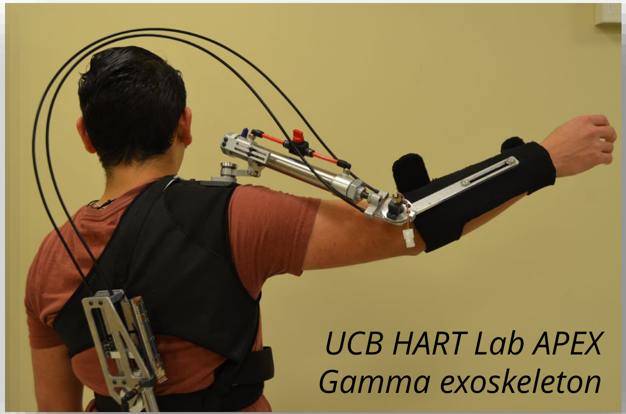
Endowing Devices with Human Dexterity

Prostheses



PISA-IIT Softhand

Exoskeletons

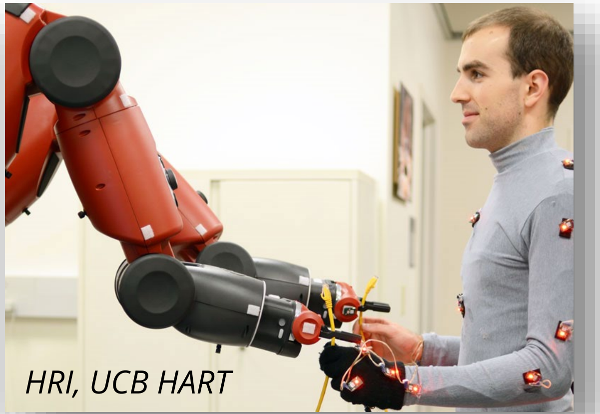


UCB HART Lab APEX Gamma exoskeleton

Teleoperation

Capio Upper Body Exoskeleton for Teleoperation, DFKI GmbH Robotics Innovation Center

Human–Robot Collaboration



HRI, UCB HART

GOAL:

Build safe, capable assistive devices that grant the human user full control authority.

Roadmap

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Toy Example: Joint-for-Joint Teleoperation

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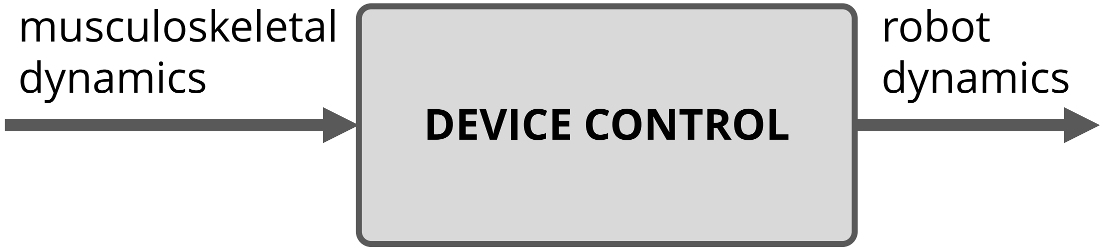

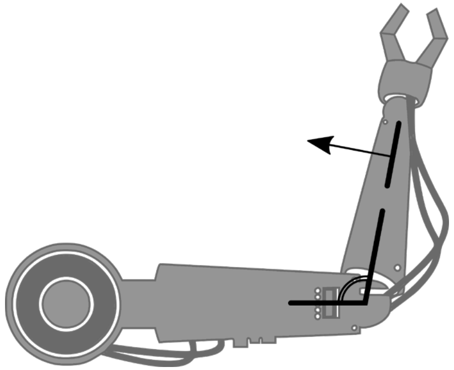

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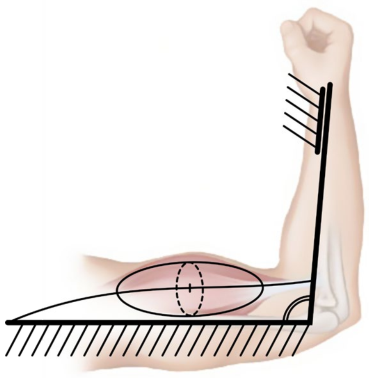

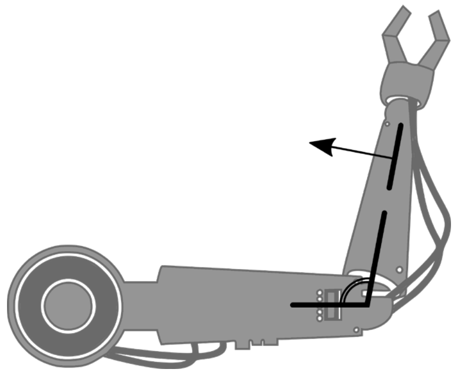

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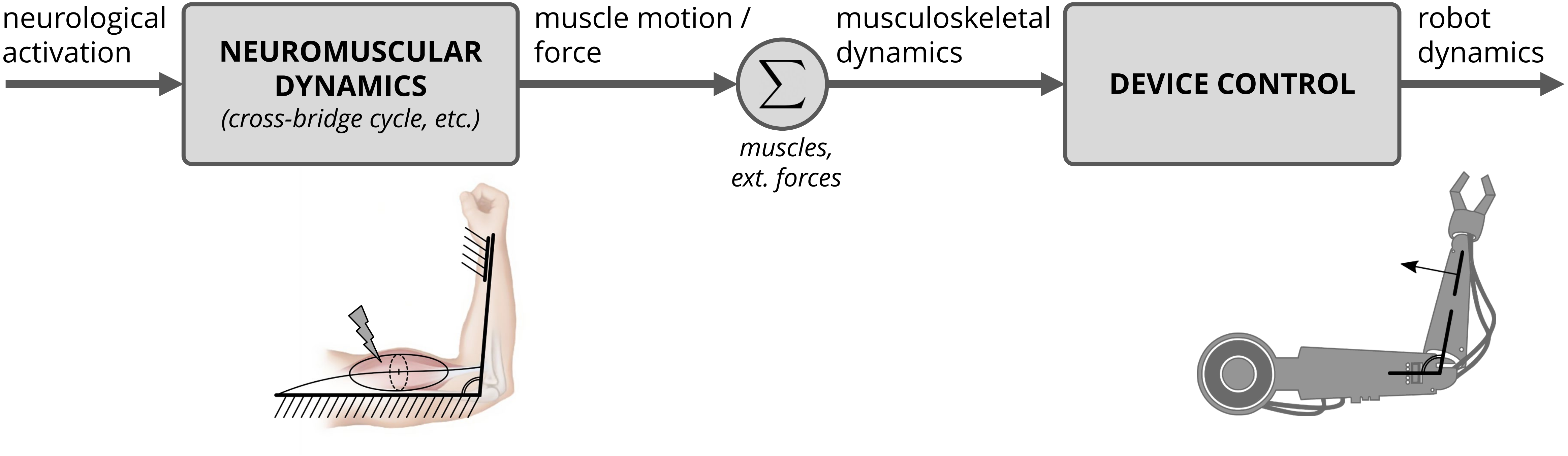

Berkeley
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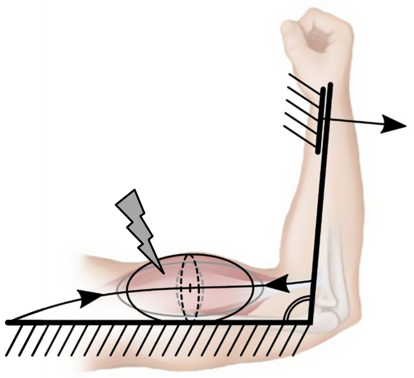

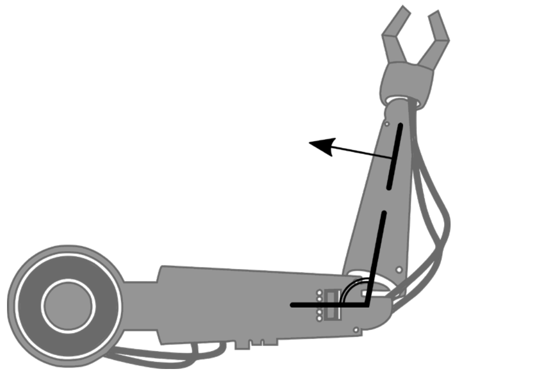

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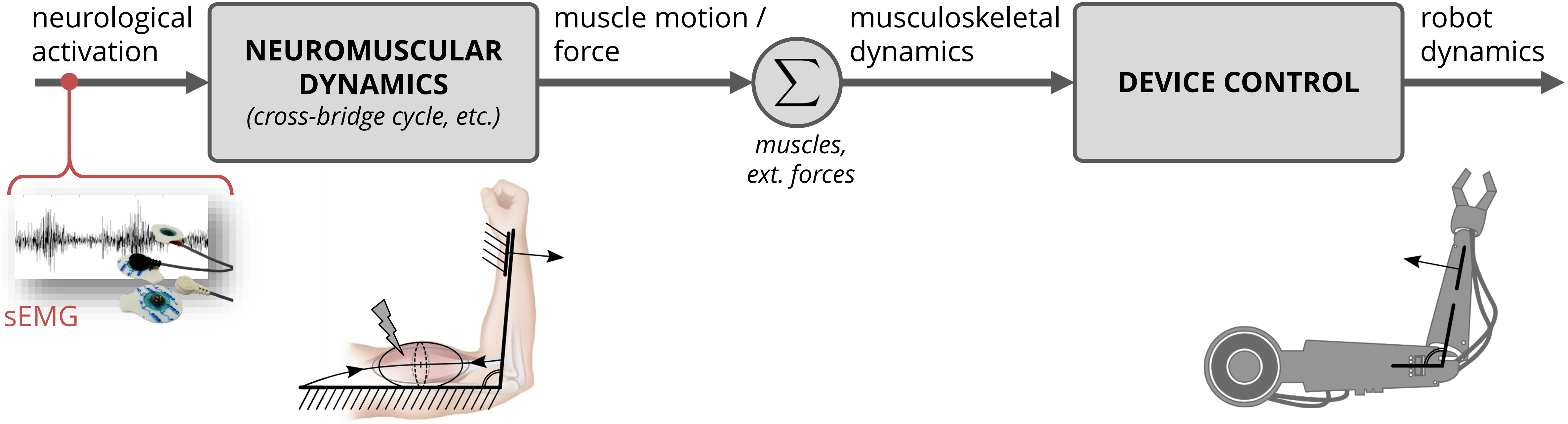

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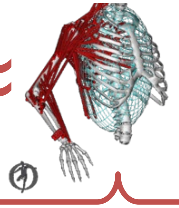
≈  modeling software

neurological activation

NEUROMUSCULAR DYNAMICS
(cross-bridge cycle, etc.)

muscle motion / force

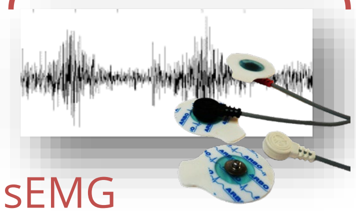
$\sum$

muscles, ext. forces

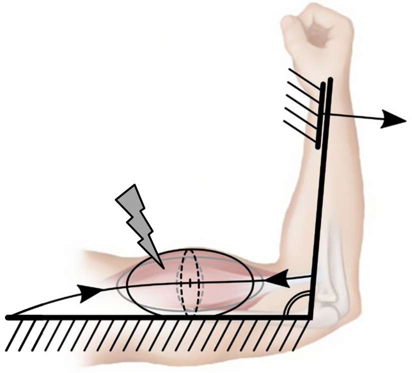
musculoskeletal dynamics

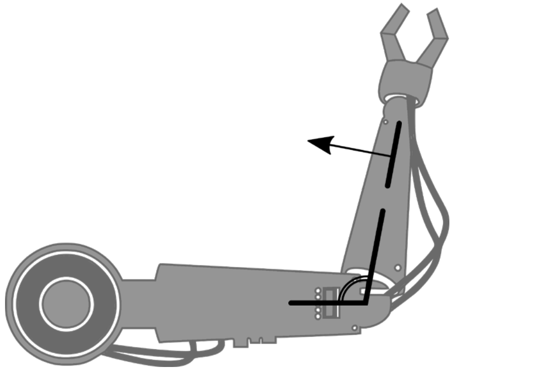
DEVICE CONTROL

robot dynamics



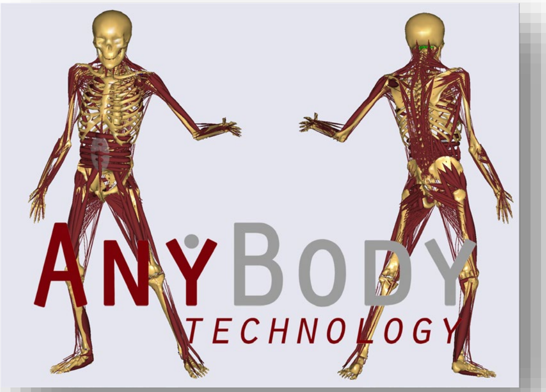
sEMG





Modeling Software Shortcomings

[Delp et al. 2007]



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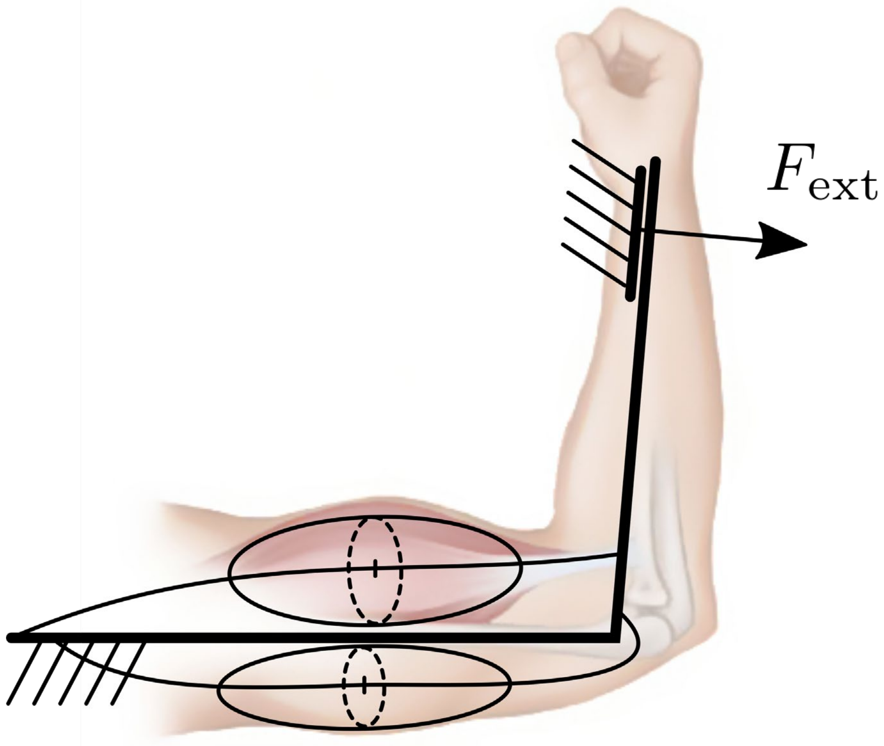

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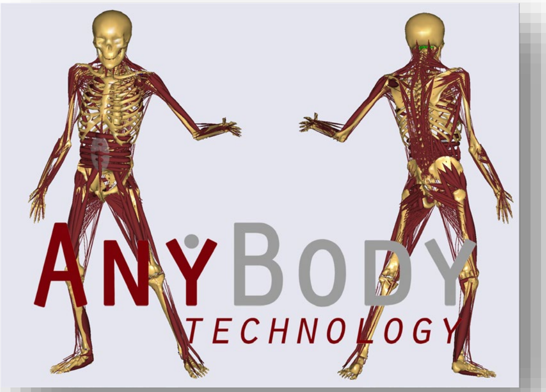

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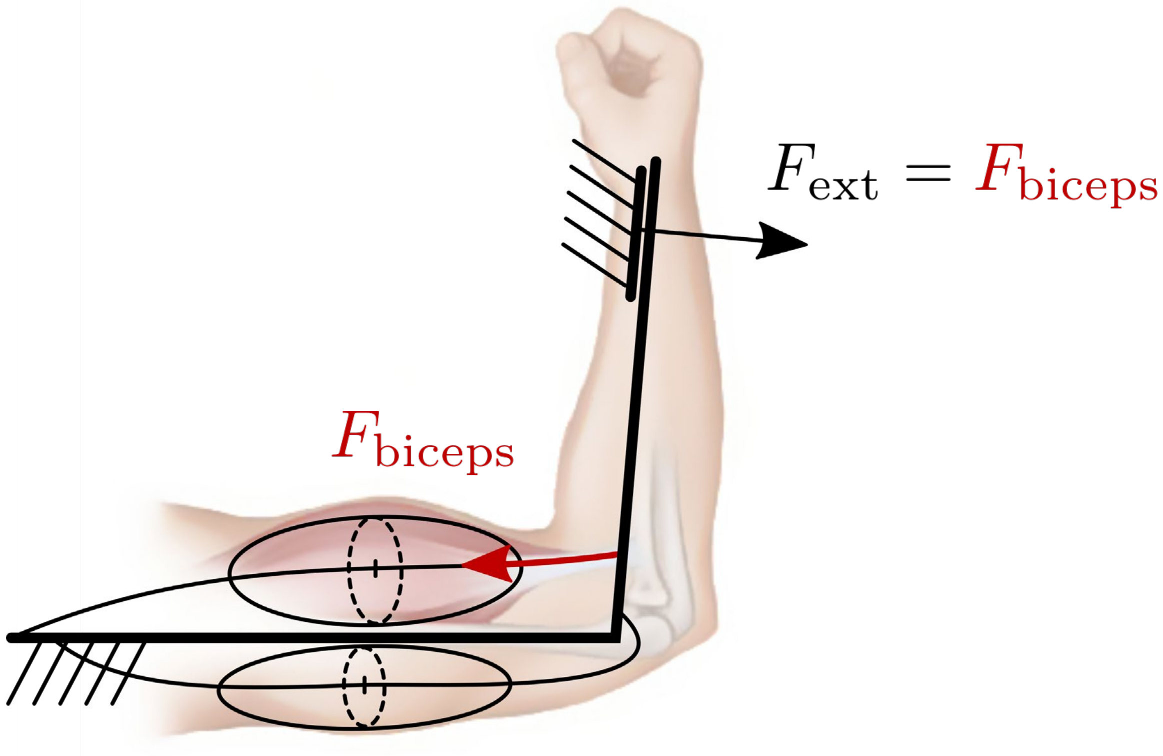

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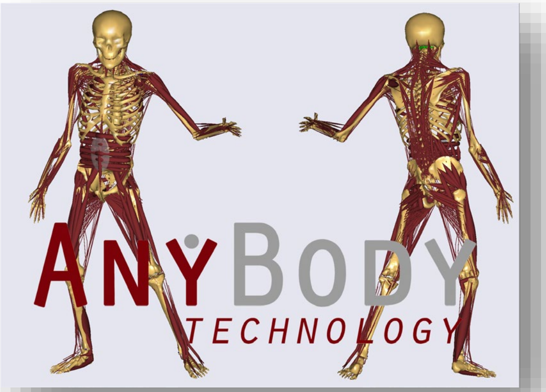

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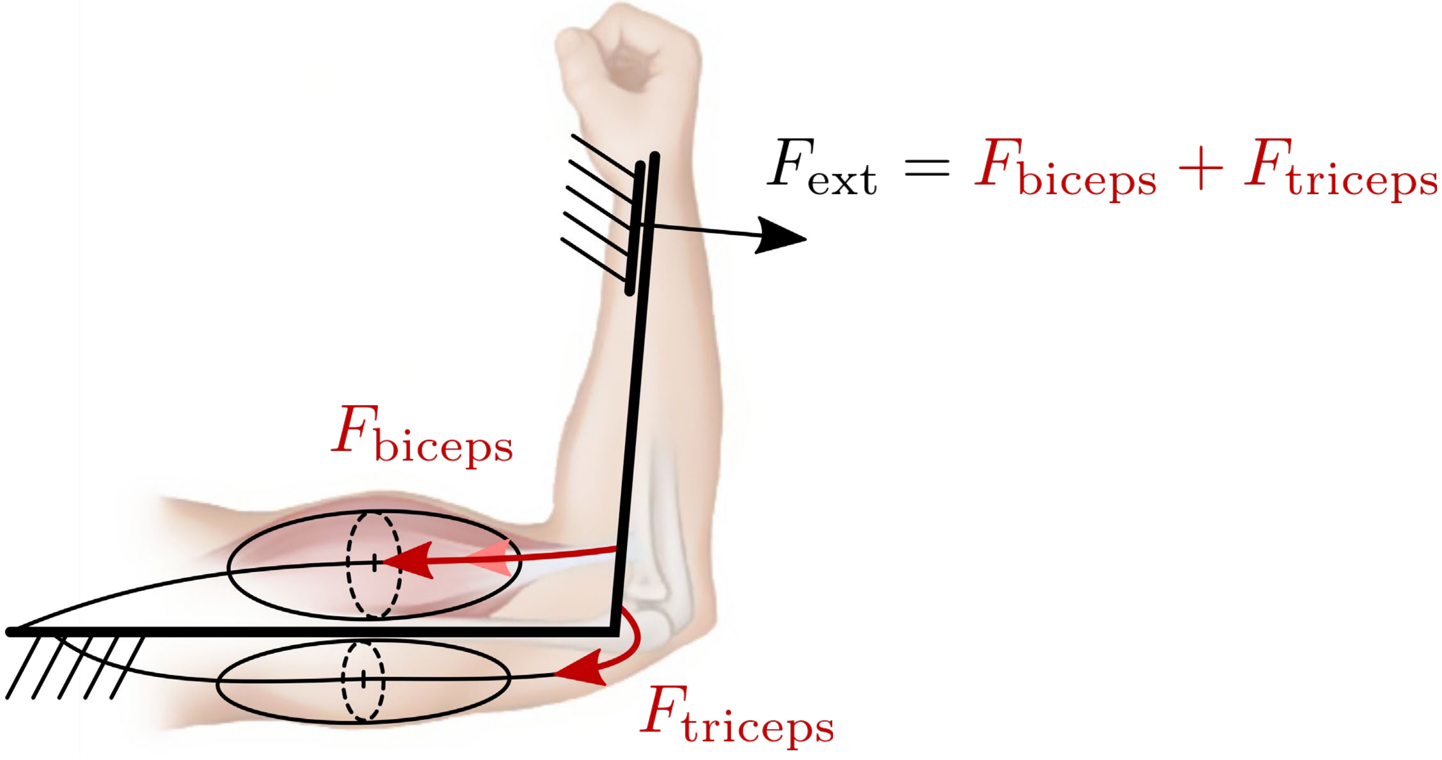

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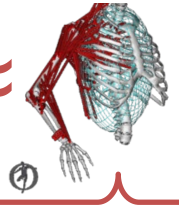
≈ 
modeling software

→ **substantial optimization-based assumptions**
→ **work best on stereotyped motions**

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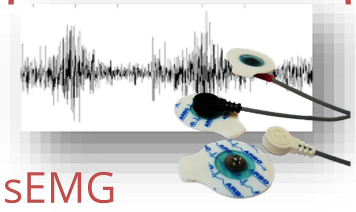
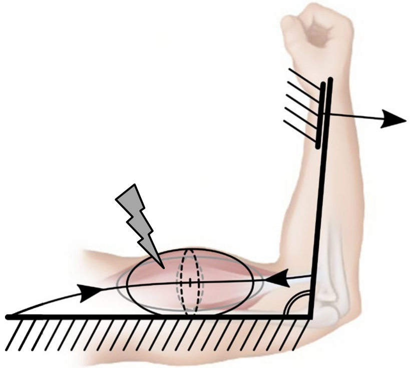
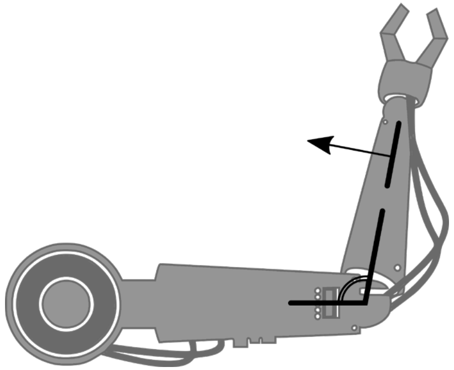


sEMG

→ **noisy**
→ **hard to spatially localize**
→ **surface muscles only**





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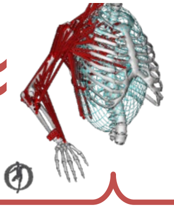
≈  modeling software

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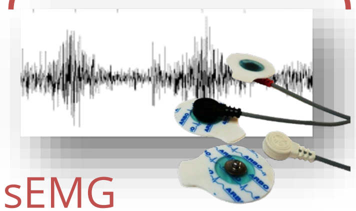

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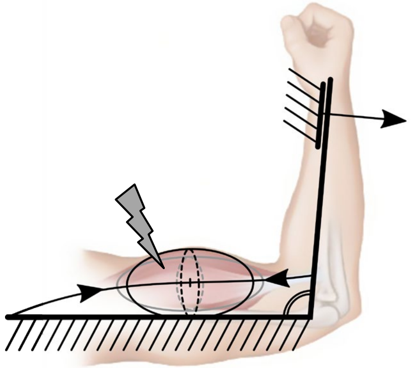

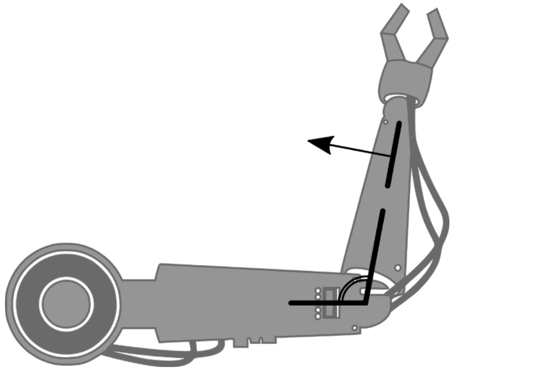

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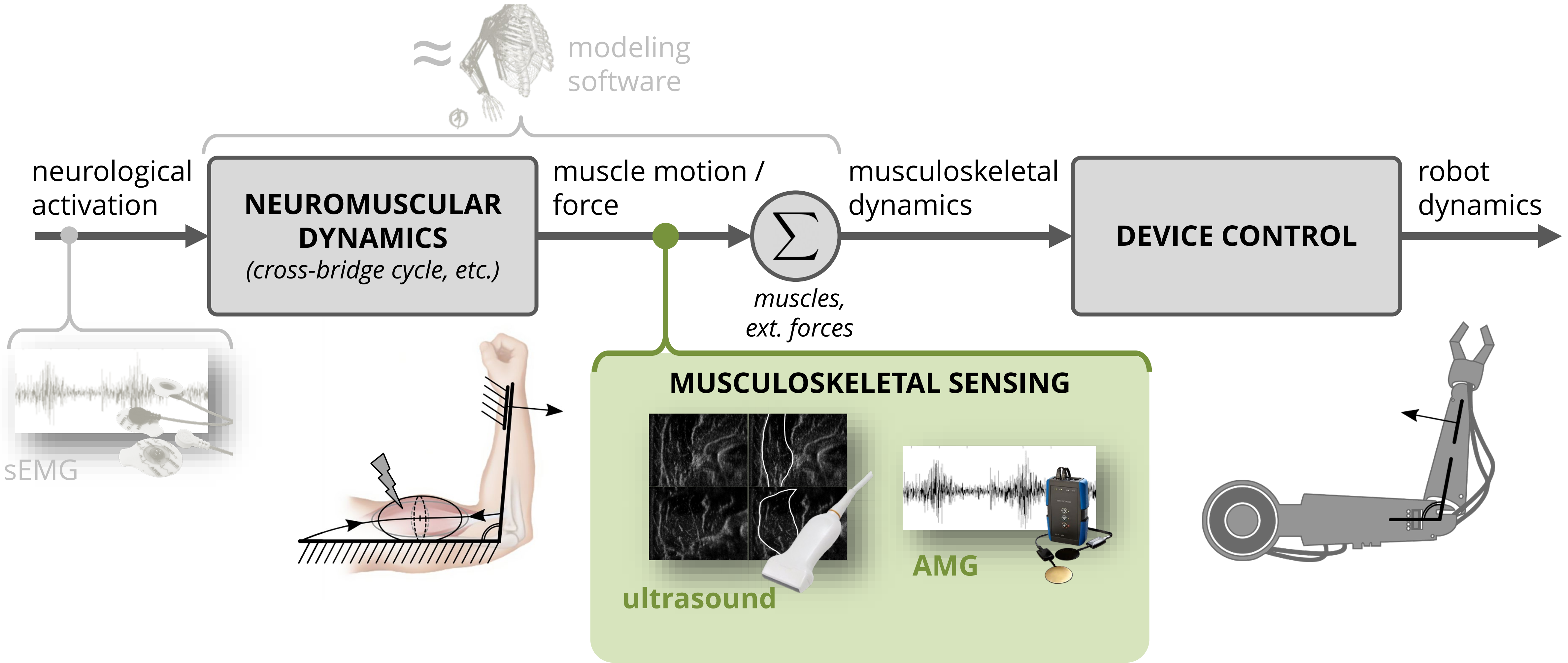

GRADUATE WORK: Advances in MSK Sensing & Modeling

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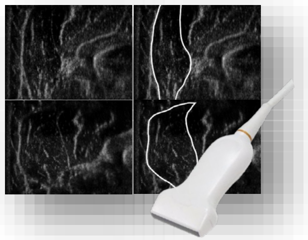
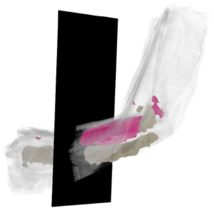
MUSCULOSKELETAL SENSING

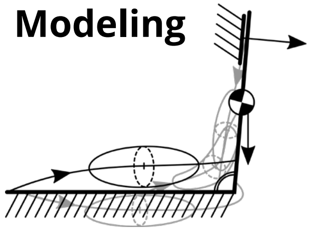
Exploratory Analysis
(2D Deformation)



Data Set Generation
(3D Deformation)



Systematic Force–Deformation Modeling



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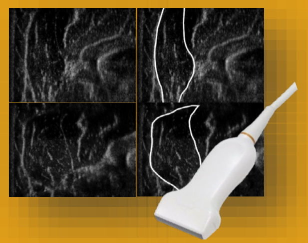

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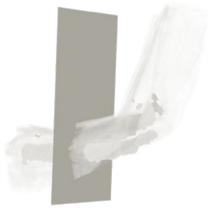

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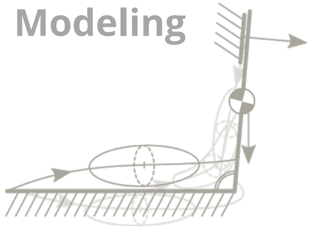
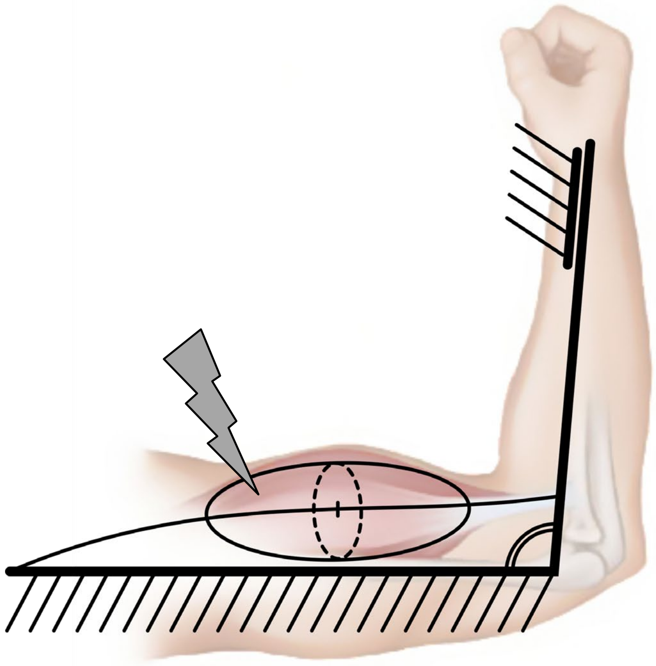


Force–Vibration Modeling

Muscle Force–Deformation Mechanics



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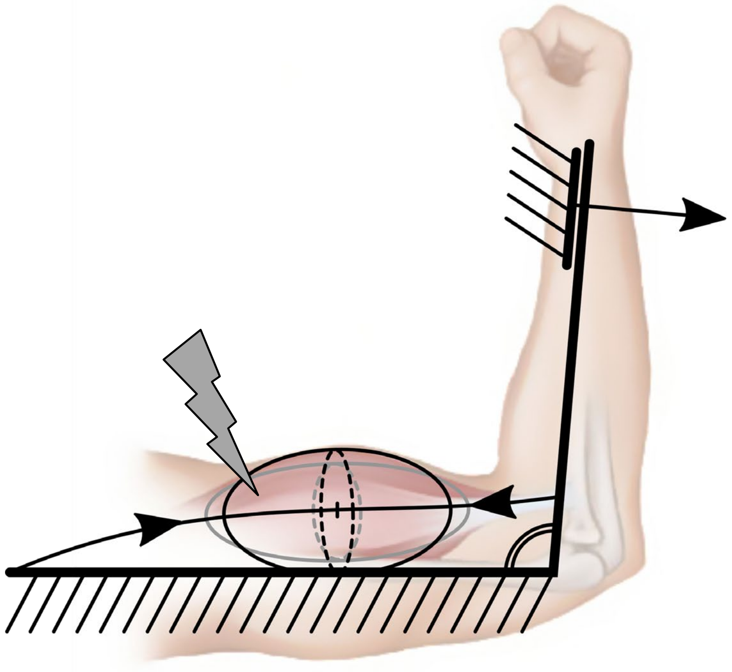
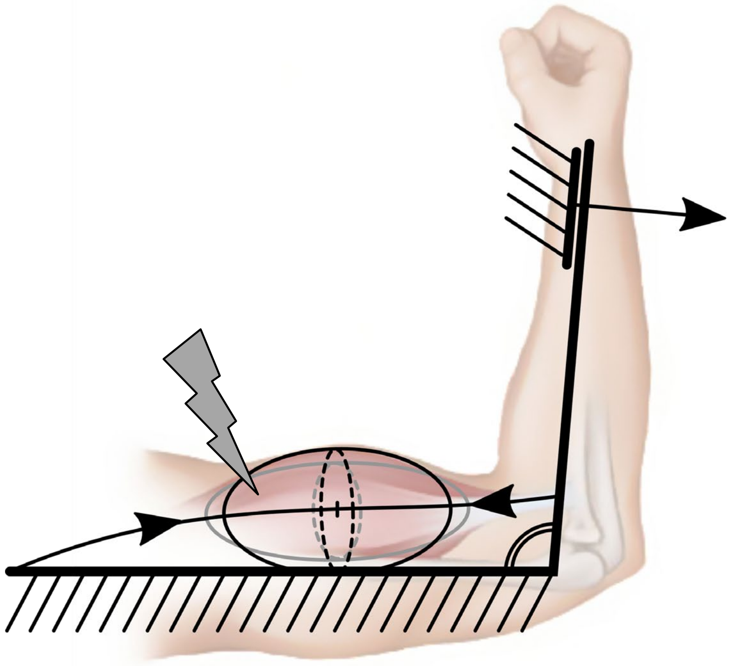
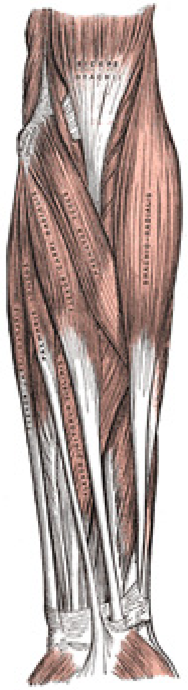
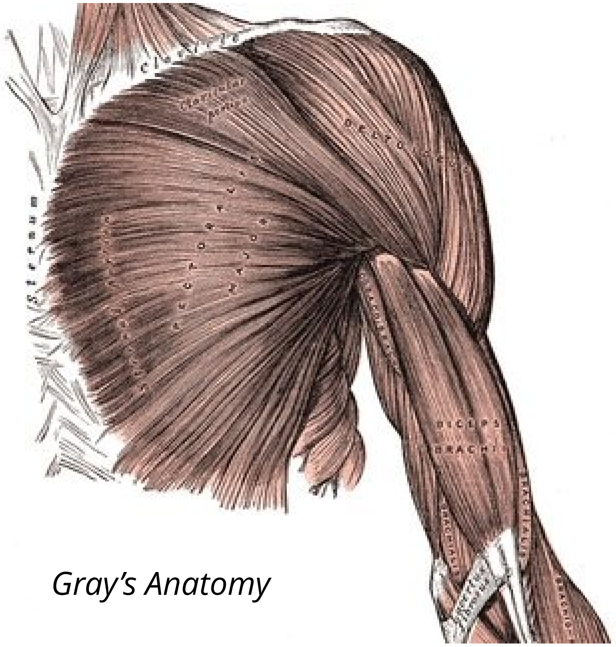


Muscle Force–Deformation Mechanics: Complexities



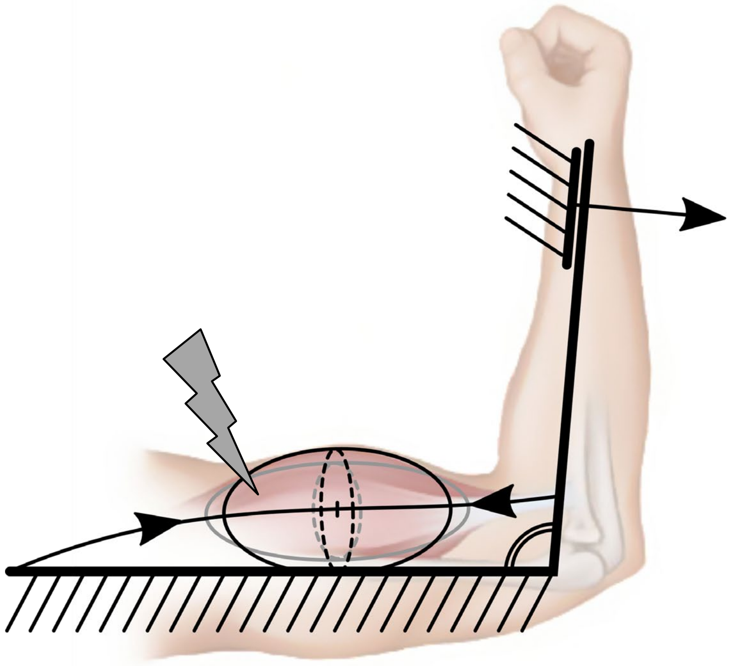


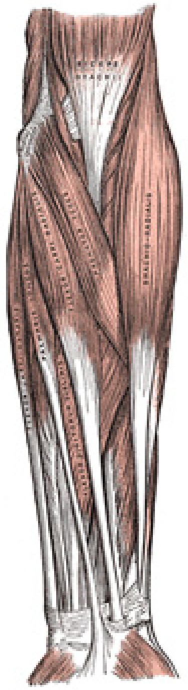


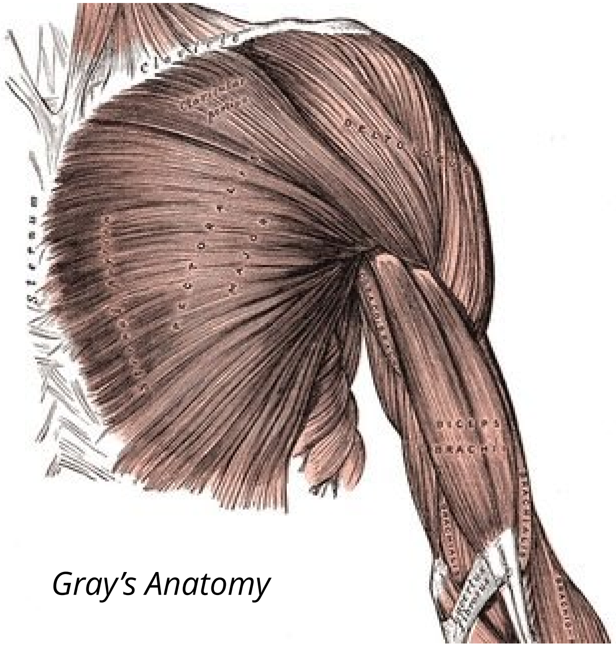
Gray's Anatomy

geometric complexity,
contact dynamics

Muscle Force–Deformation Mechanics: Complexities







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geometric complexity, contact dynamics

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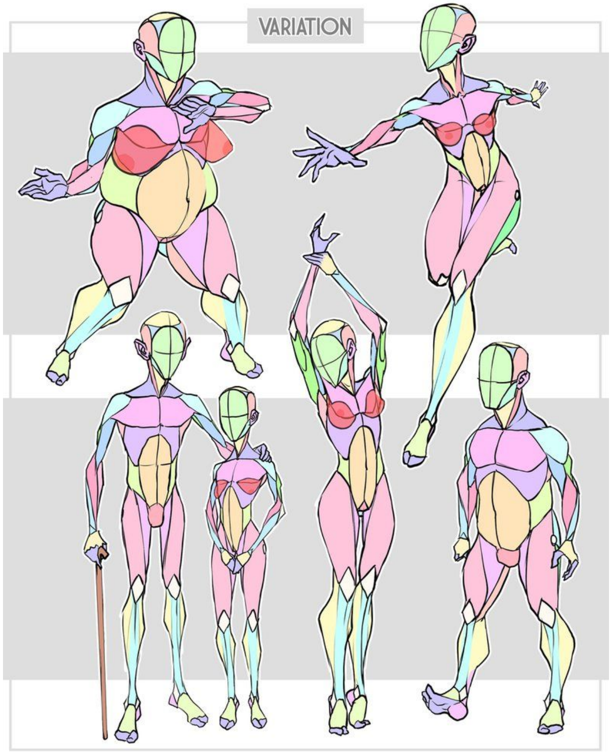

Sycra, DeviantArt

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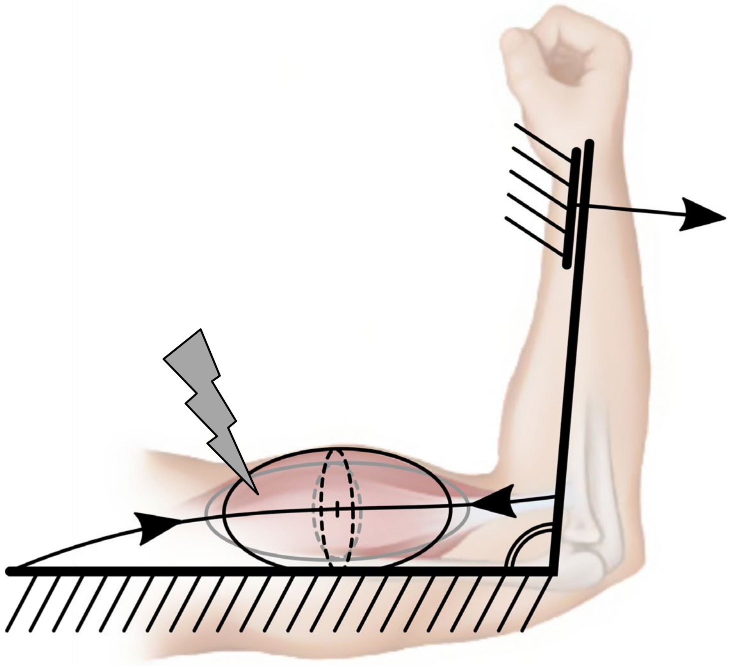

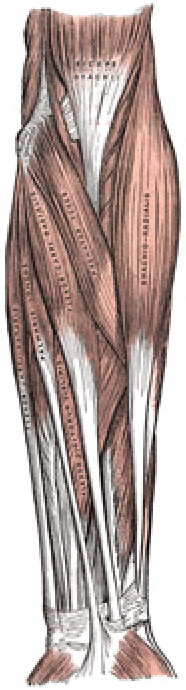

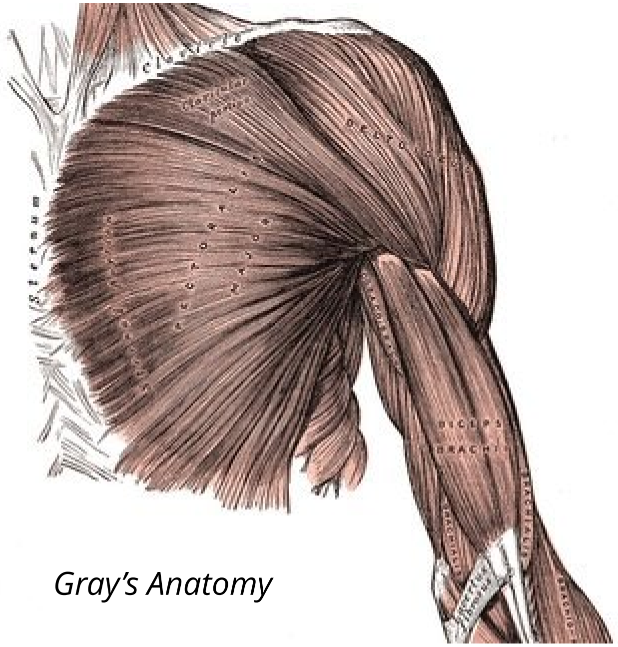

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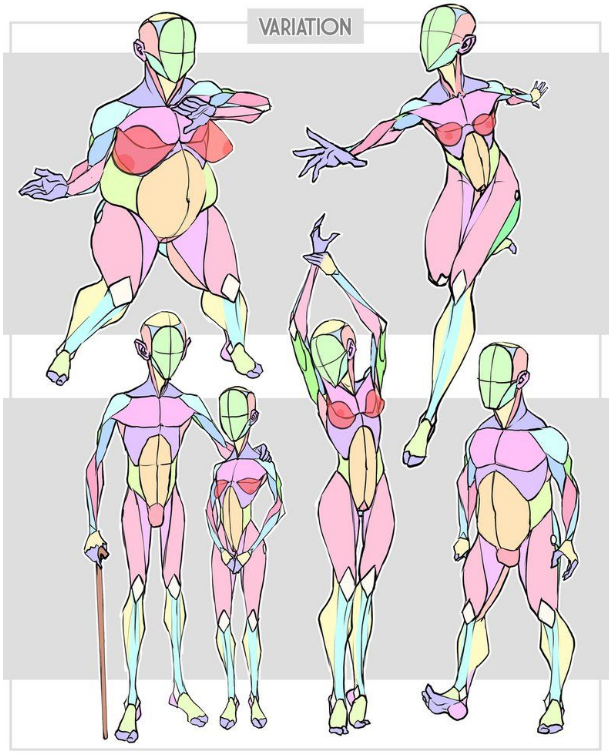
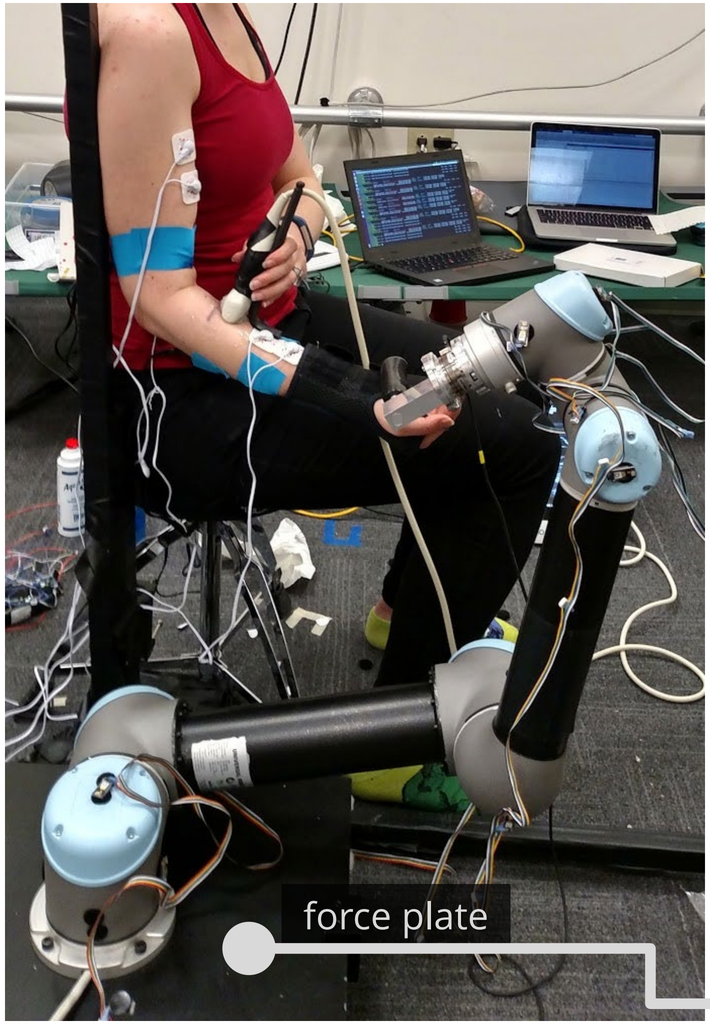
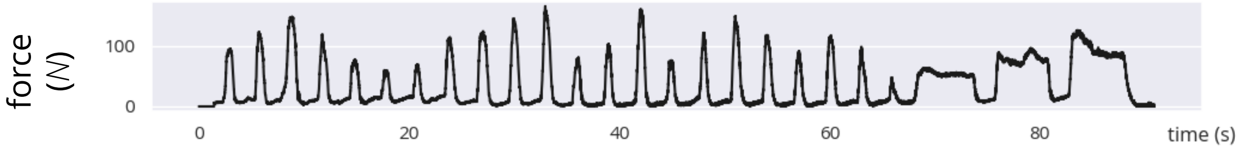


Sycra, DeviantArt

Starting point: Can we correlate simple muscle deformation signals with output force?

Correlation Analysis: Data Collection





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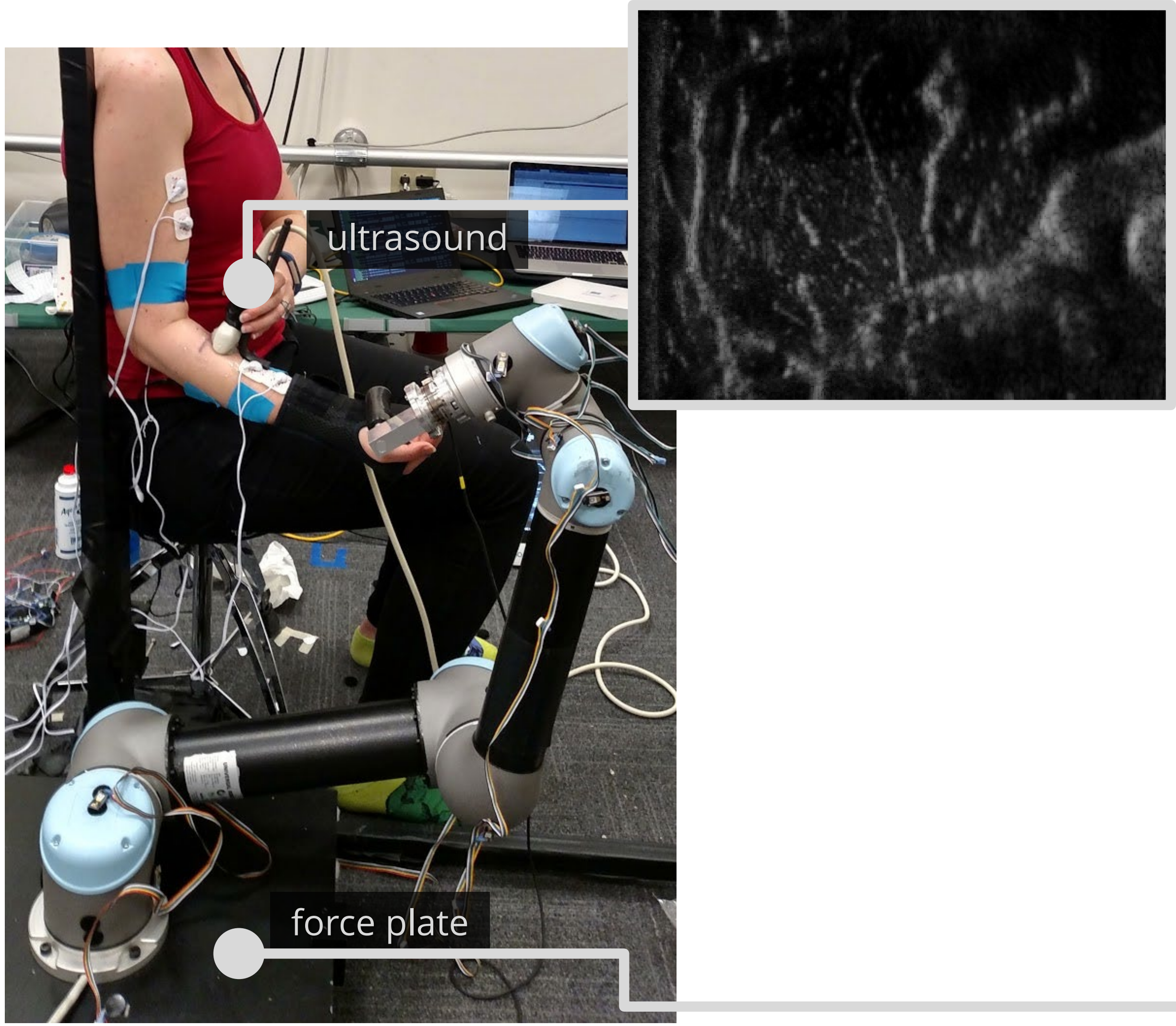

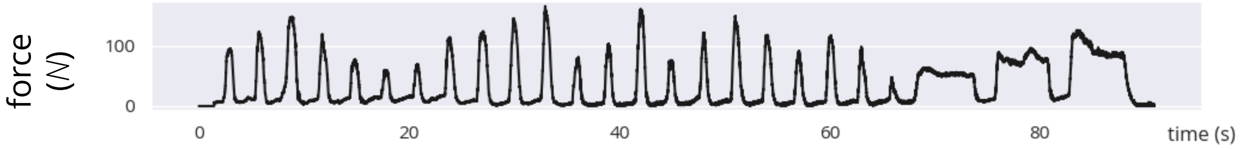

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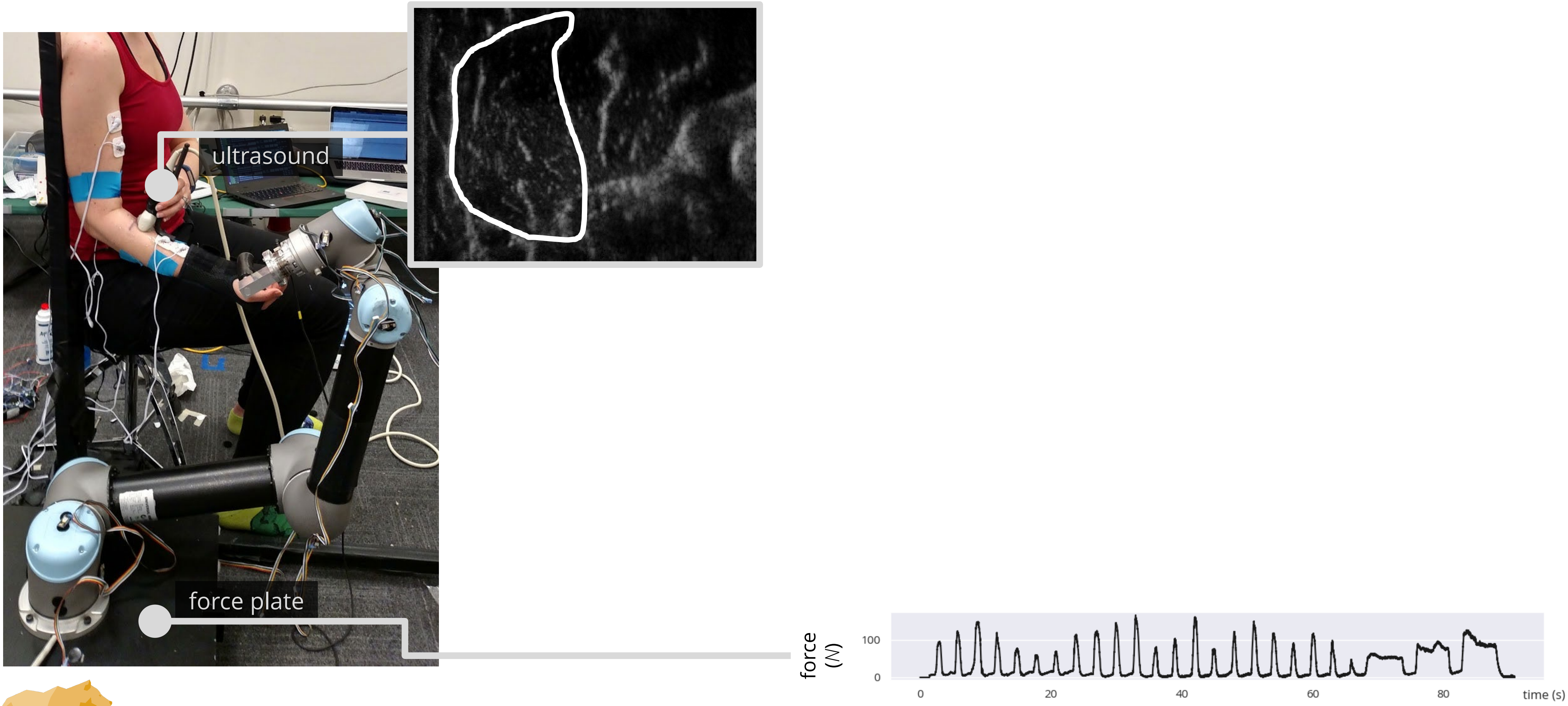

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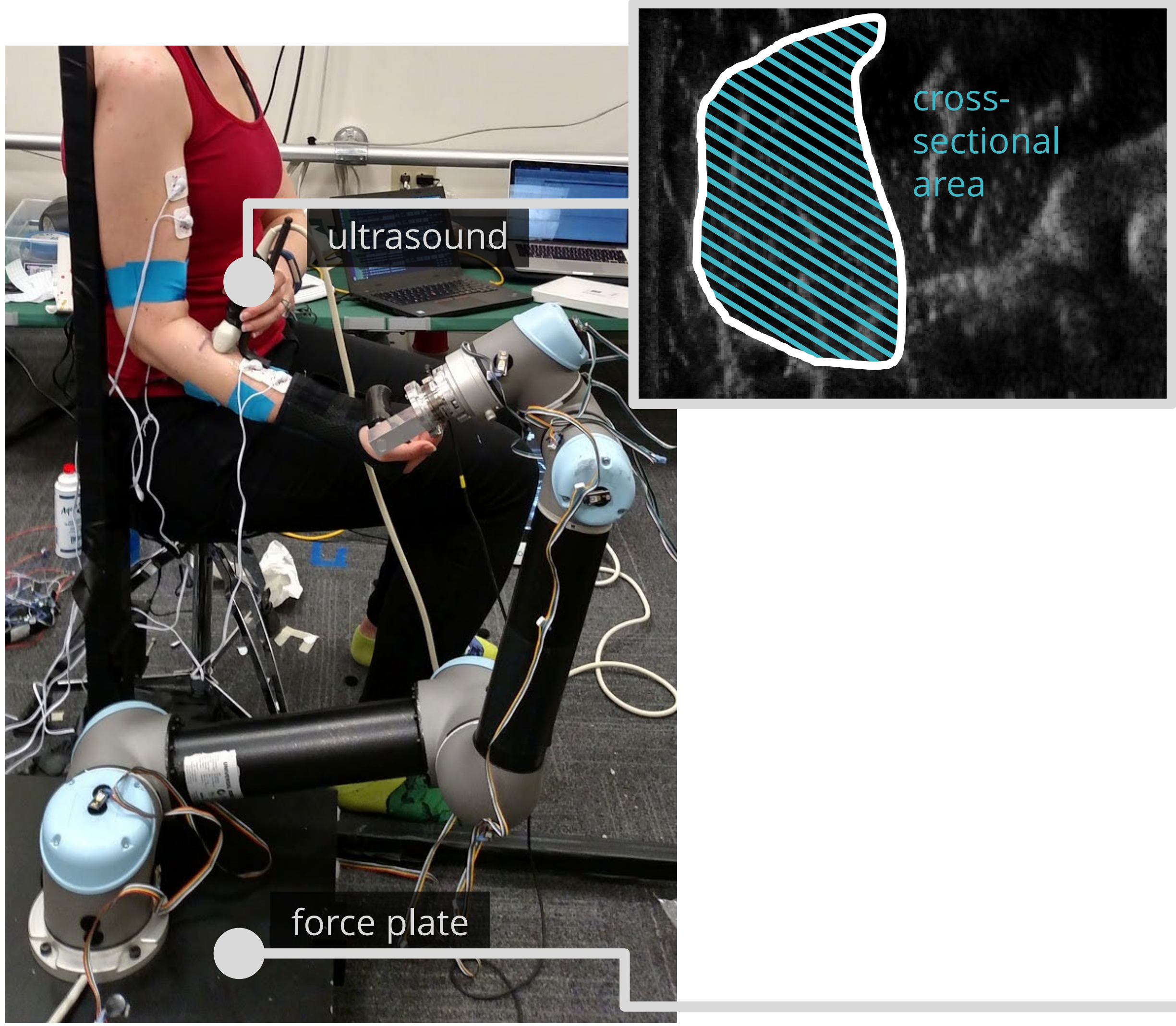

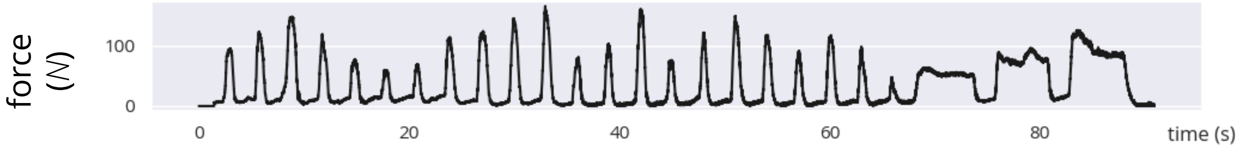

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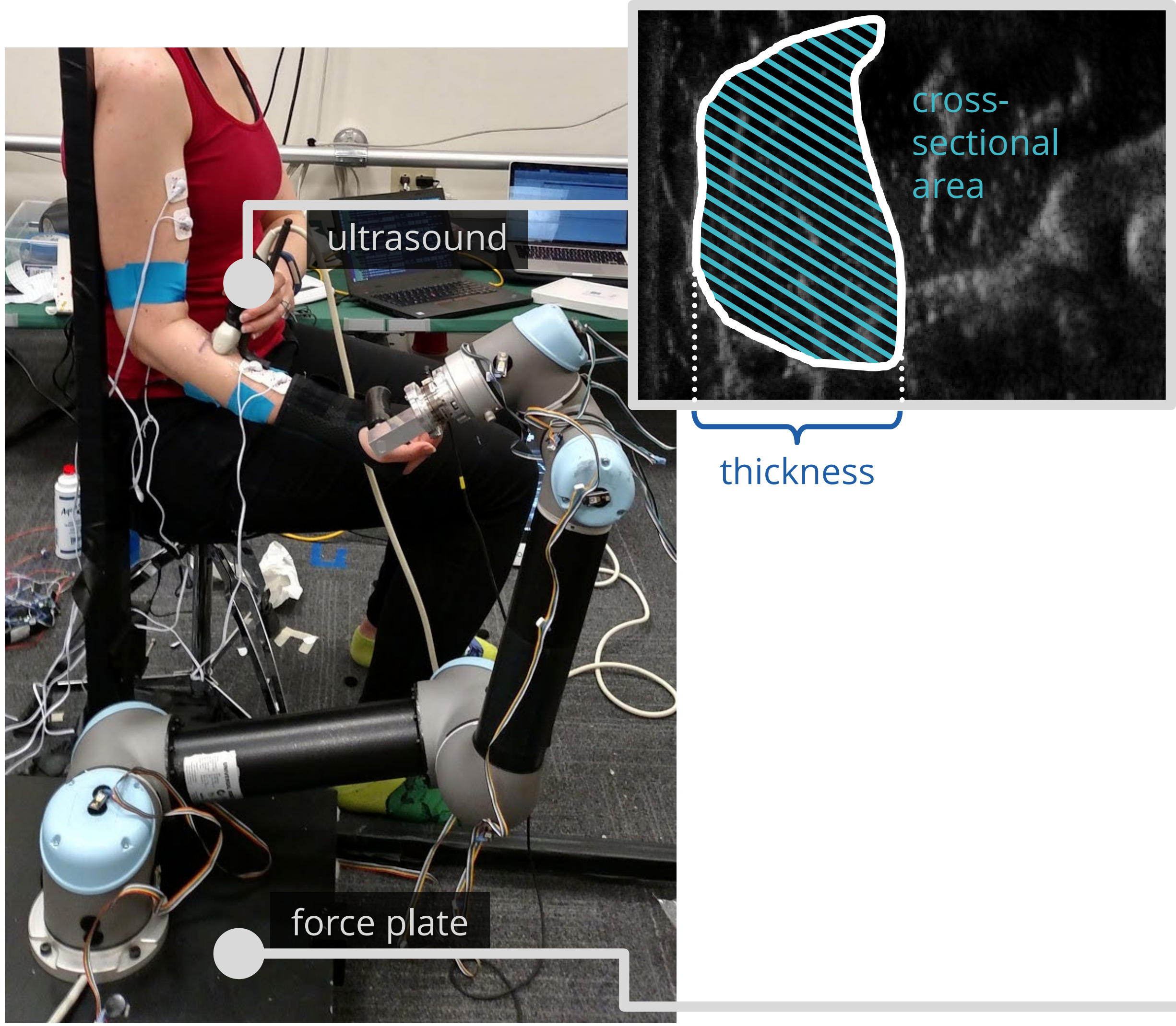
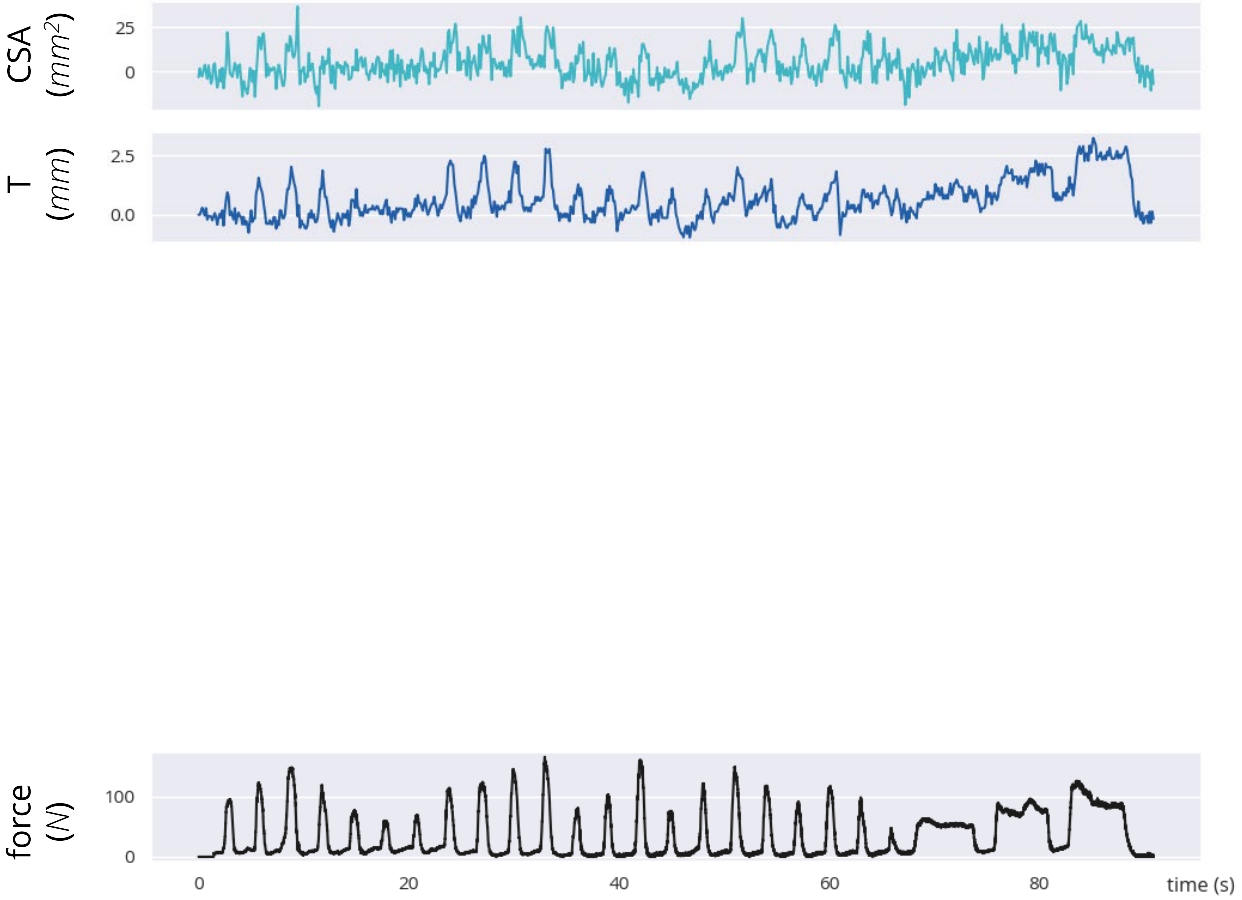
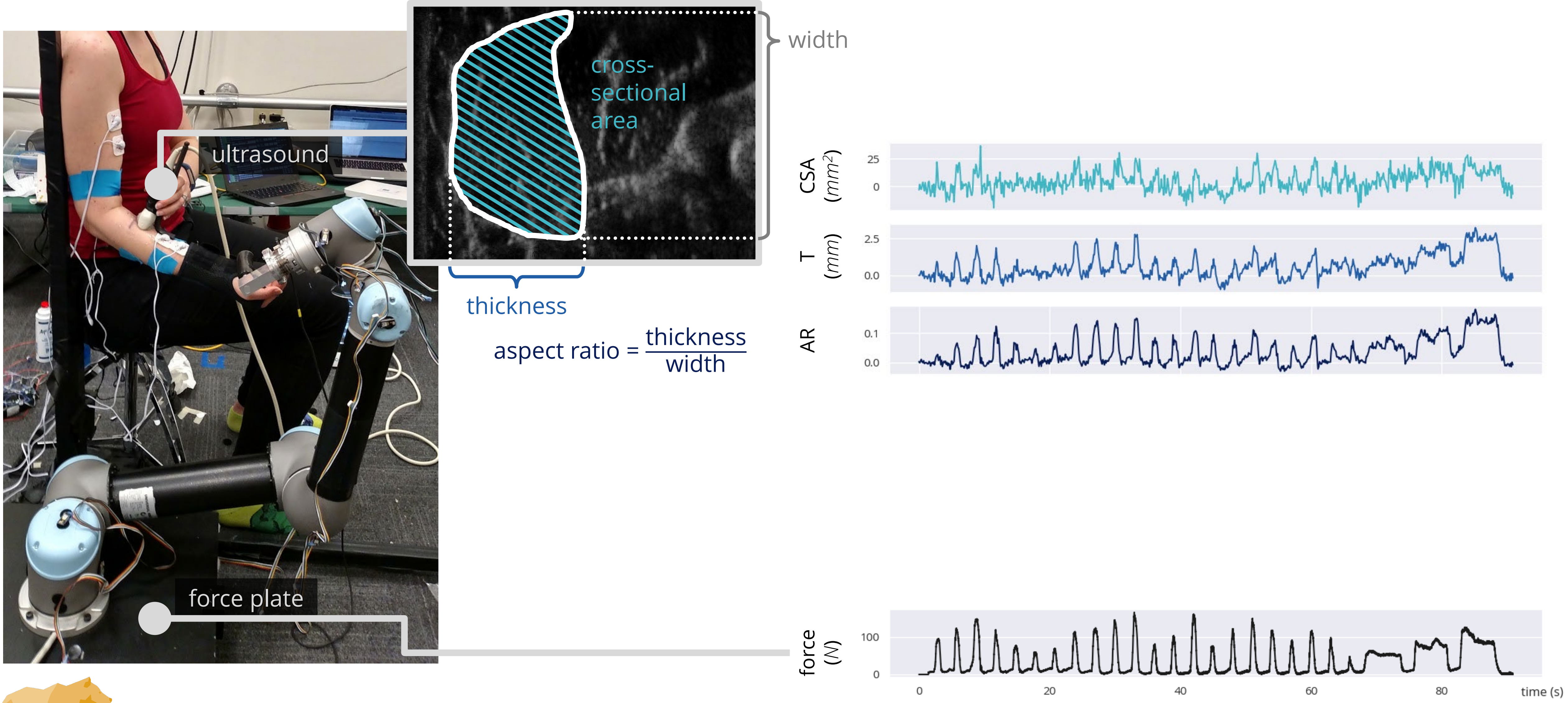




Correlation Analysis: Data Collection



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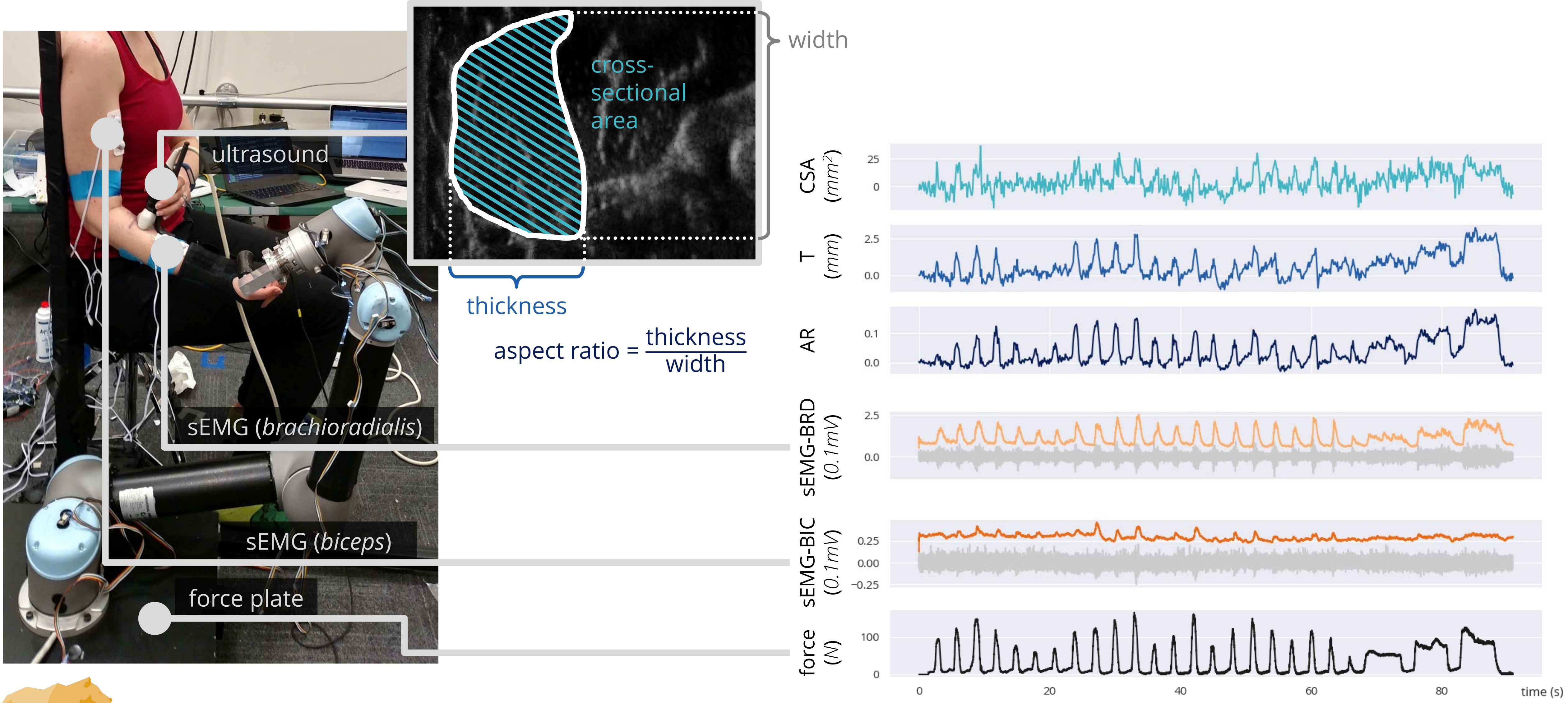
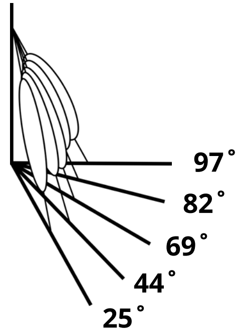
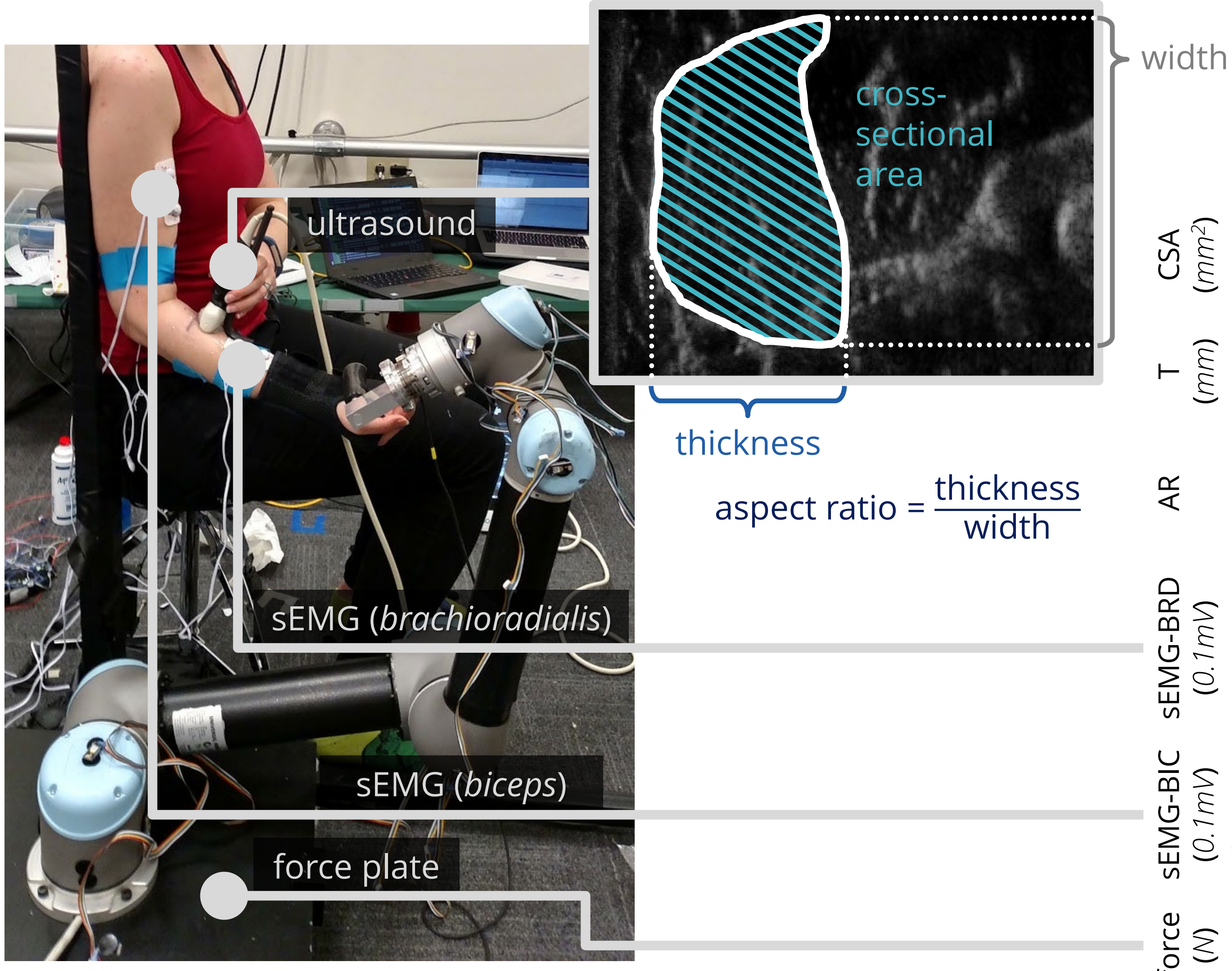


Correlation Analysis: Data Collection

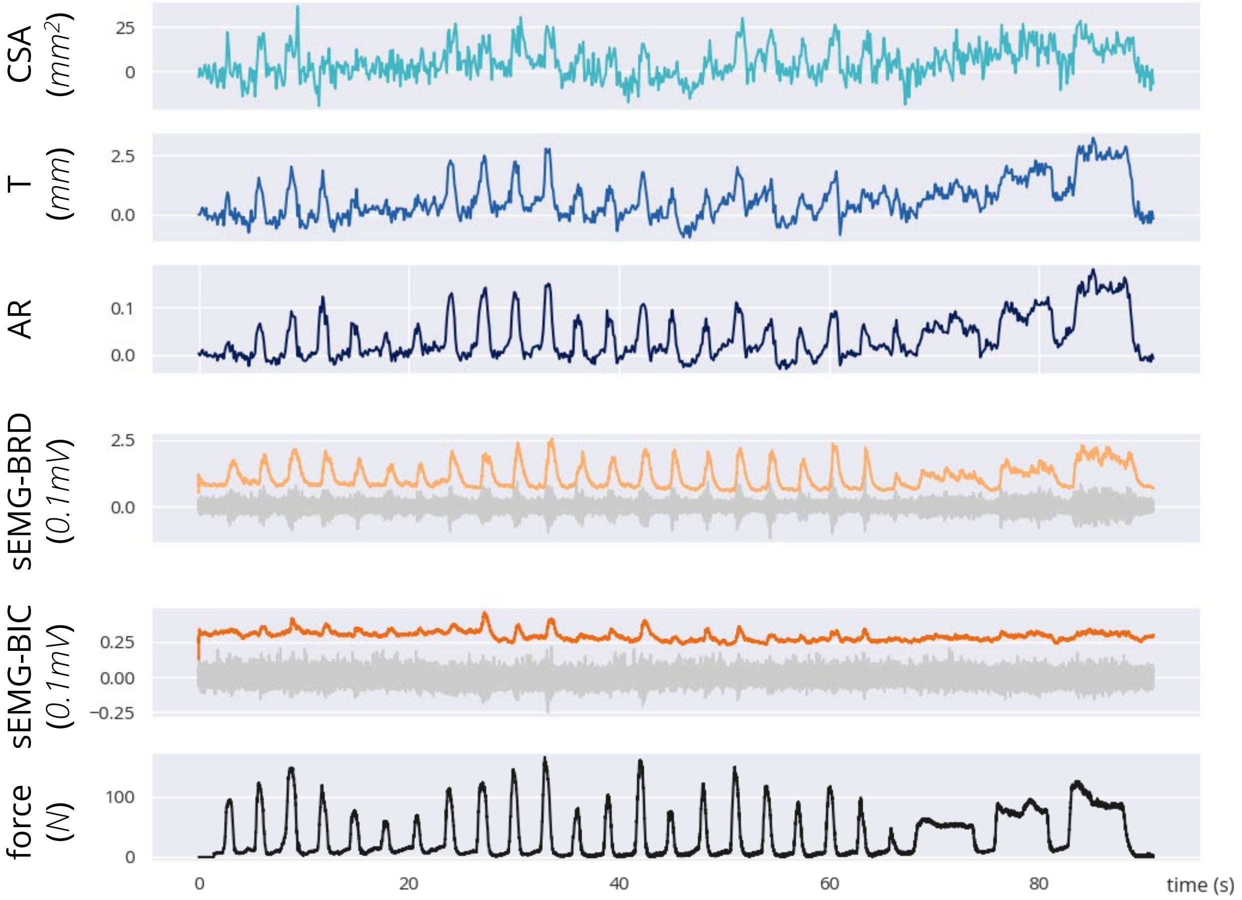
SCOPE:

5 elbow angles
5 subjects





$$\text{aspect ratio} = \frac{\text{thickness}}{\text{width}}$$

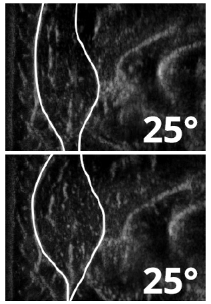


[**Hallock**, Velu, Schwartz, Bajcsy, BioRob 2020]

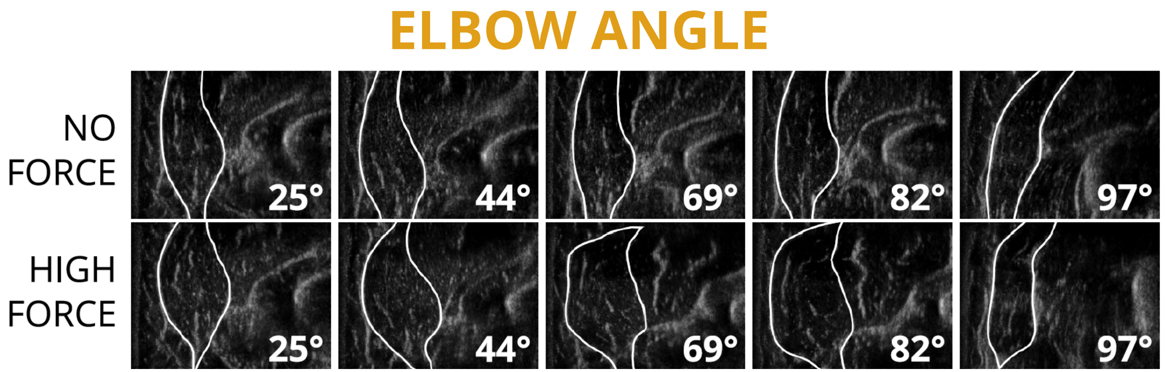
Correlation Analysis

NO
FORCE

HIGH
FORCE



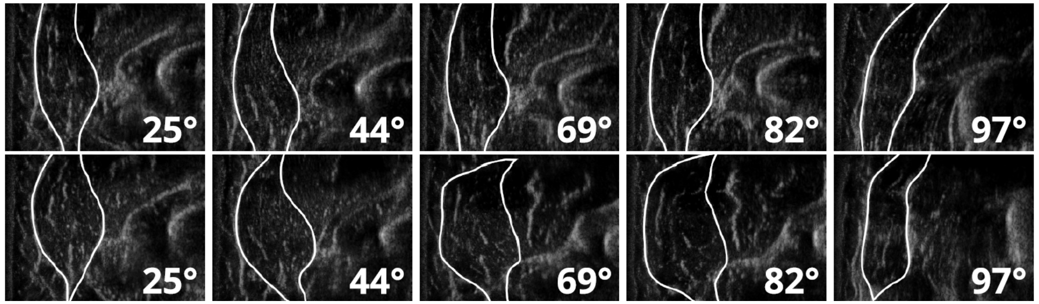
Correlation Analysis



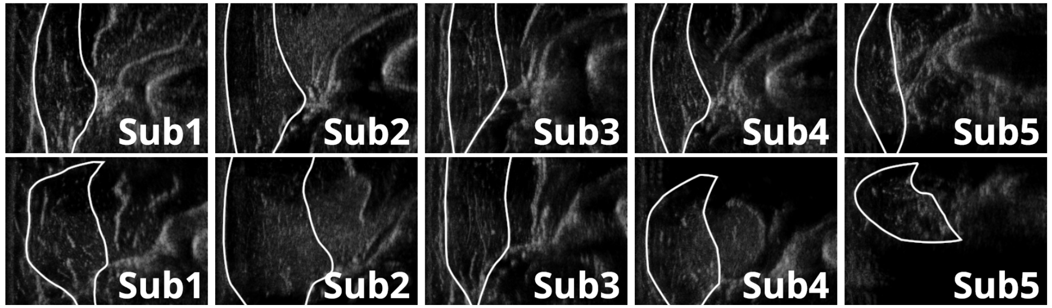
[**Hallock**, Velu, Schwartz, Bajcsy, BioRob 2020]

Correlation Analysis

ELBOW ANGLE



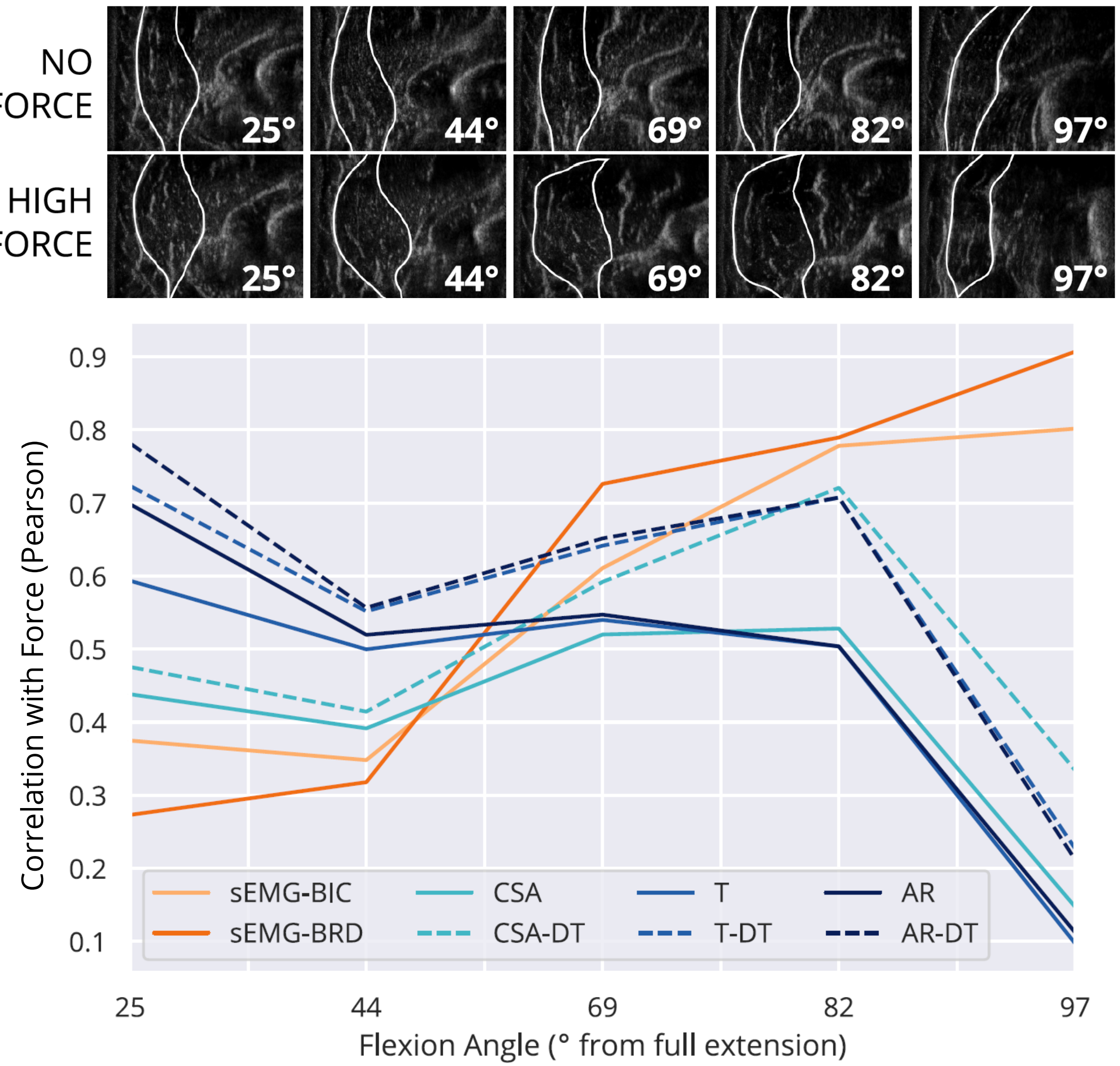
SUBJECT



[*Hallock*, Velu, Schwartz, Bajcsy, BioRob 2020]

Correlation Analysis

ELBOW ANGLE



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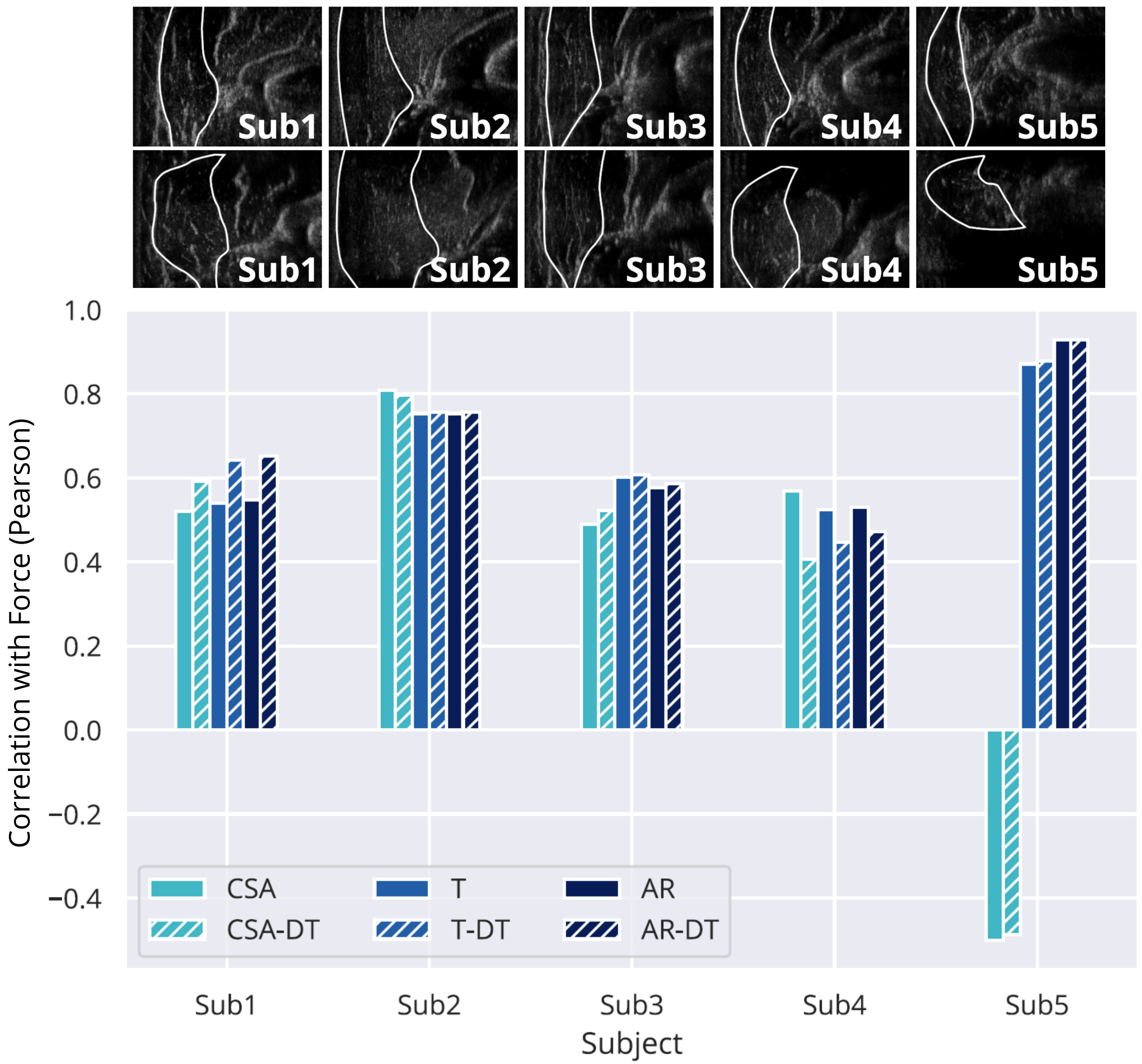
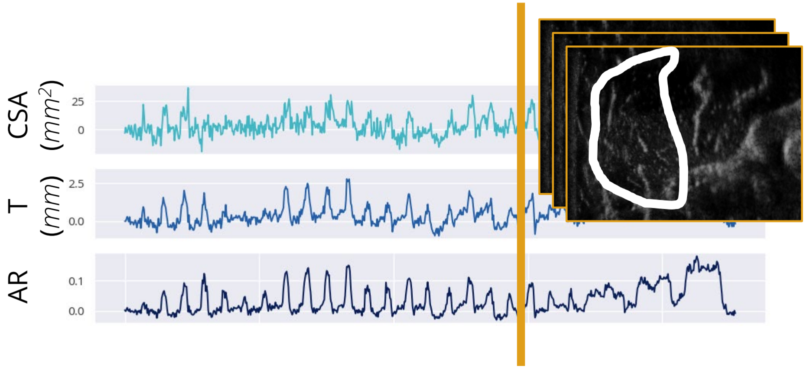


System Identification: Two Challenges

1. Manual annotation is **prohibitively time-intensive** and **can't be done in real time**.



× *O*(1000)

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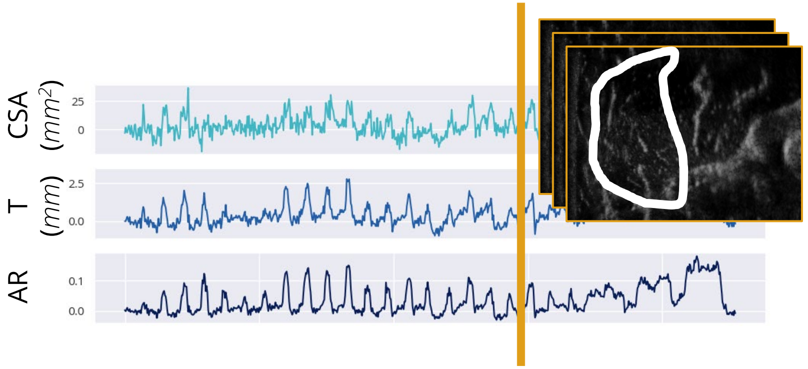
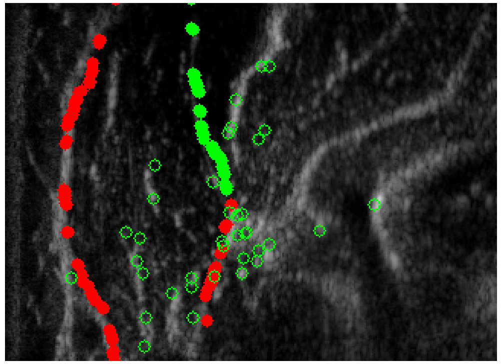


× *O*(1000)

Track muscle contours via Lucas–Kanade optical flow.



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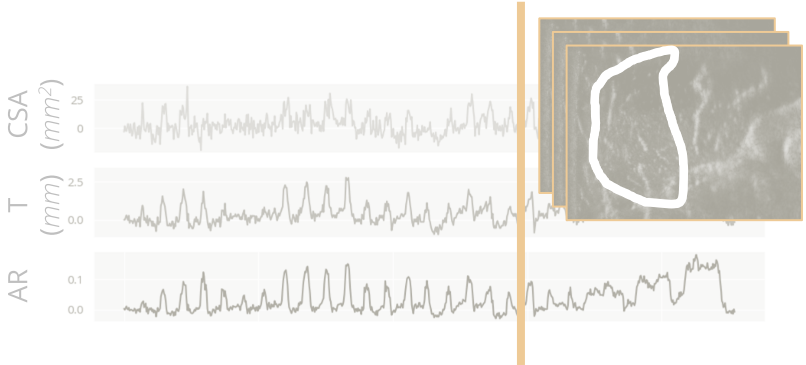

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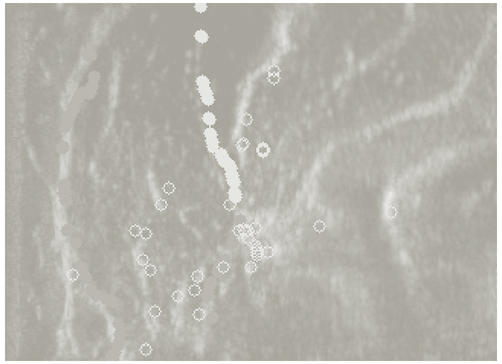
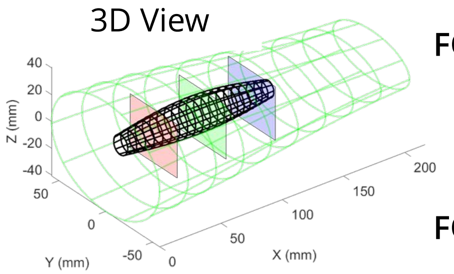
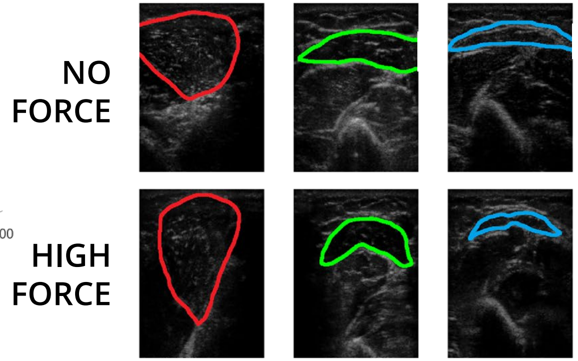


2. It's still unclear **what** deformation signals we should use, and **where** we should collect them.





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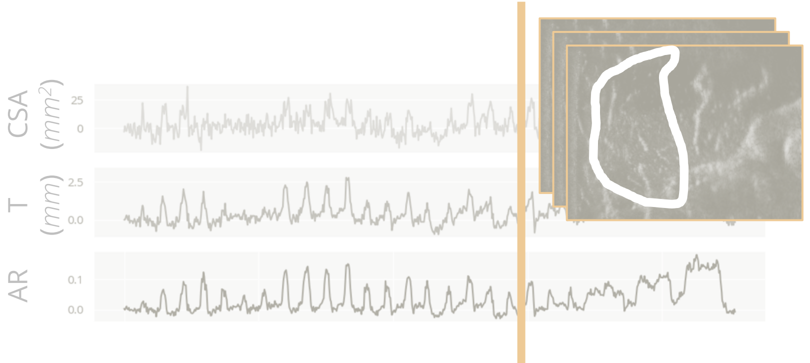

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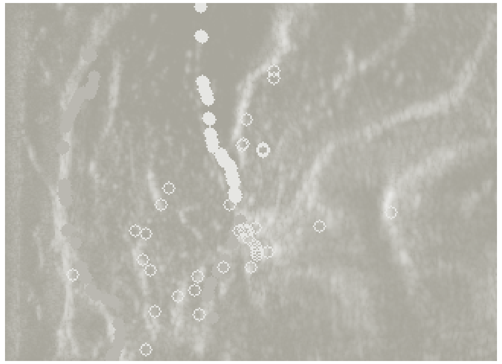

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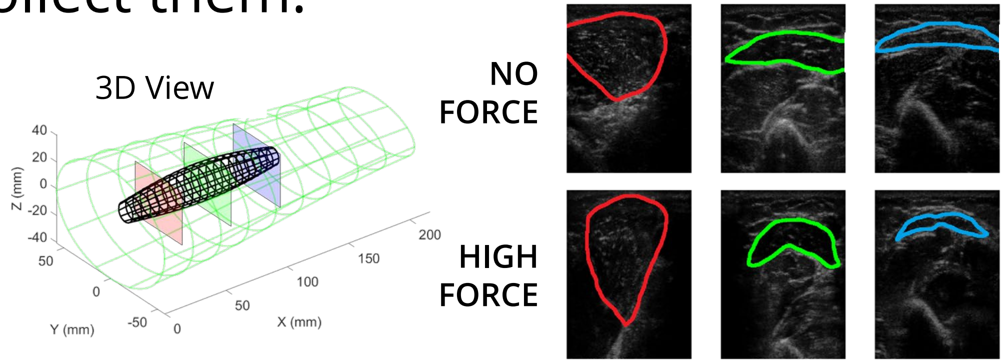


Observe the **entire muscle** under **multiple joint positions** and **loading conditions**.

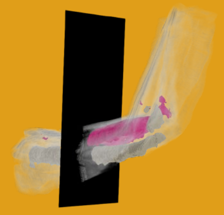
GRADUATE WORK: Advances in MSK Sensing & Modeling

neurological activation → **NEUROMUSCULAR DYNAMICS** *(cross-bridge cycle, etc.)* → musculoskeletal dynamics → **DEVICE CONTROL** → robot dynamics

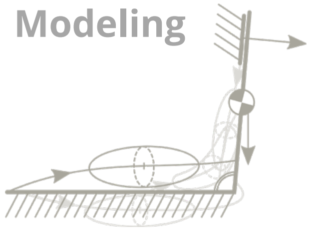
MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

Data Set Generation
(3D Deformation)



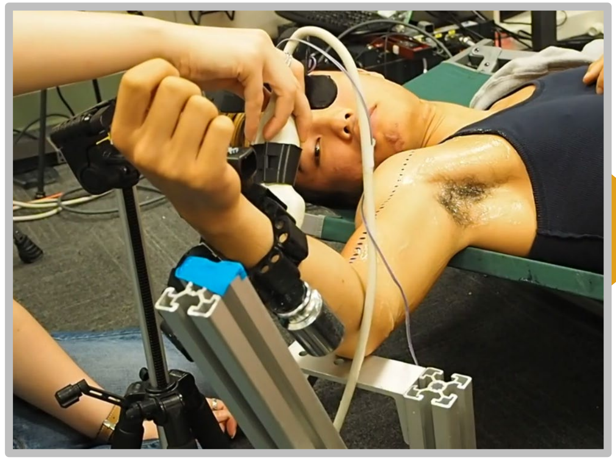
Systematic Force–Deformation Modeling



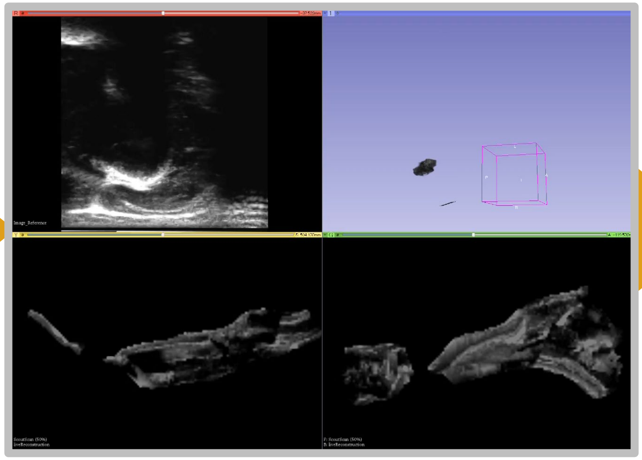
Force–Vibration Modeling

Data Collection Setup: Ultrasound + Motion Capture

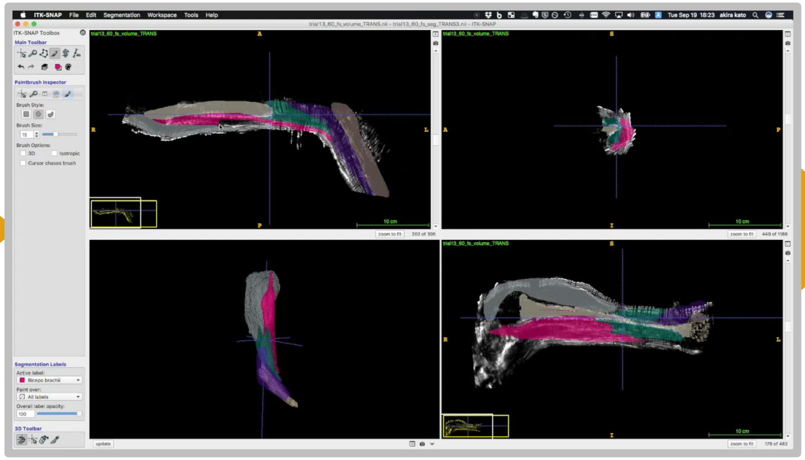
Raw Data Collection
via Ultrasound & Motion Capture



Volumetric Reconstruction
via PLUS Toolkit



Tissue Segmentation
in ITK-SNAP

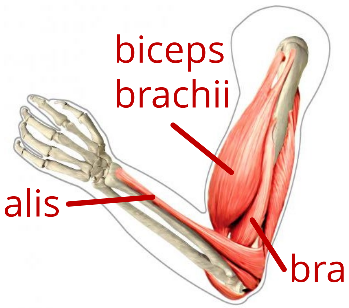


Using **motion capture** to track the **ultrasound probe position**, we can generate **full 3D scans** of the arm under **static conditions**.

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

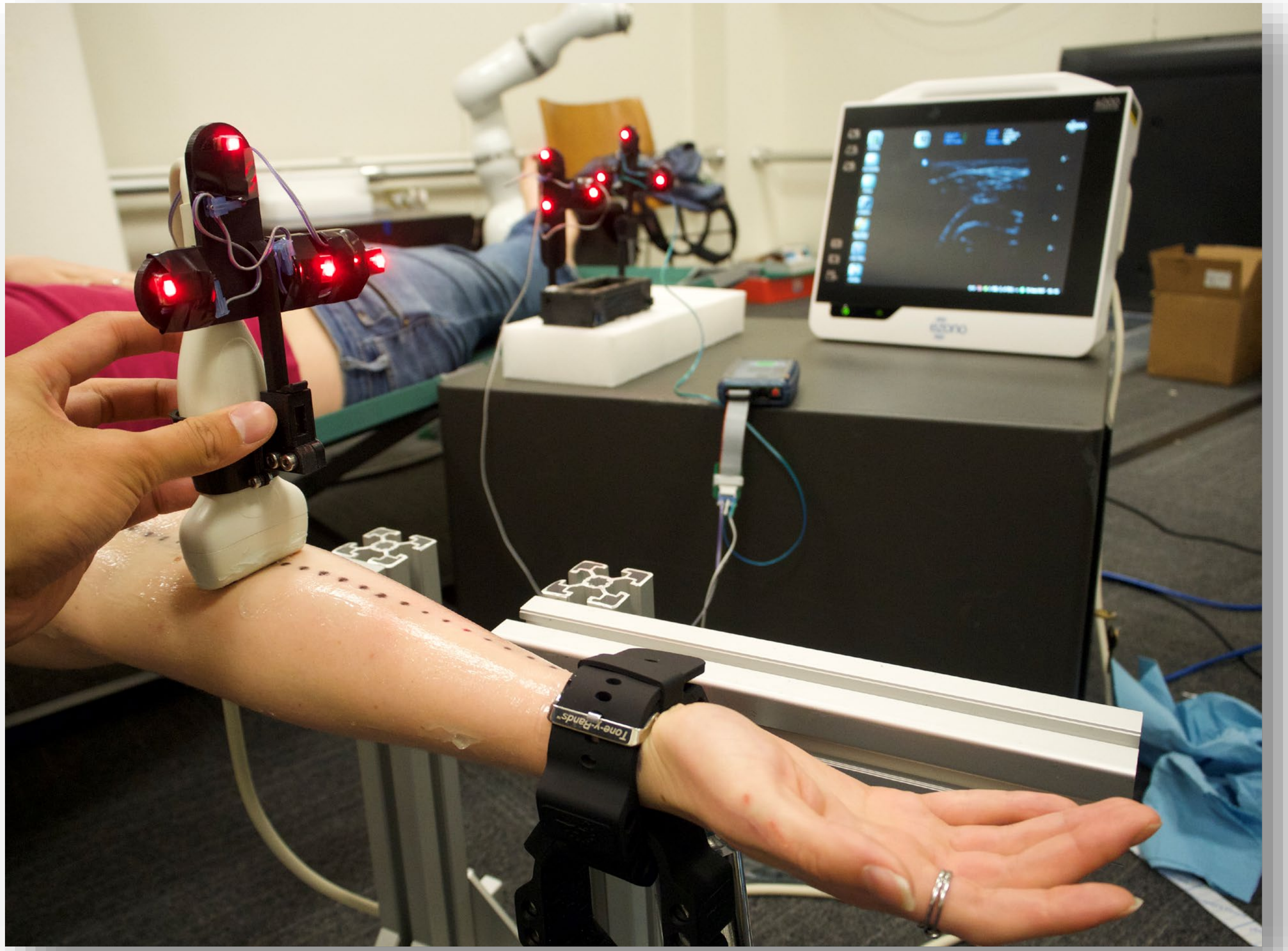
Preliminary Data Set

Model target: elbow flexors



Data set:

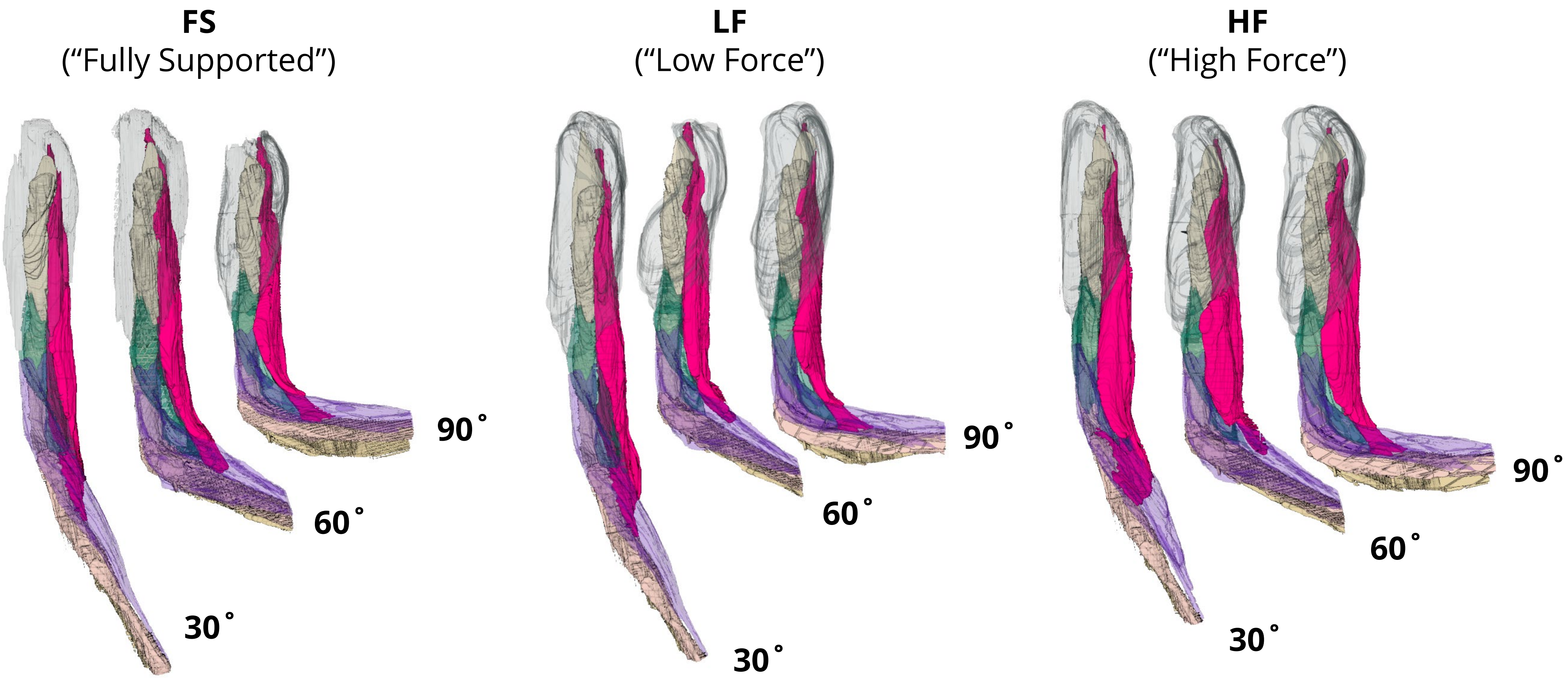
- 3 subjects (1 F, 2 M)
- full arm ultrasound volumetric scan
- 4 elbow flexion angles, 0–90˚
- 5 loading conditions
  - ***FS***: fully supported
  - ***GC***: gravity compensation only
  - ***LF***: light wrist weight (~225g)
  - ***MF***: medium wrist weight (~725g)
  - ***HF***: heavy wrist weight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



Ultrasound volumetric data collection, HART Lab 2017

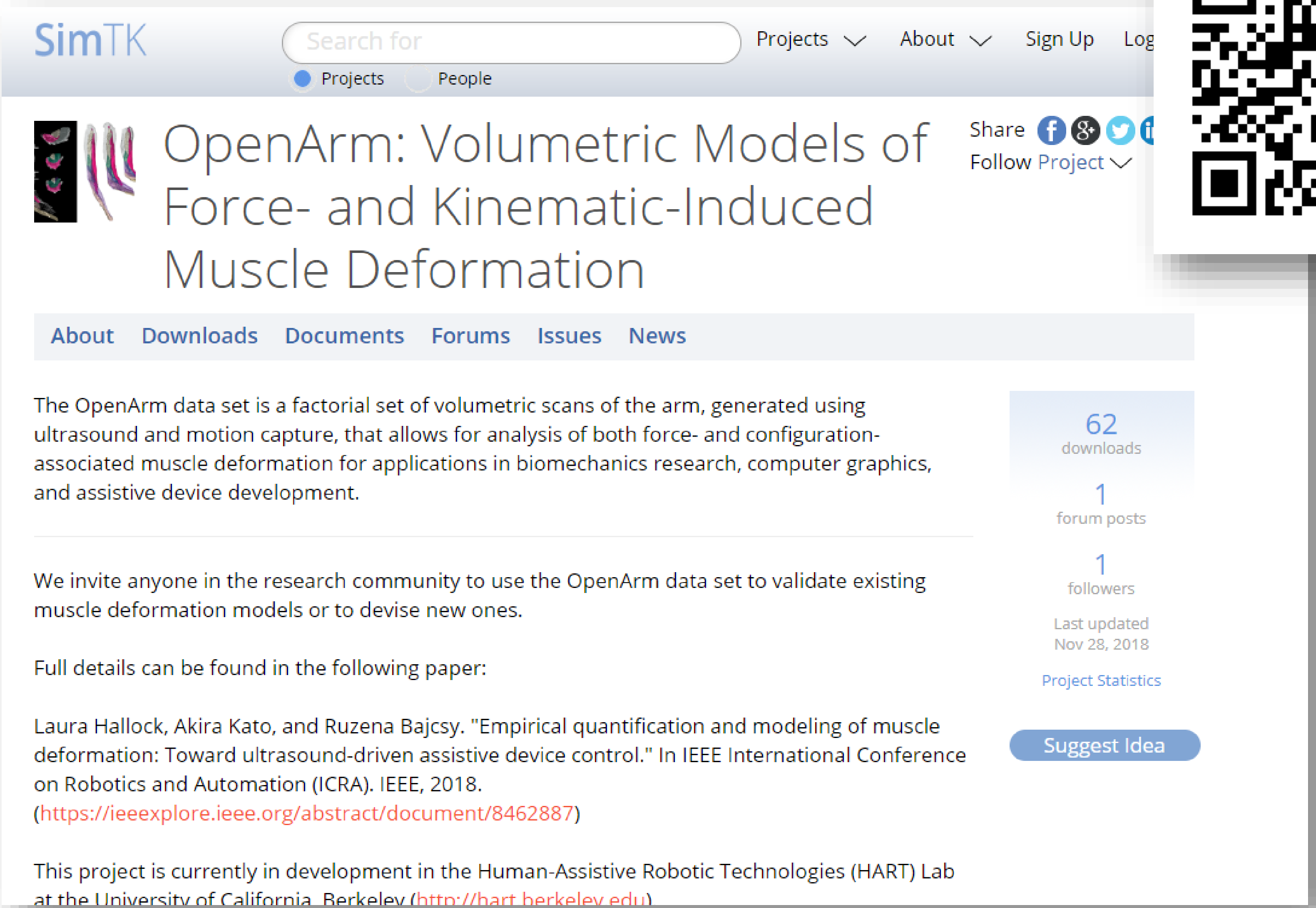
*[**Hallock**, Kato, Bajcsy, ICRA 2018]*

Preliminary Results: Qualitative



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

Data Set Release: OpenArm 1.0



SimTK

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OpenArm: Volumetric Models of Force- and Kinematic-Induced Muscle Deformation

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The OpenArm data set is a factorial set of volumetric scans of the arm, generated using ultrasound and motion capture, that allows for analysis of both force- and configuration-associated muscle deformation for applications in biomechanics research, computer graphics, and assistive device development.

We invite anyone in the research community to use the OpenArm data set to validate existing muscle deformation models or to devise new ones.

Full details can be found in the following paper:

Laura Hallock, Akira Kato, and Ruzena Bajcsy. "Empirical quantification and modeling of muscle deformation: Toward ultrasound-driven assistive device control." In IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018. (https://ieeexplore.ieee.org/abstract/document/8462887)

This project is currently in development in the Human-Assistive Robotic Technologies (HART) Lab at the University of California, Berkeley (http://hart.berkeley.edu)

62 downloads

1 forum posts

1 followers

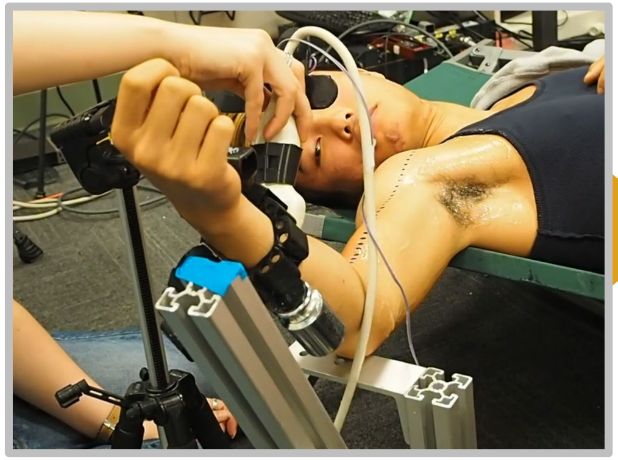
Last updated Nov 28, 2018

Project Statistics

Suggest Idea

Data Collection: Challenges & Shortcomings

Raw Data Collection
via Ultrasound & Motion Capture



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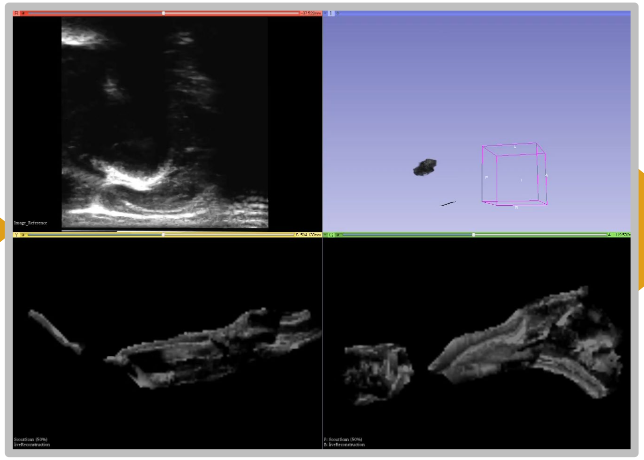

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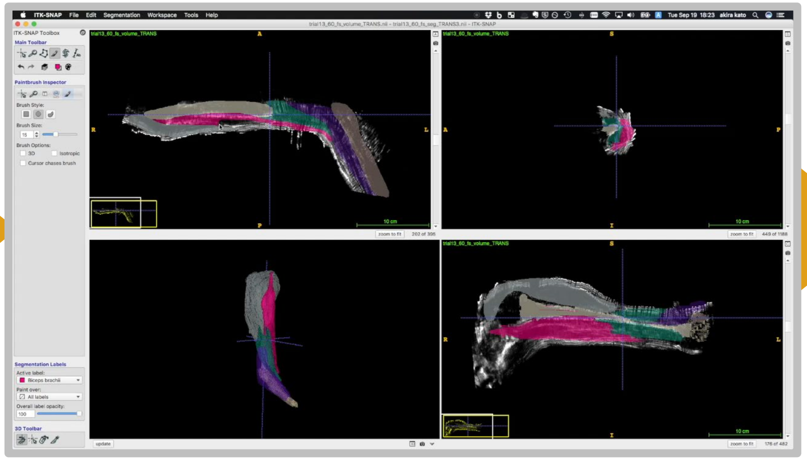
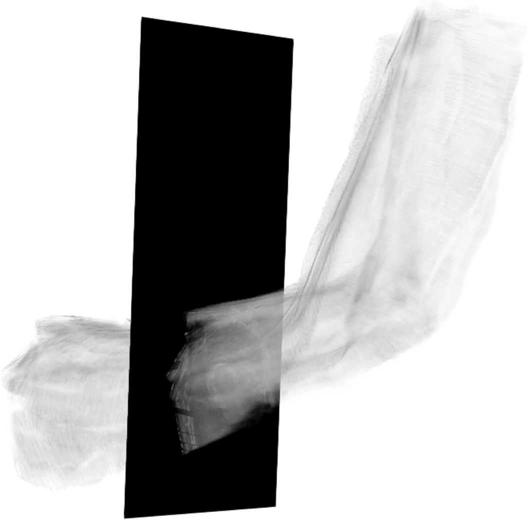


PROHIBITIVELY time intensive

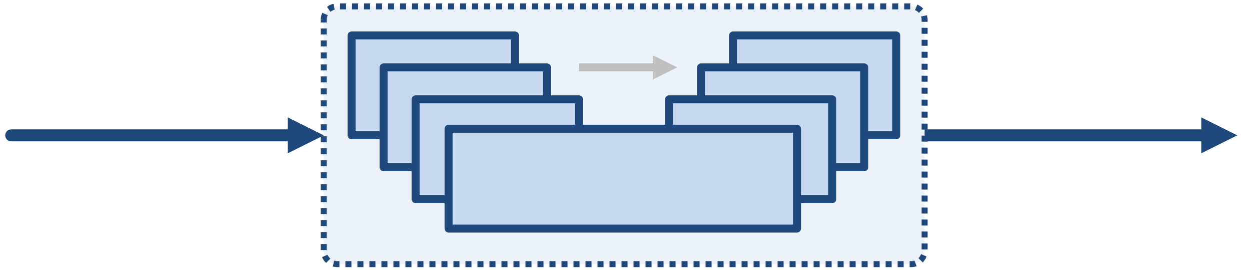
Using **motion capture** to track the **ultrasound probe position**, we can generate **full 3D scans** of the arm under **static conditions**.

Automated Tissue Segmentation: U-Net

intensity map (2D slice)

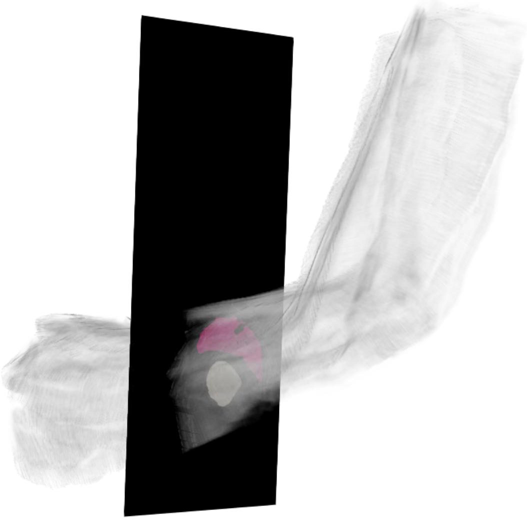


(2D) **U-Net**



[Ronneberger et al. 2015]

output segmentation (2D slice)



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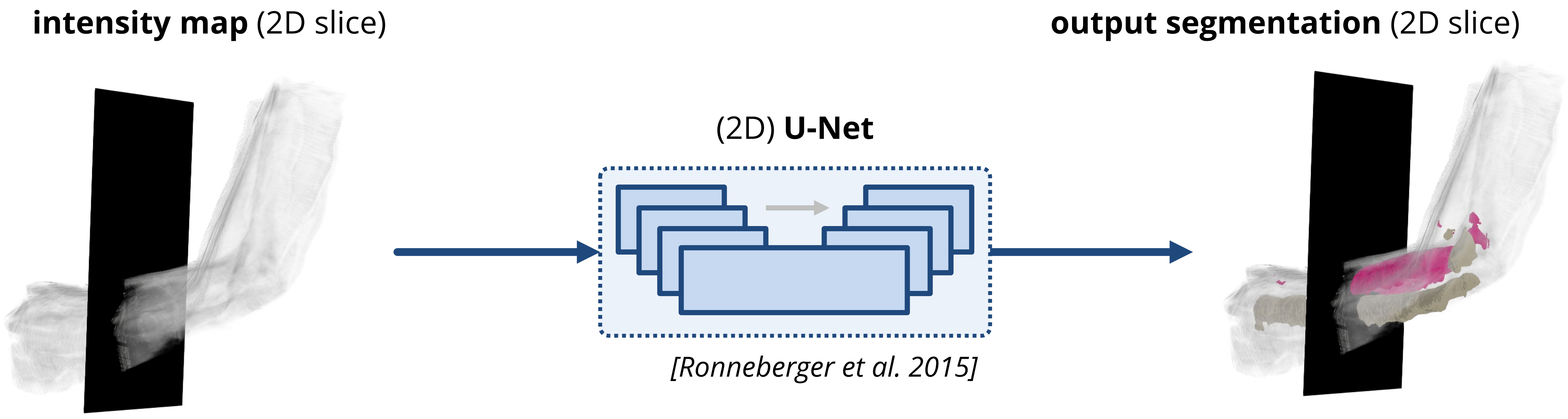

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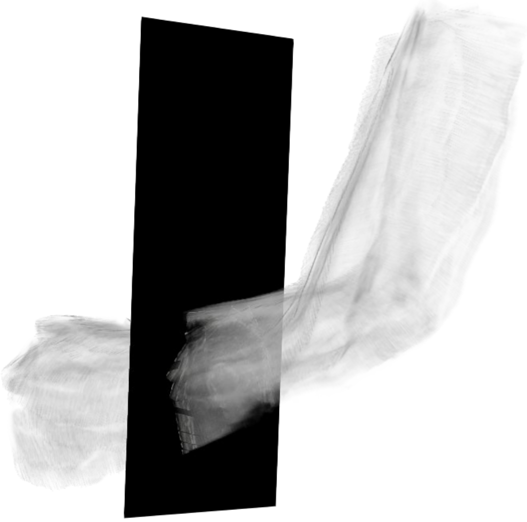

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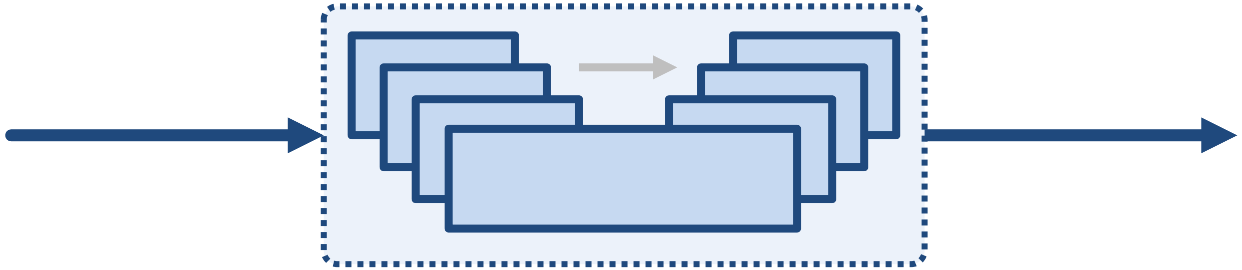

[Ronneberger et al. 2015]

output segmentation (2D slice)

CNN-based segmentation performs better than classical registration on the **center of the muscle**, where we focus our modeling analyses.

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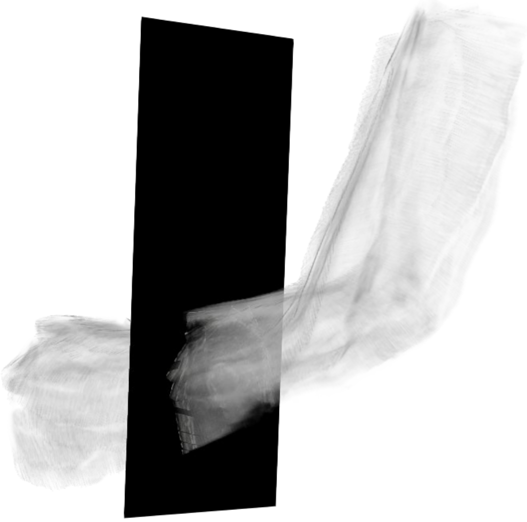

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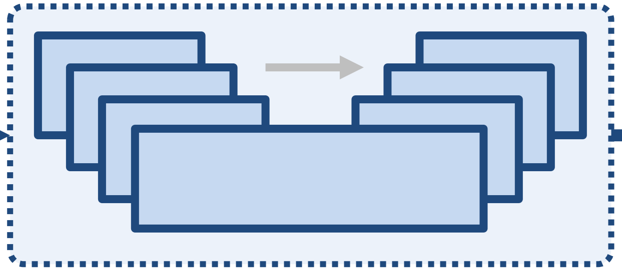

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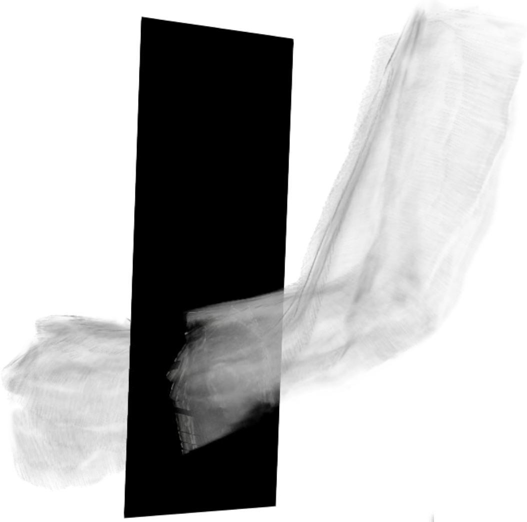

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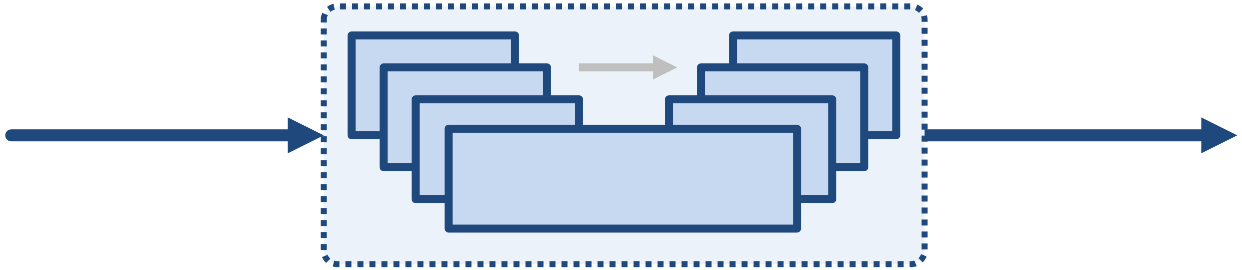

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OpenArm 2.0!

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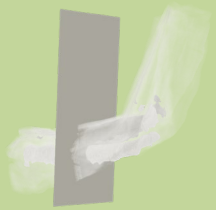

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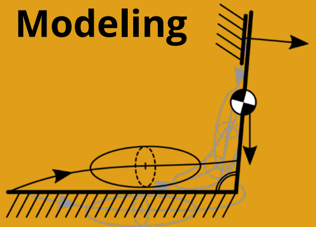
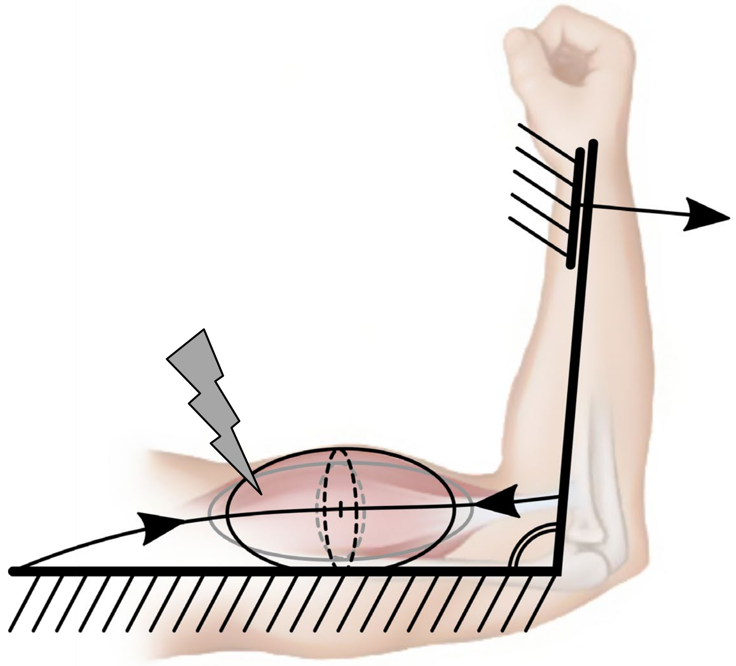


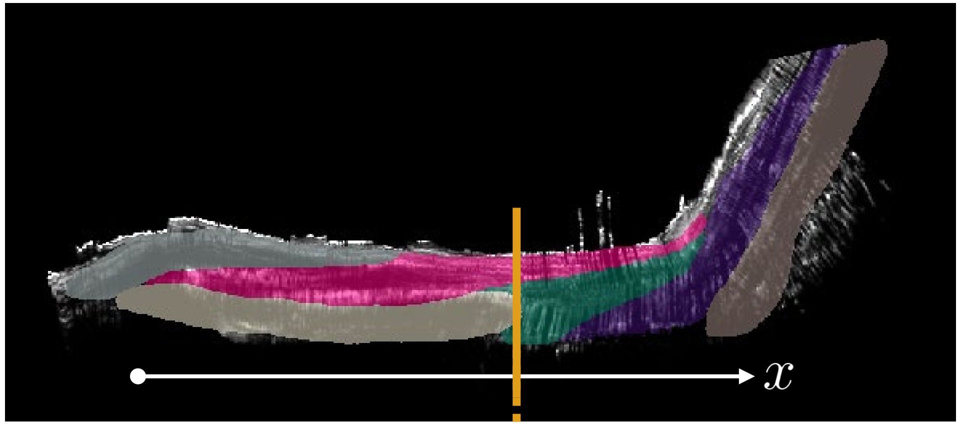
Force–Vibration Modeling

(Simplified) **Biological Mechanism**



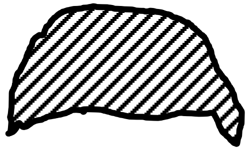
How close is what we observe to the simplified model?

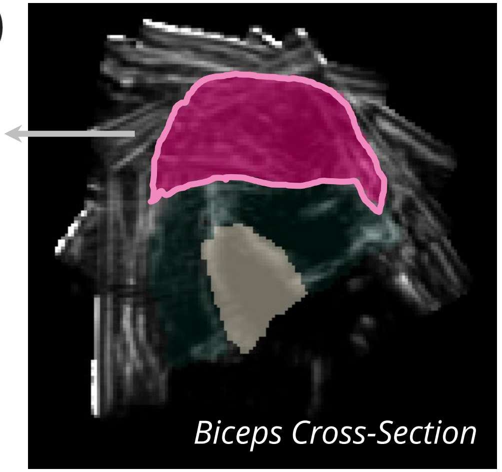
Spatial Analysis: OpenArm 1.0

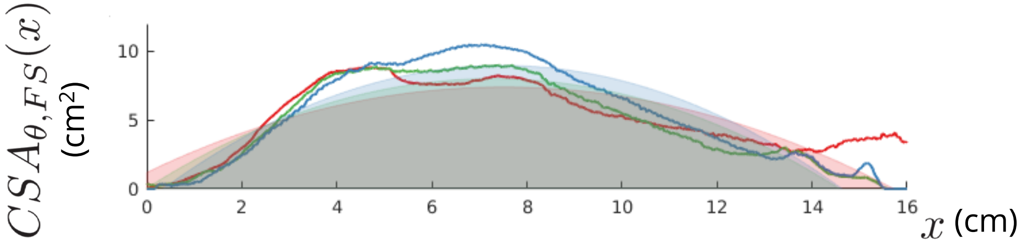


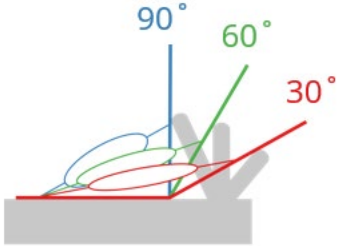
Cross-Sectional Area

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

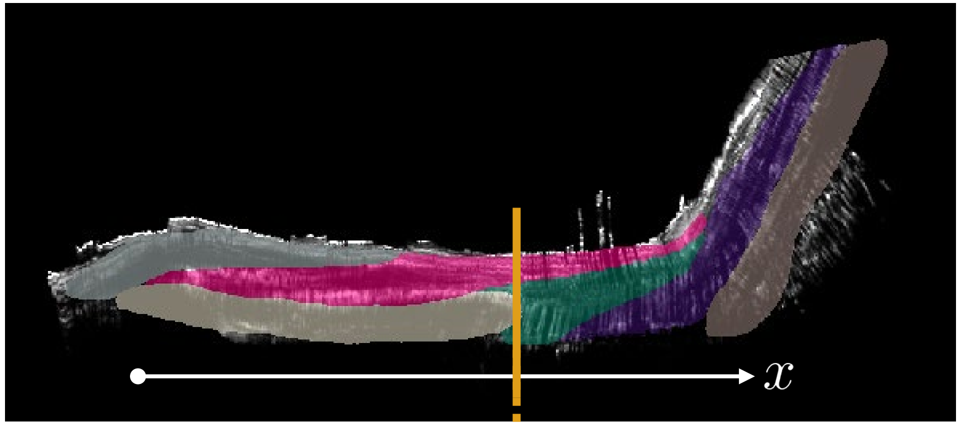








Spatial Analysis: OpenArm 1.0



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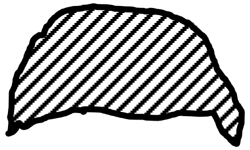

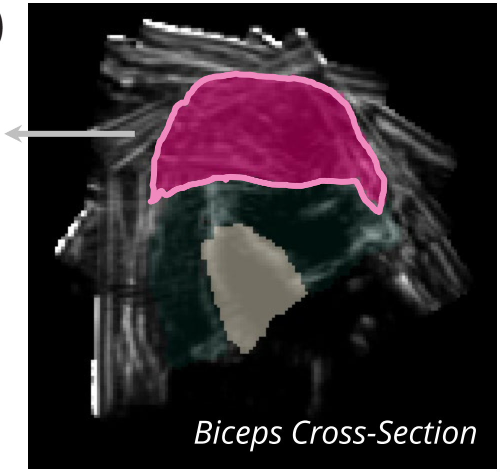

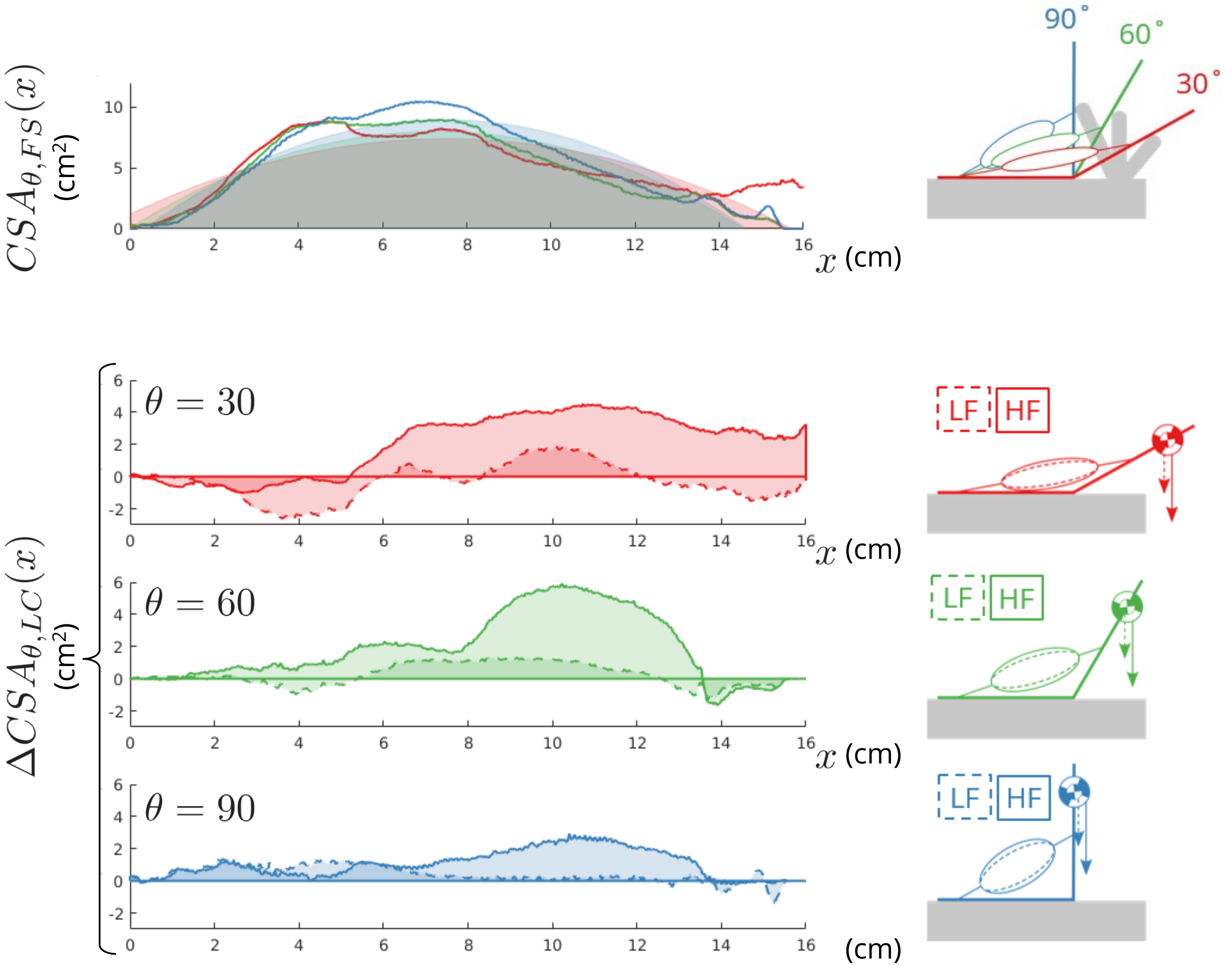

[**Hallock**, Kato, Bajcsy, ICRA 2018]

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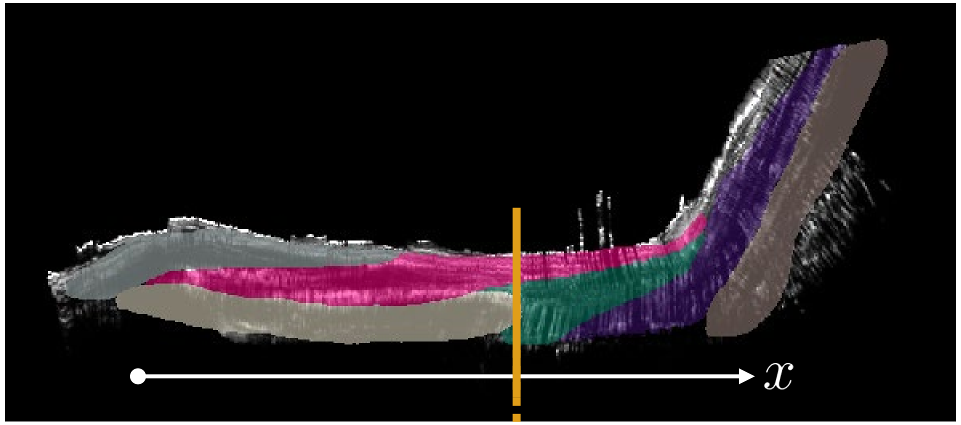

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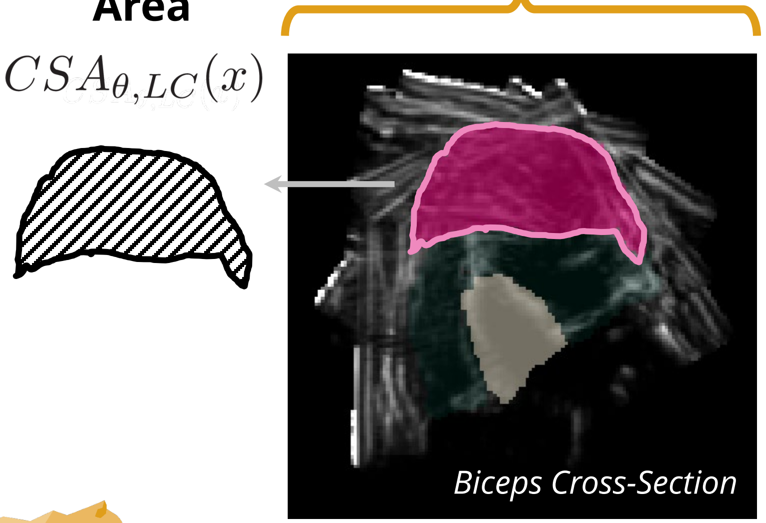
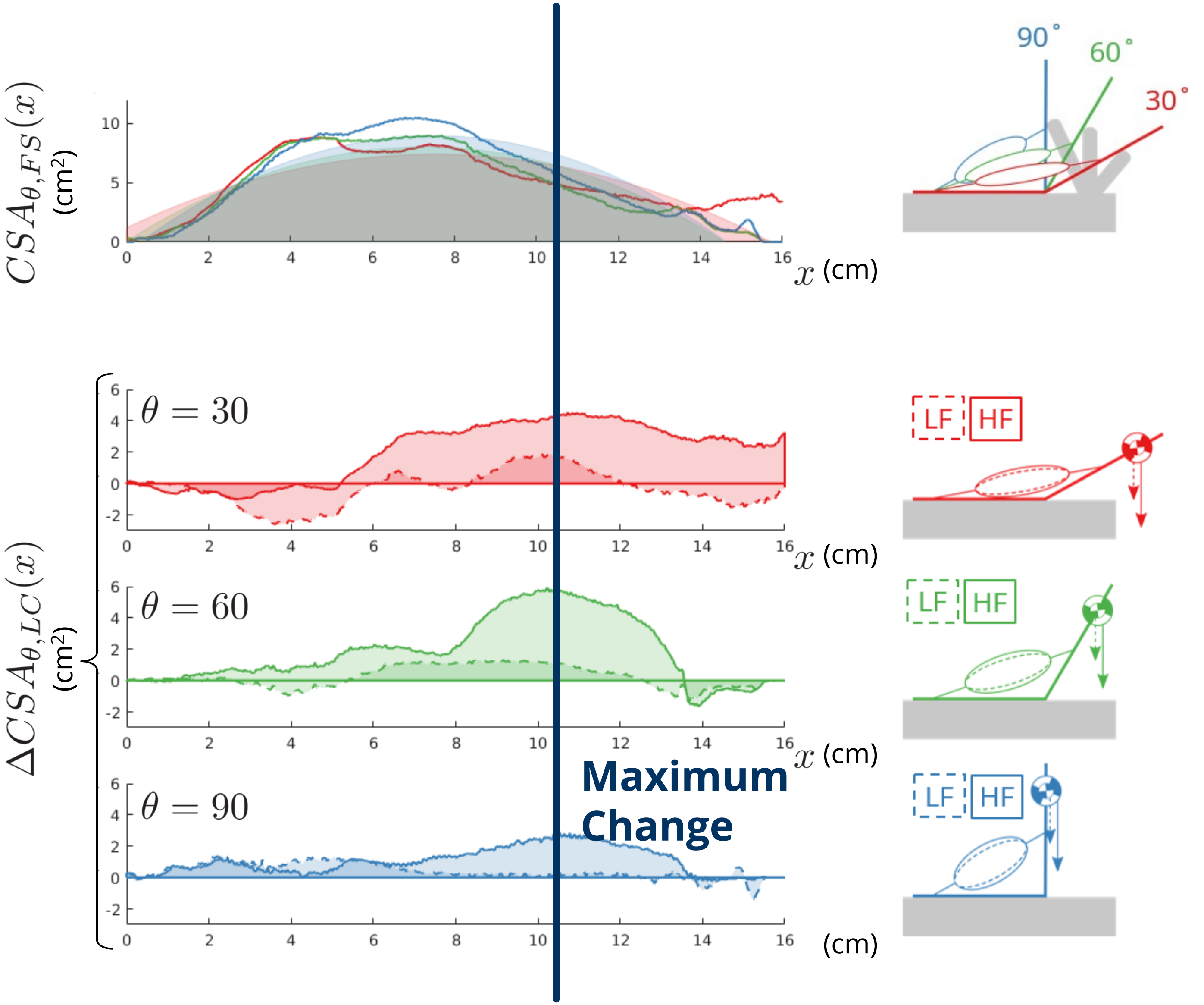
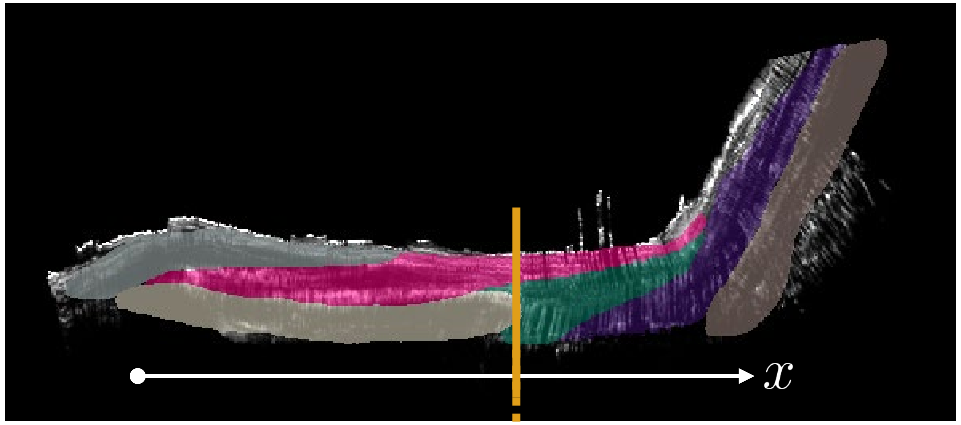


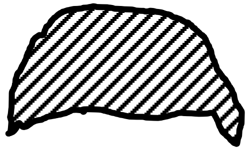


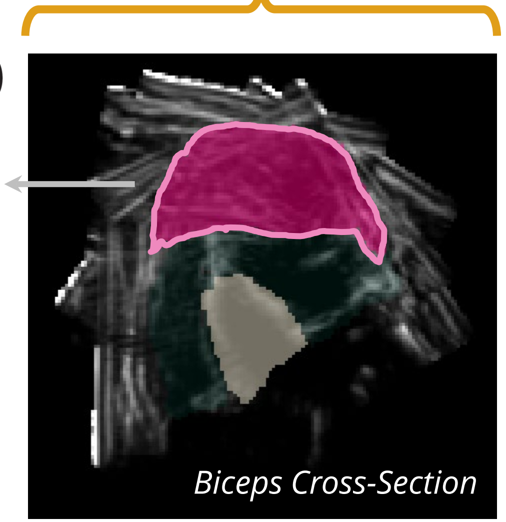
Spatial Analysis: OpenArm 1.0

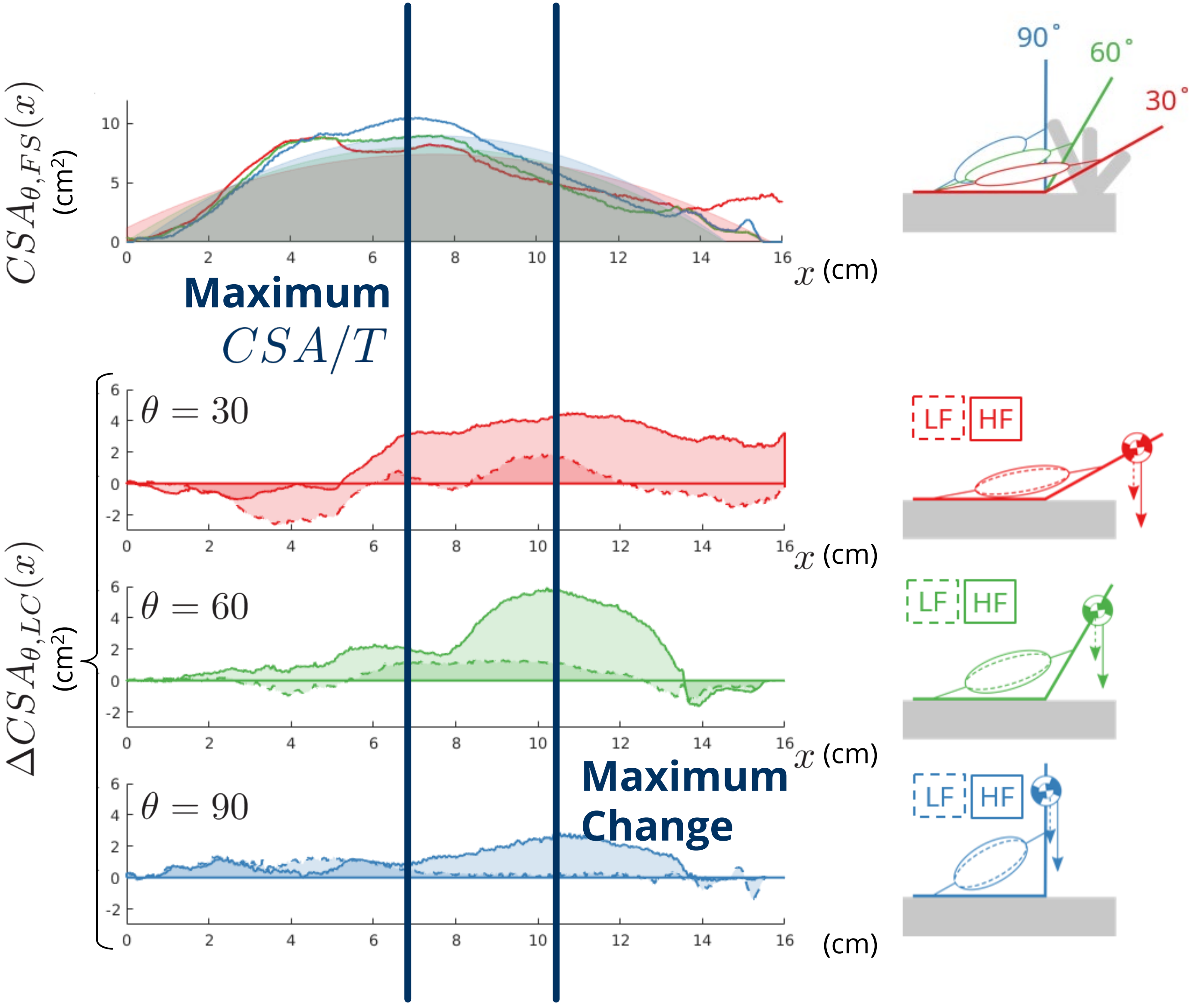


Cross-Sectional Area

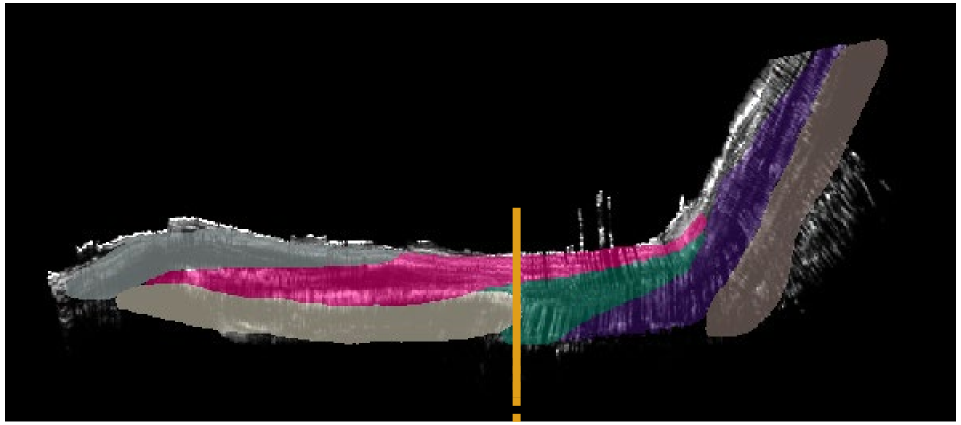
$CSA_{\theta,LC}(x)$





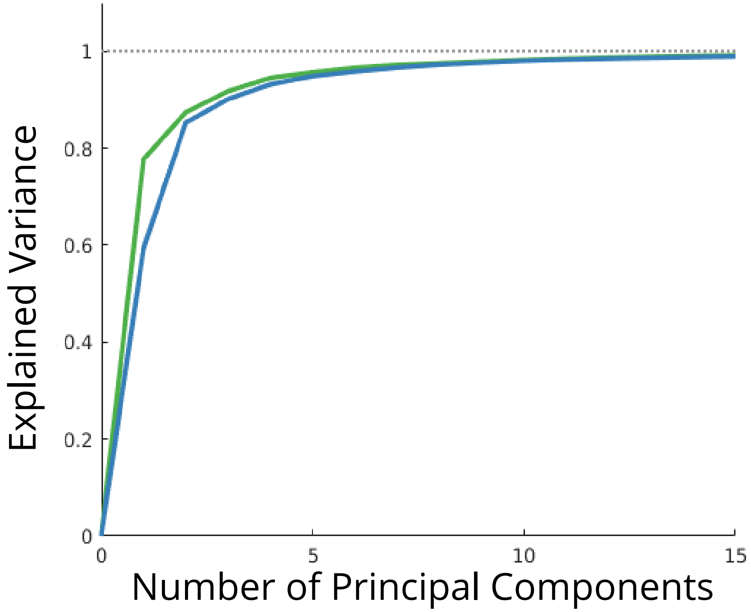


Spatial Analysis: Statistical Shape Modeling



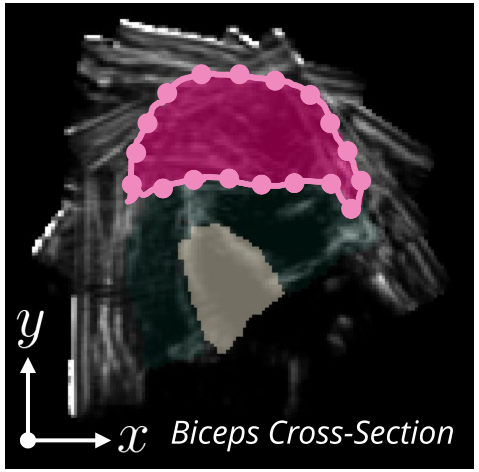
SHAPE DECOMPOSITION :

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



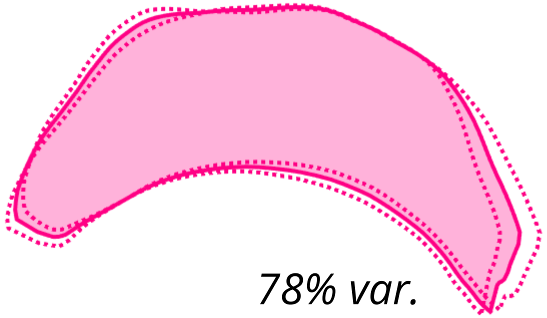
Shape

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



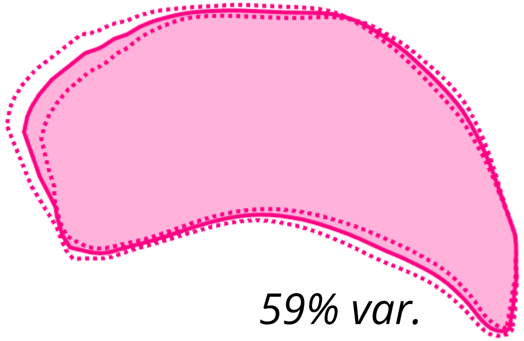
First Shape Modes

No Force, Vary Angle



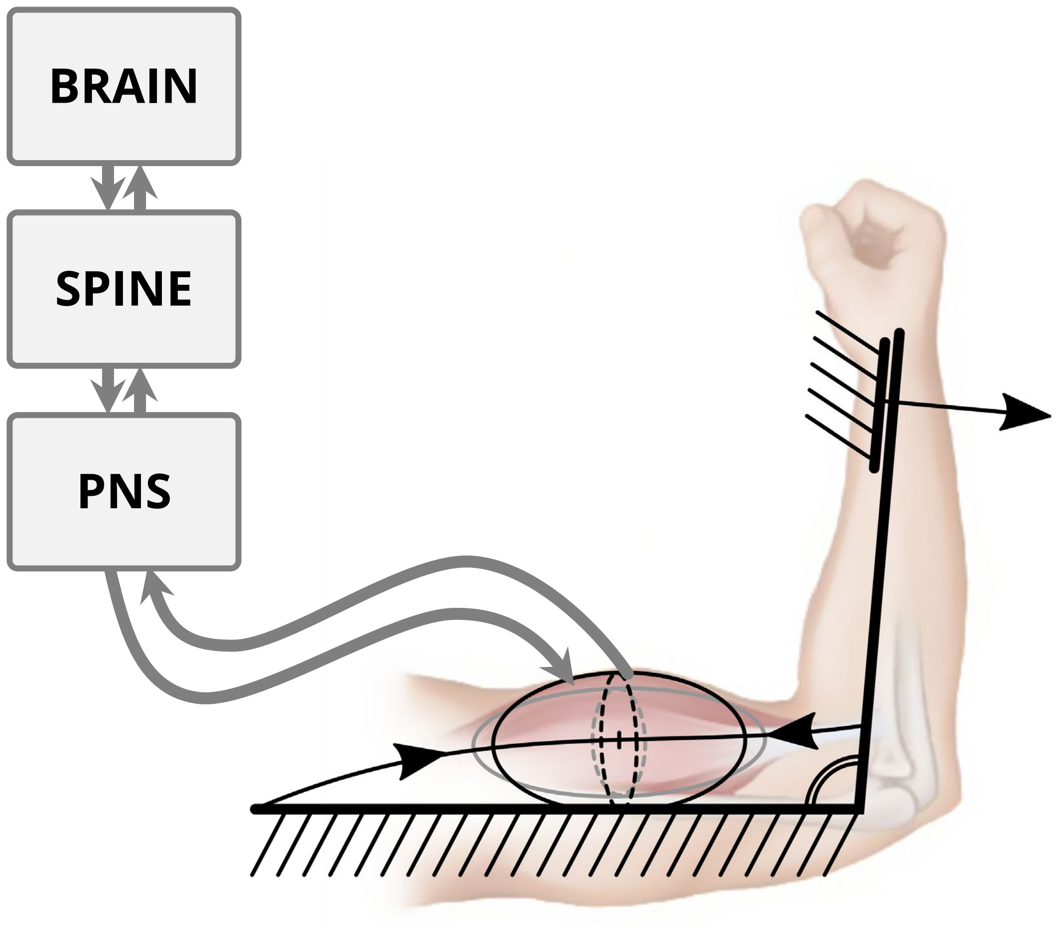
78% var.

30˚ Angle, Vary Force



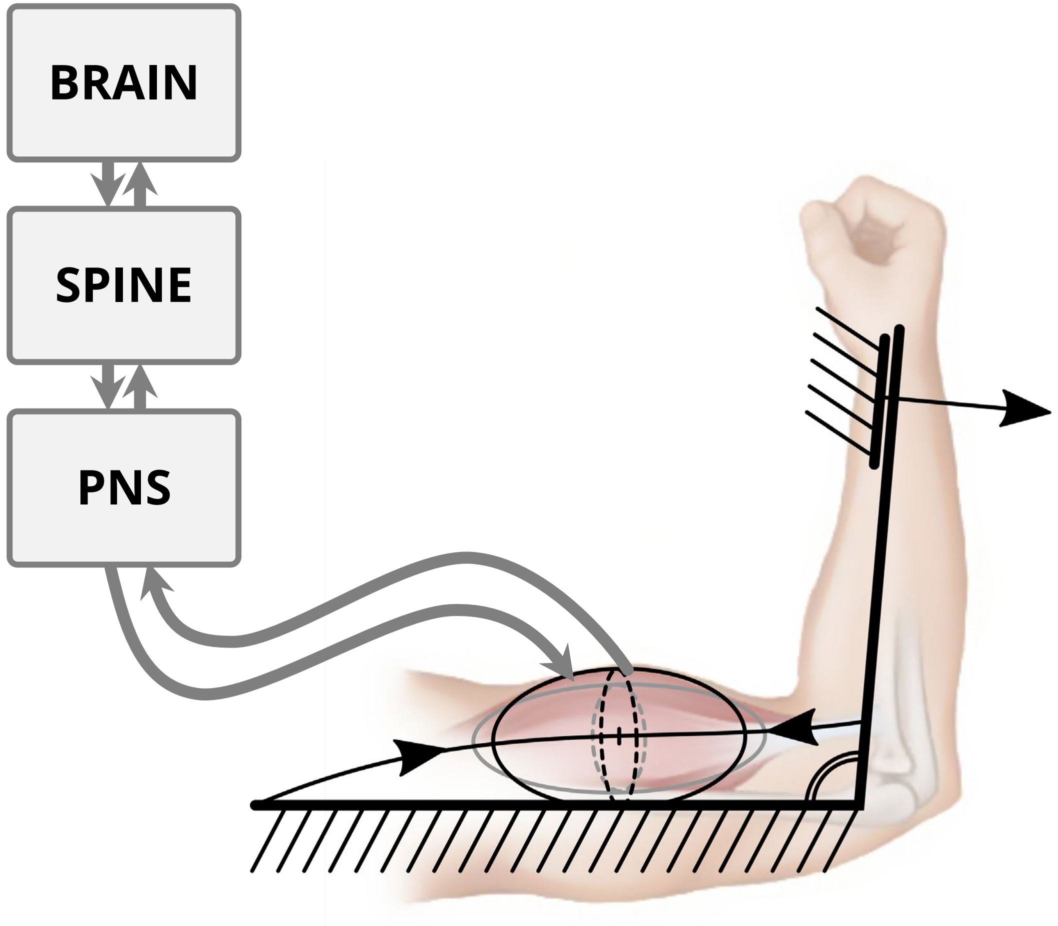
59% var.

Expanded Biological Mechanism



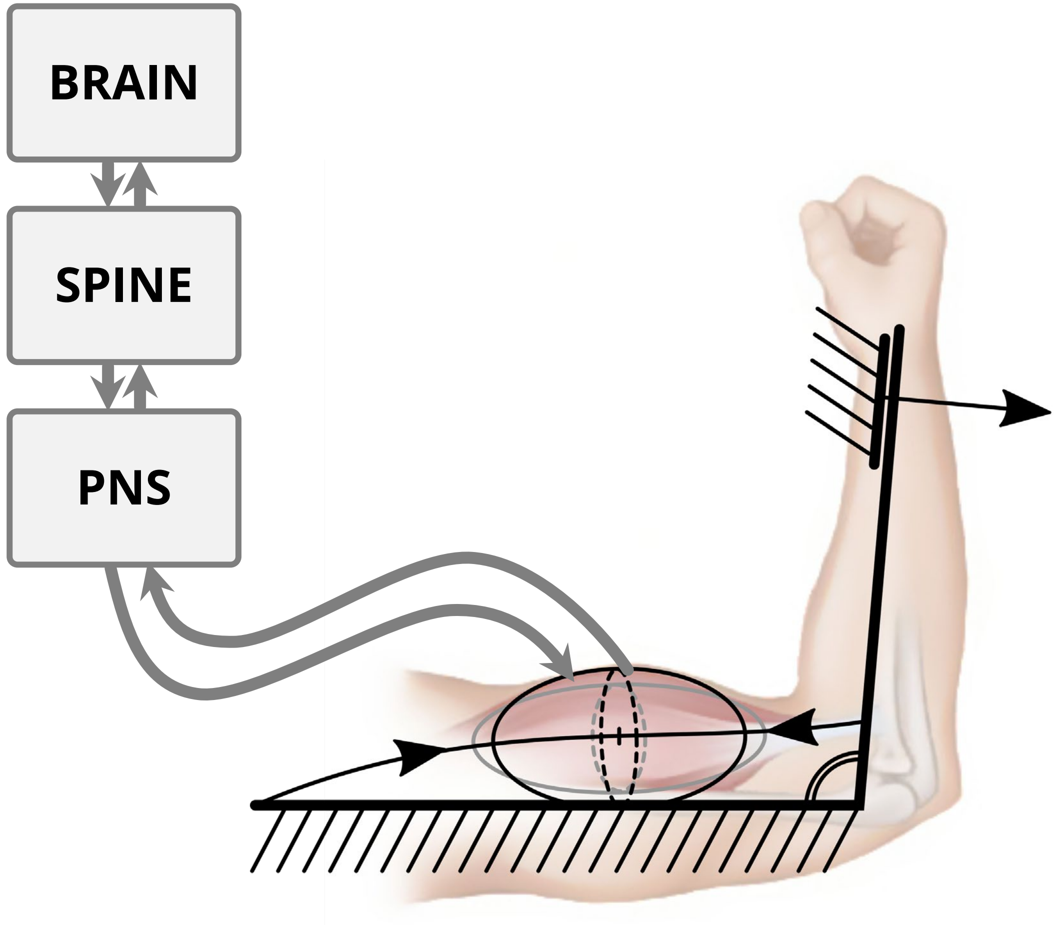
- **Multi-muscle dynamics**
  - synergies
  - contact forces

Expanded Biological Mechanism



- **Multi-muscle dynamics**
  - synergies
  - contact forces
- **Geometric complexity**
  - nonlinear, config-specific “line of action”
  - pennation angle
  - tendon/aponeurosis thickness

Expanded Biological Mechanism



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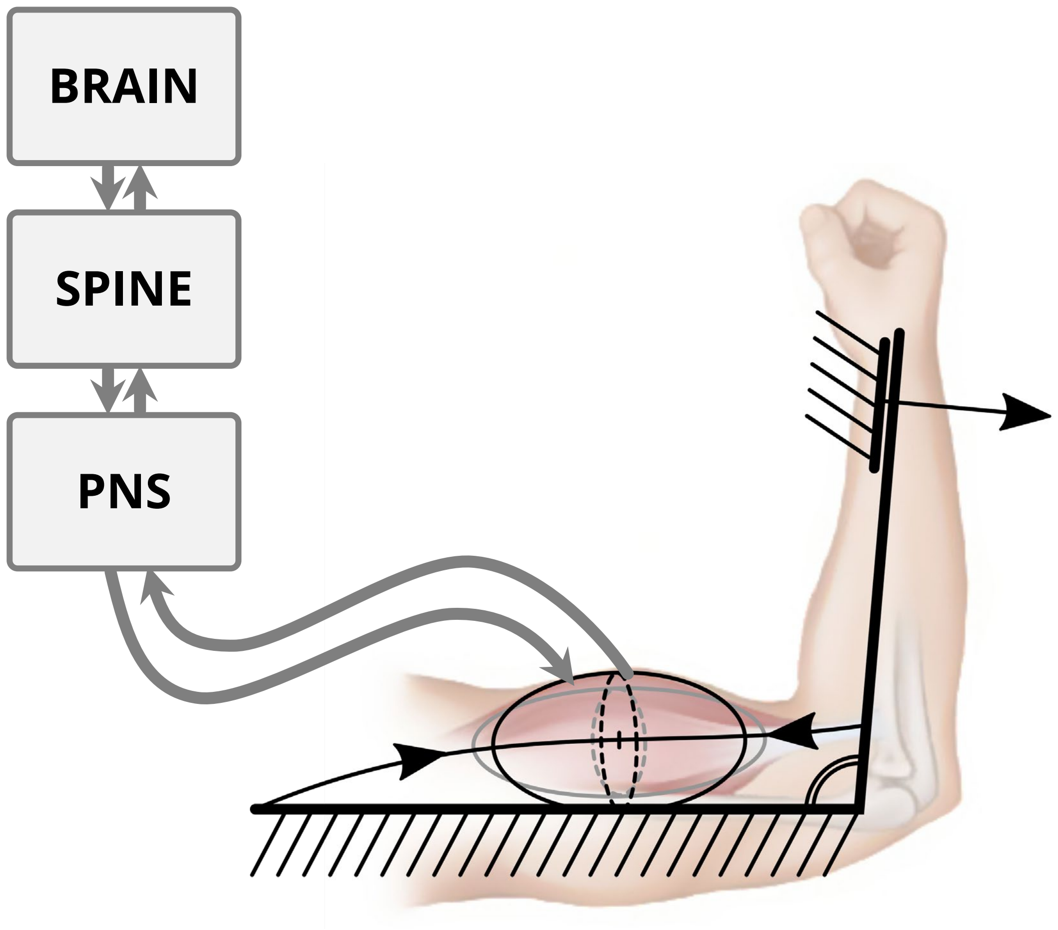
- **Mechanical complexity**
  - fiber type (I or II)
  - hysteresis
  - concentric vs. eccentric contraction
  - fatigue

Expanded Biological Mechanism



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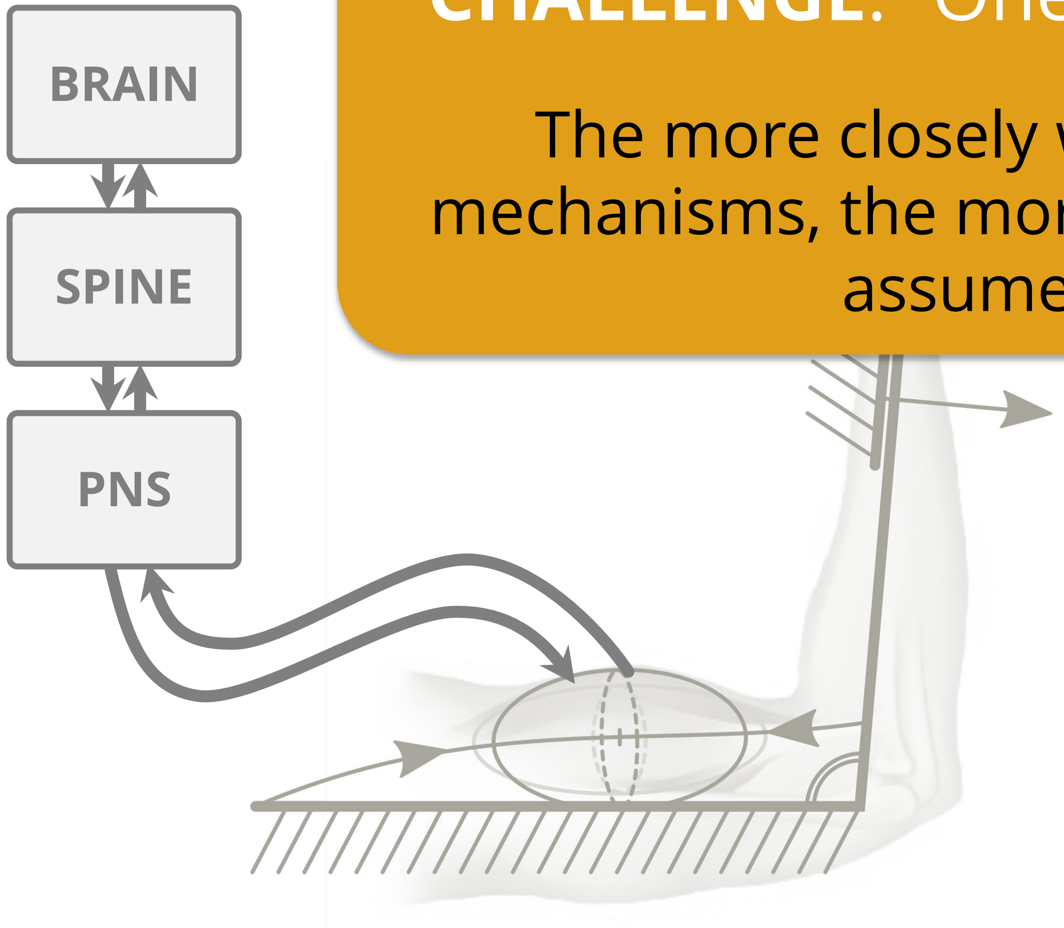
- **Neurological complexity**
  - motor unit distribution
  - tetanic vs. subtetanic contraction
  - feedback vs. feedforward control

Expanded Biological Mechanism



CHALLENGE: "One step forward, one step back"

The more closely we attempt to model biological mechanisms, the more values and parameters we must assume based on literature.

f action"

- tendon/aponeurosis thickness

- **Mechanical complexity**
  - fiber type (I or II)
  - hysteresis
  - concentric vs. eccentric contraction
  - fatigue
- **Neurological complexity**
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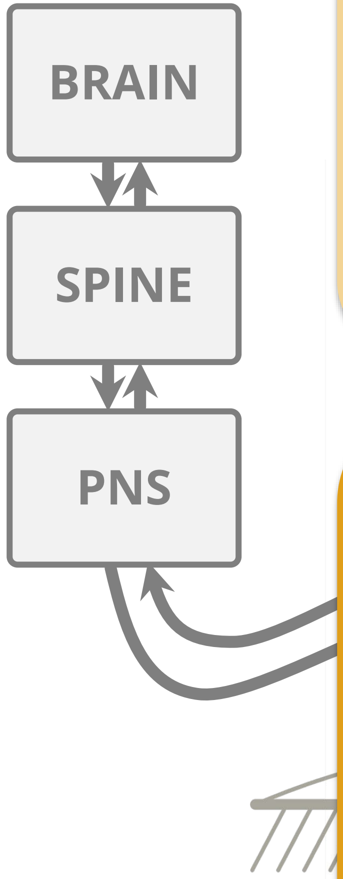
Expanded Biological Mechanism



CHALLENGE: “One step forward, one step back”

The more closely we attempt to model biological mechanisms, the more values and parameters we must assume based on literature.

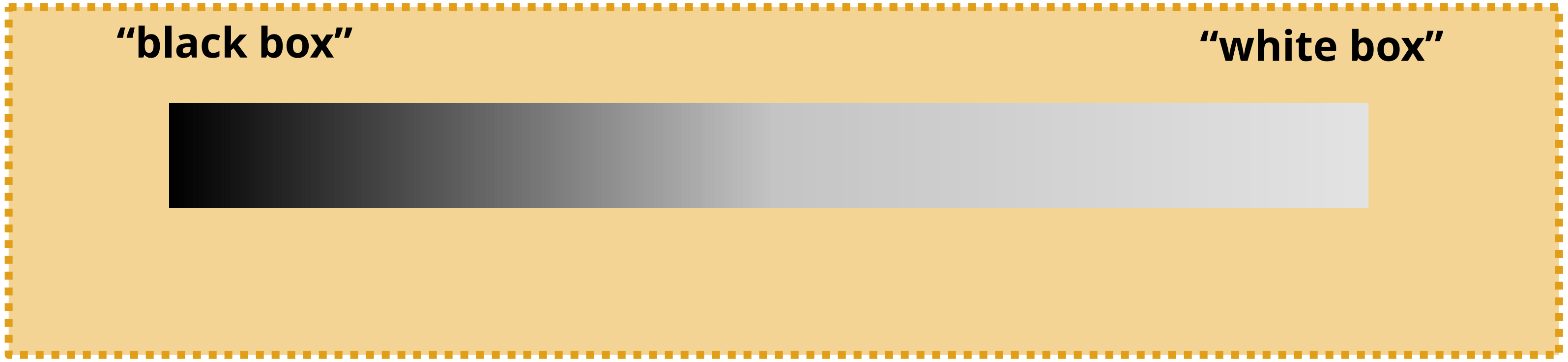
GOAL

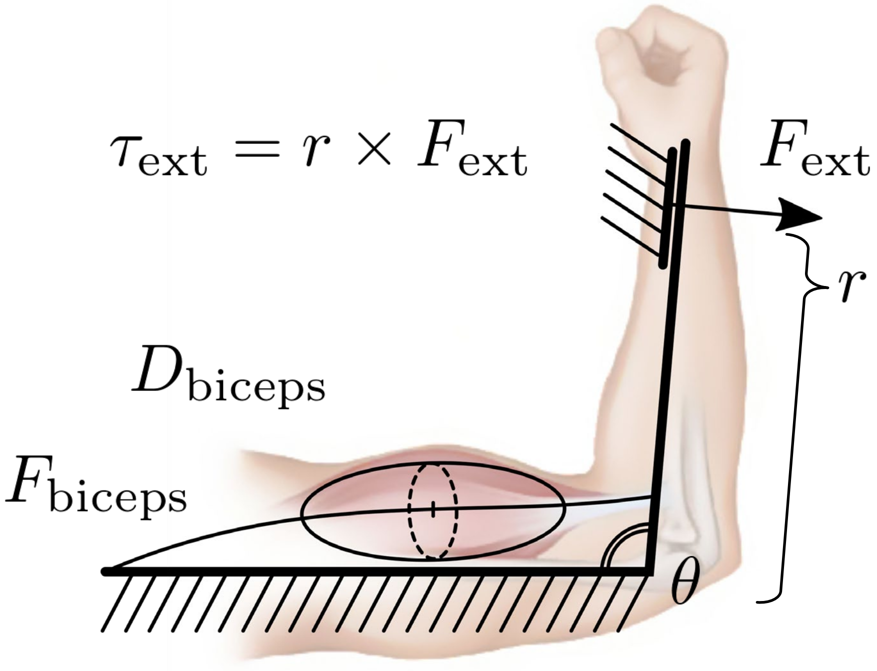
build up a **principled suite of models** that make varying trade-offs between **collected data** and **literature values** in a **quantifiable manner**

(sidenote: this work can also help validate those literature values!)

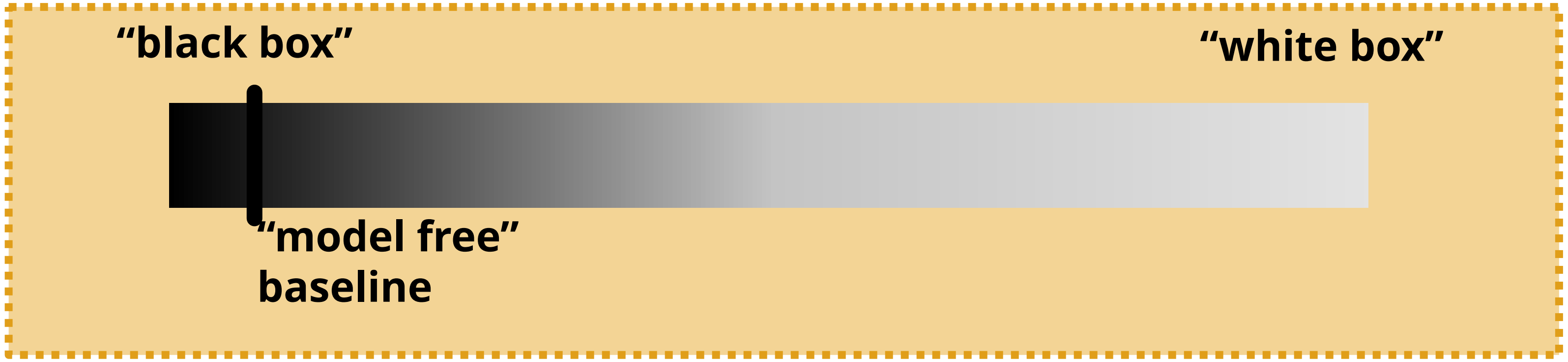
– feedback vs. feedforward control

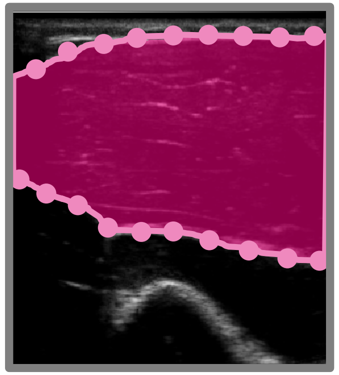
(Proposed) **Suite of Models**

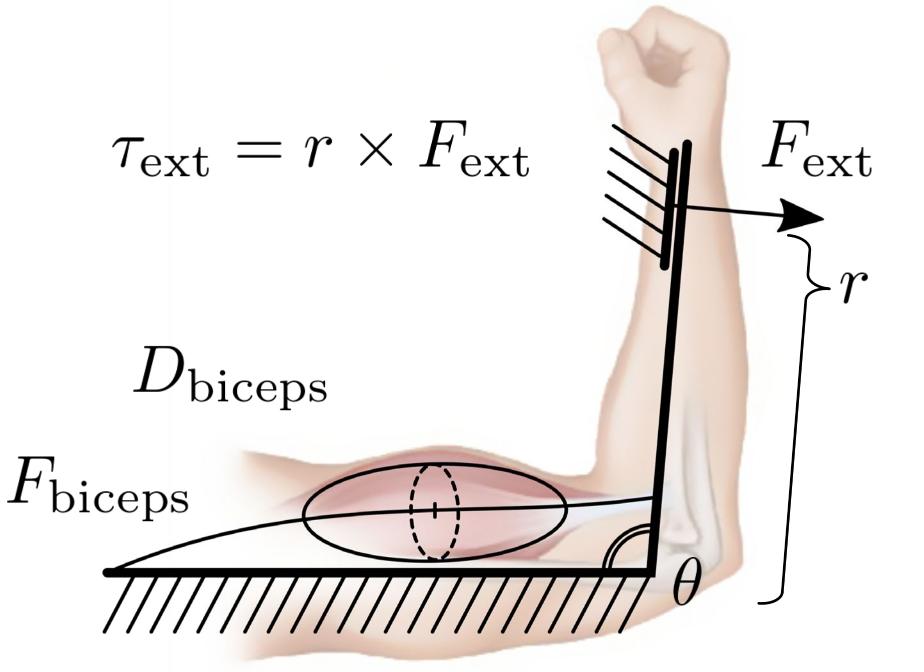


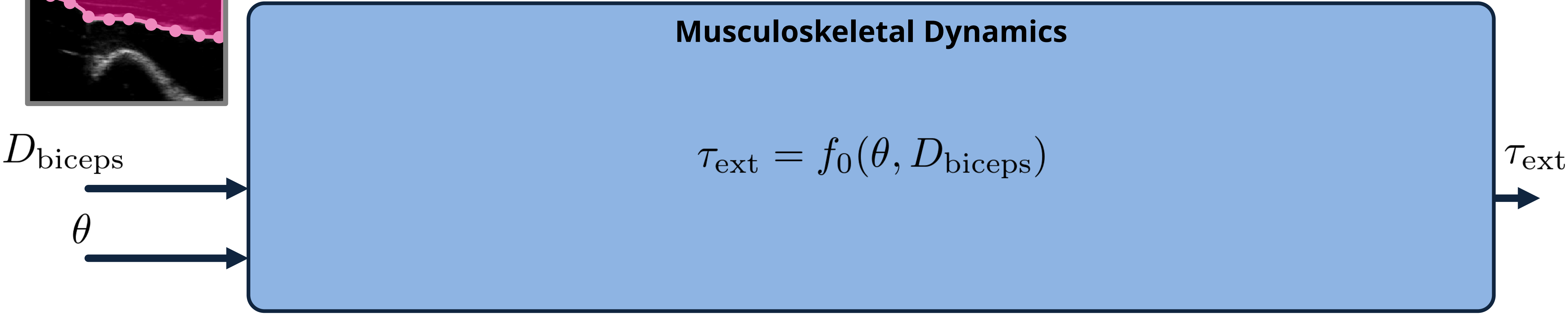


(Proposed) **Suite of Models**

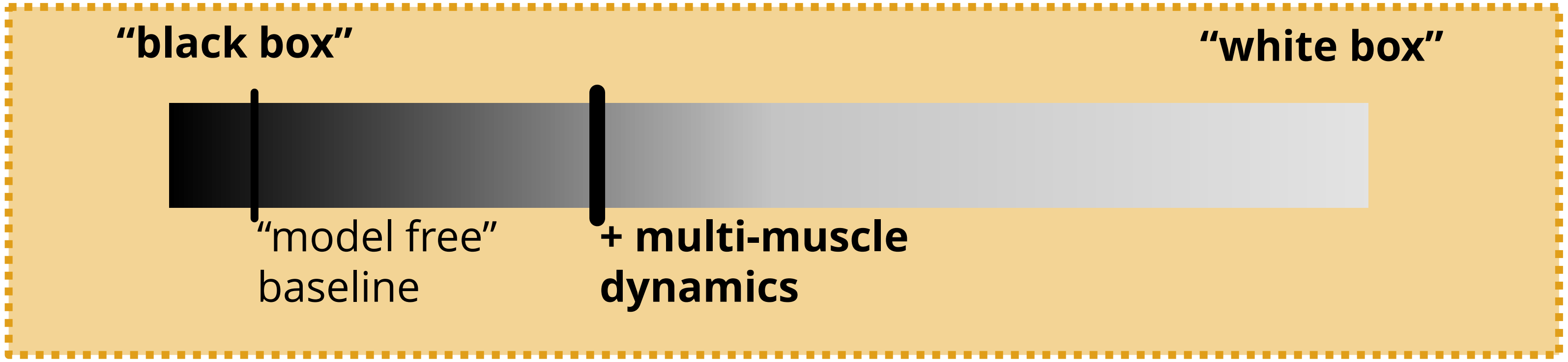


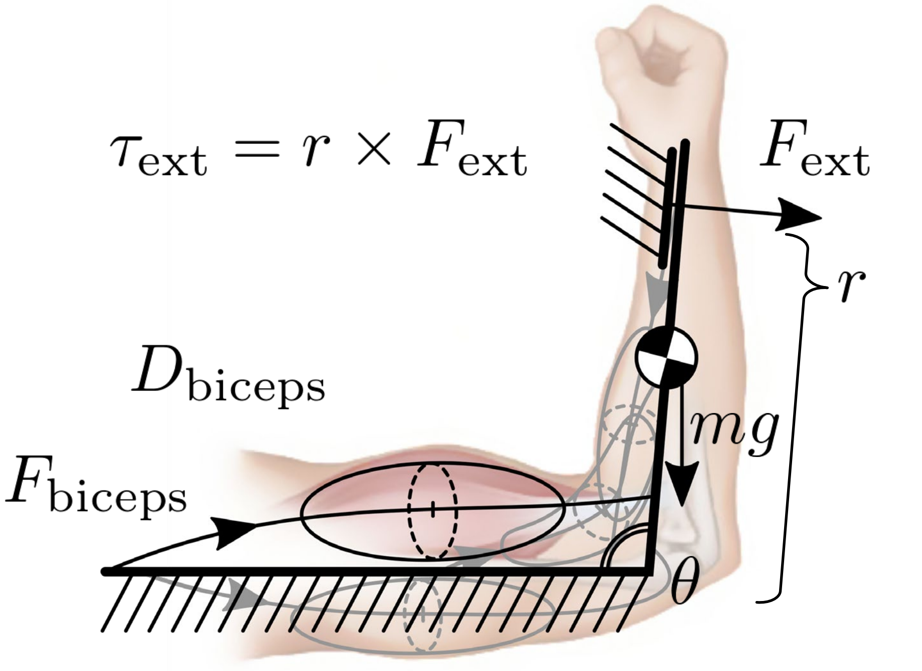


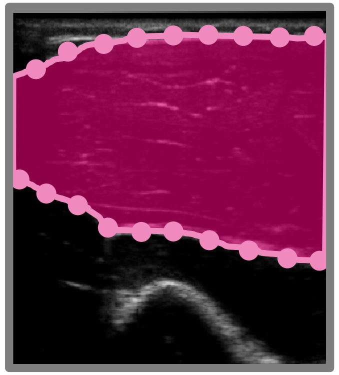


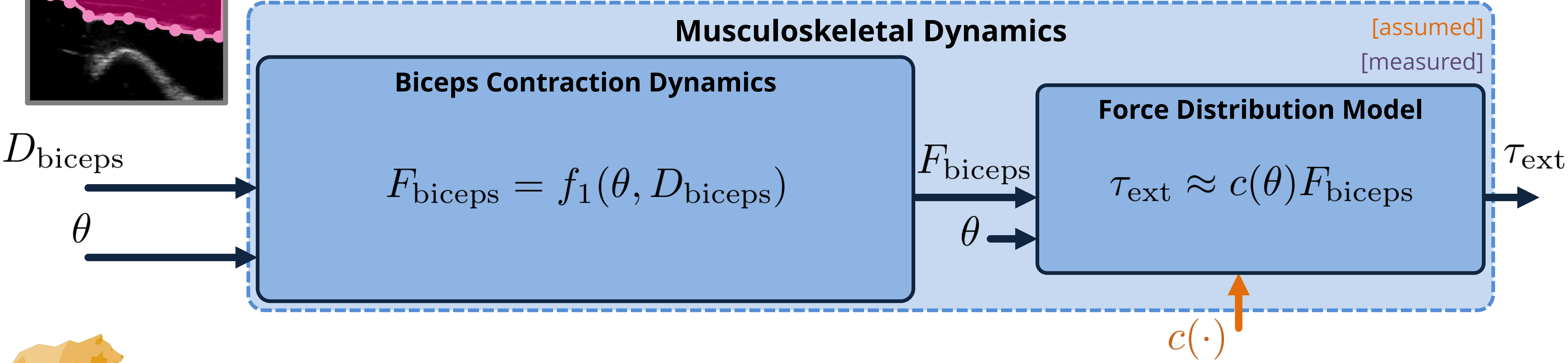


(Proposed) **Suite of Models**







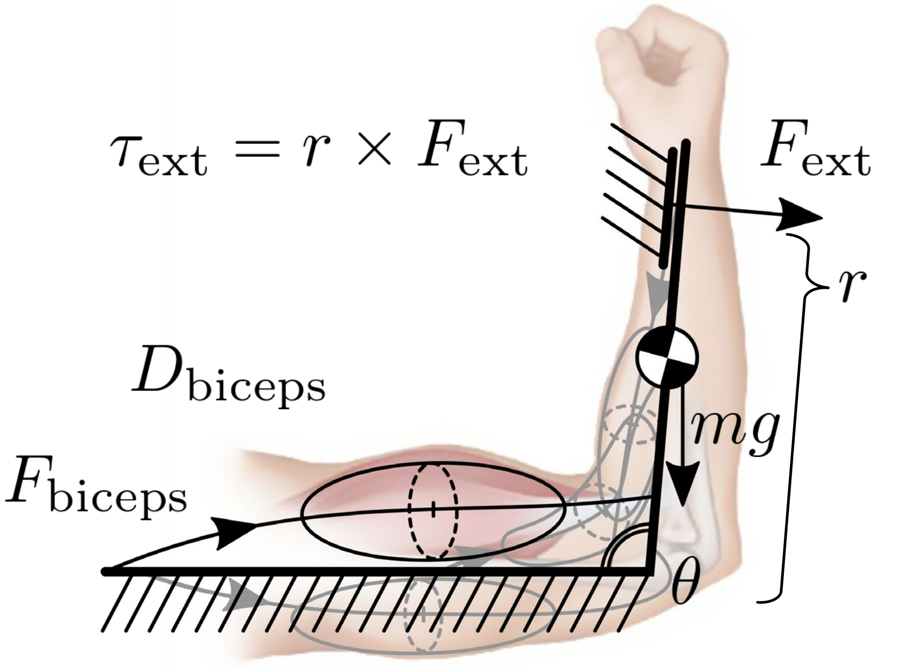


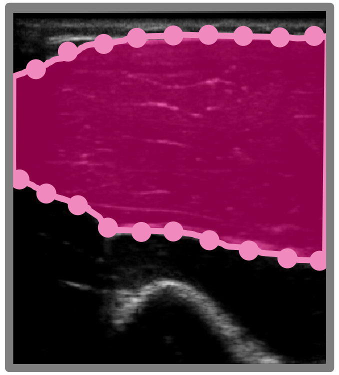
(Proposed) **Suite of Models**

"black box" **"white box"**

"model free" baseline

+ multi-muscle dynamics





Musculoskeletal Dynamics

[assumed]
[measured]

Inputs: D_{biceps}, θ

Biceps Contraction Dynamics

$$F_{\text{biceps}} = f_1(\theta, D_{\text{biceps}})$$

F_{biceps}, θ

Force Distribution Model

Muscle Geometry

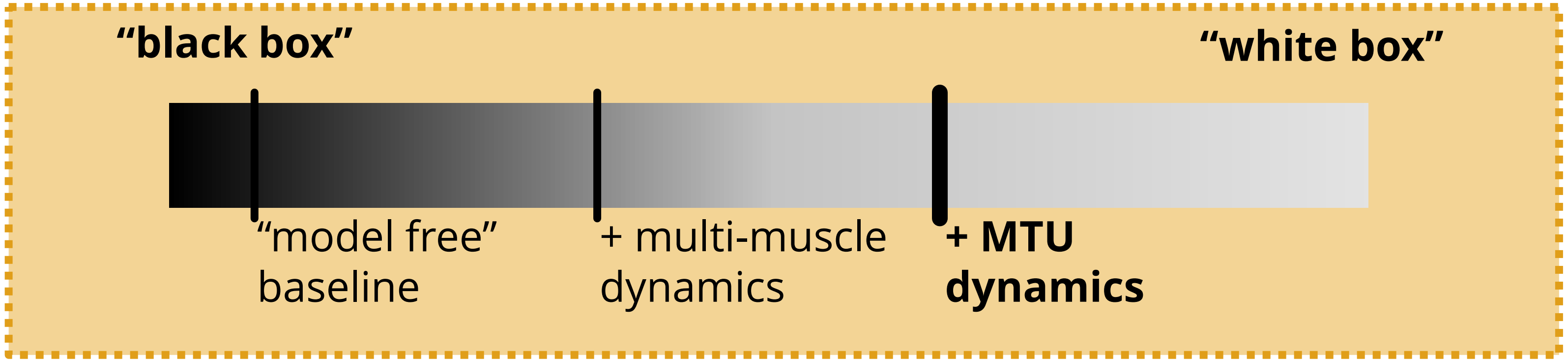
$$\tau_{\text{biceps}} = r_{\text{biceps}}(\theta) \times F_{\text{biceps}}$$

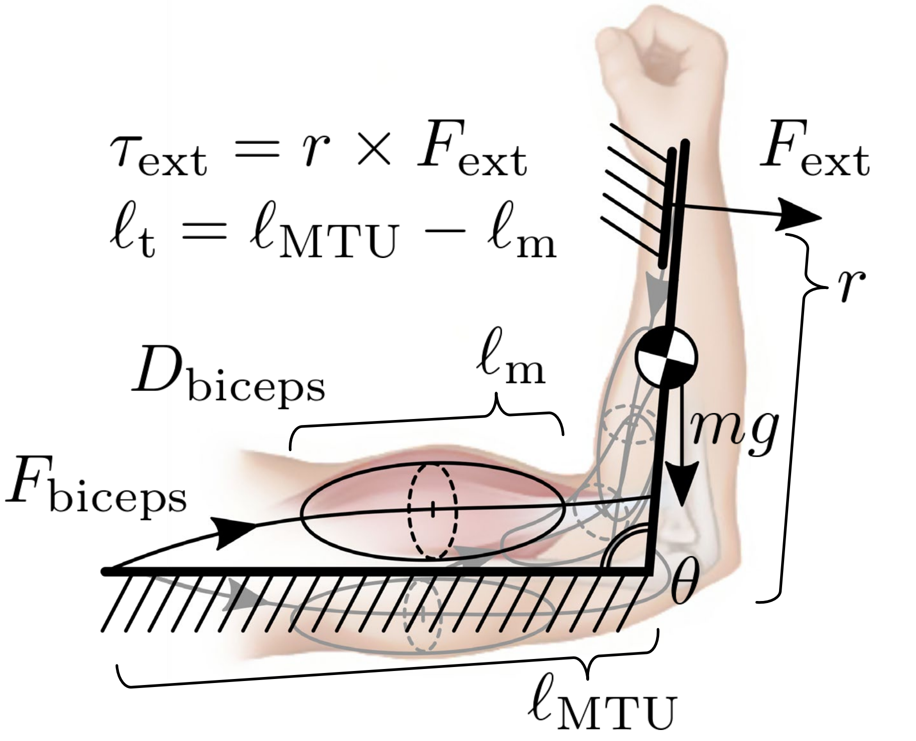
τ_{biceps} $+$ τ_{ext}

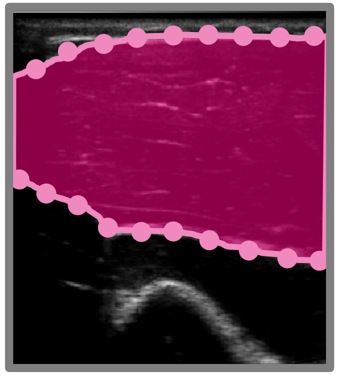
$r_{\text{biceps}}(\cdot)$

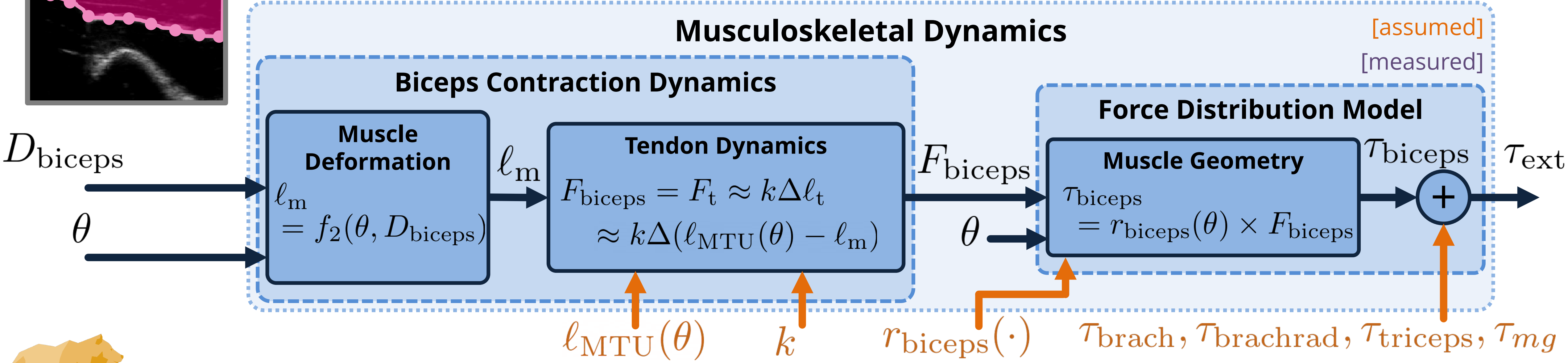
$\tau_{\text{brach}}, \tau_{\text{brachrad}}, \tau_{\text{triceps}}, \tau_{mg}$

(Proposed) **Suite of Models**

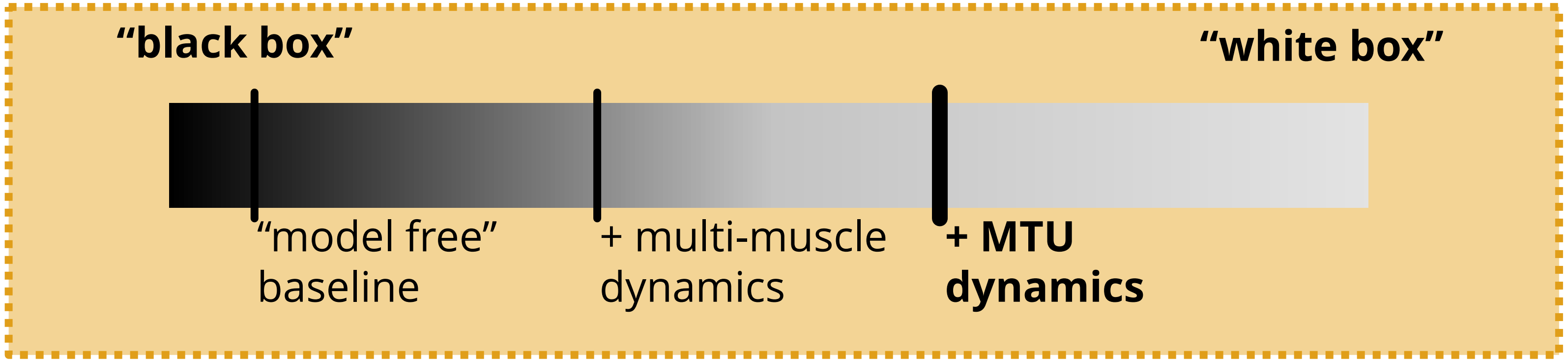


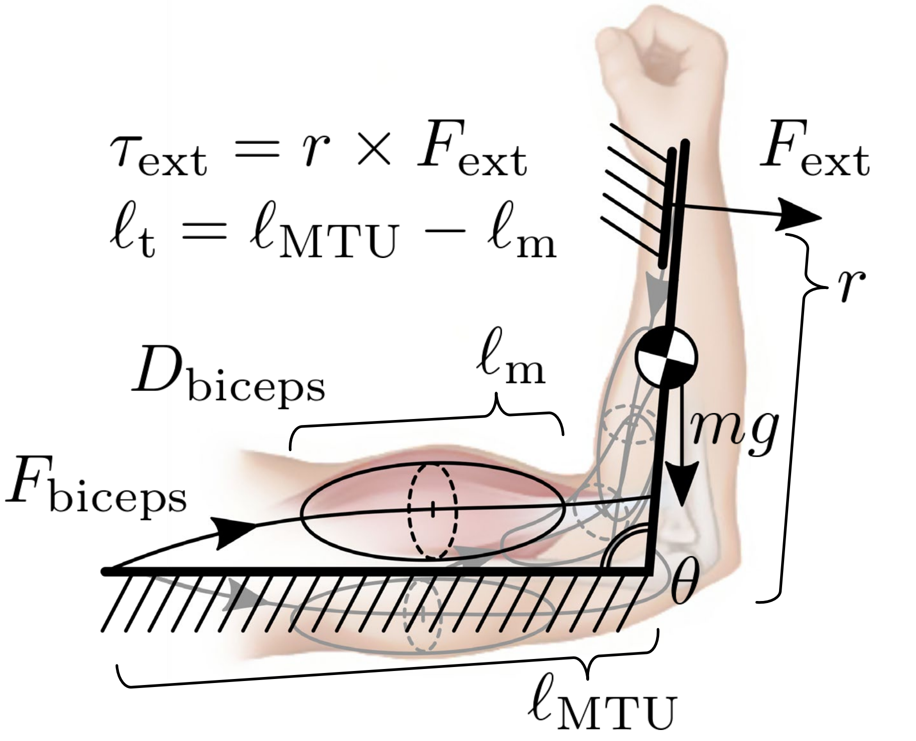


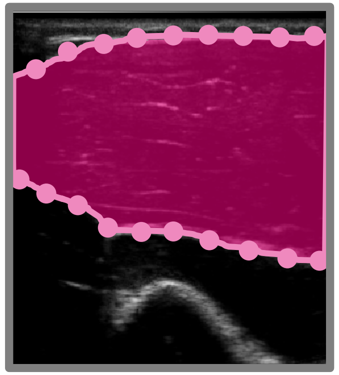


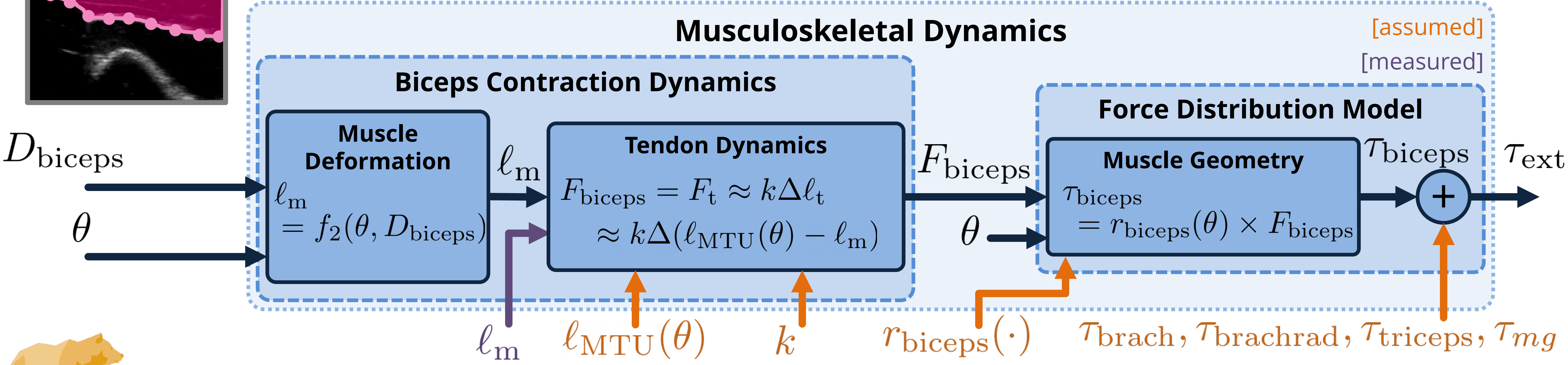


(Proposed) **Suite of Models**

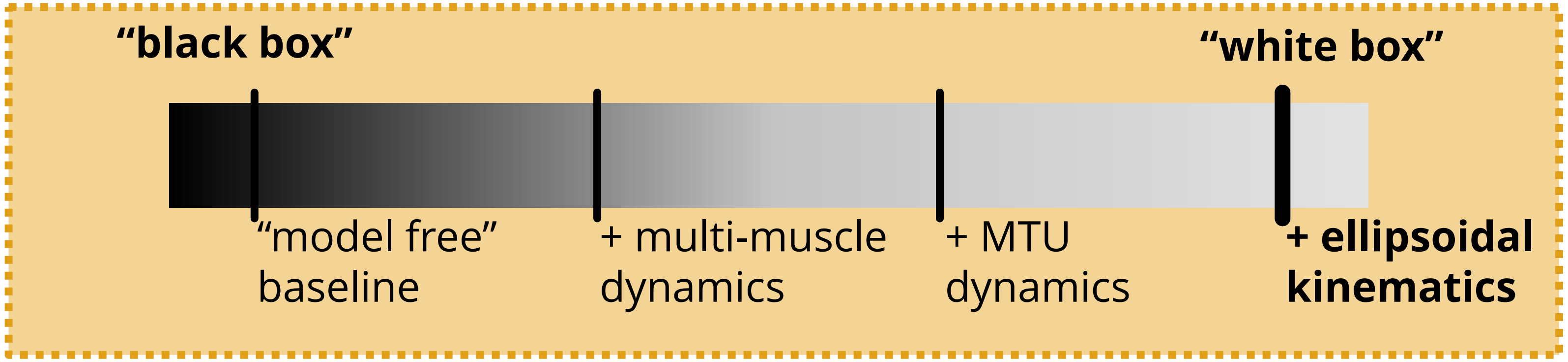


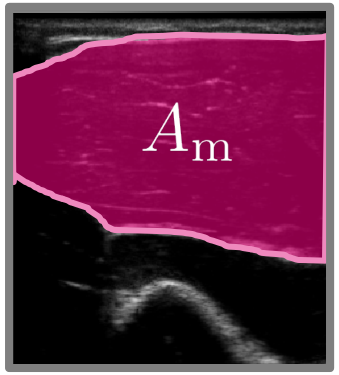


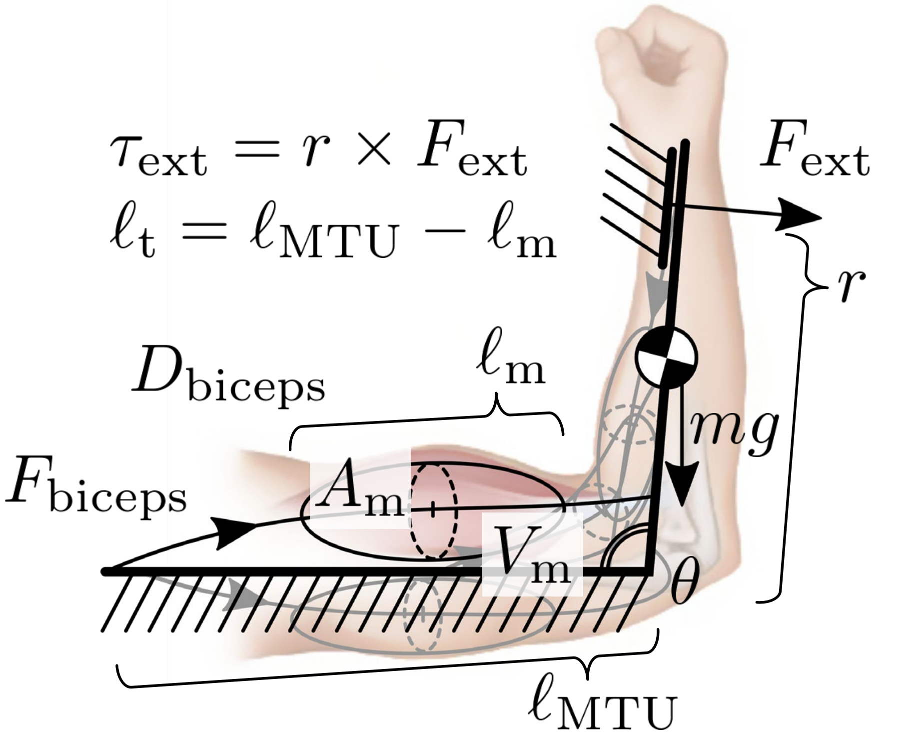


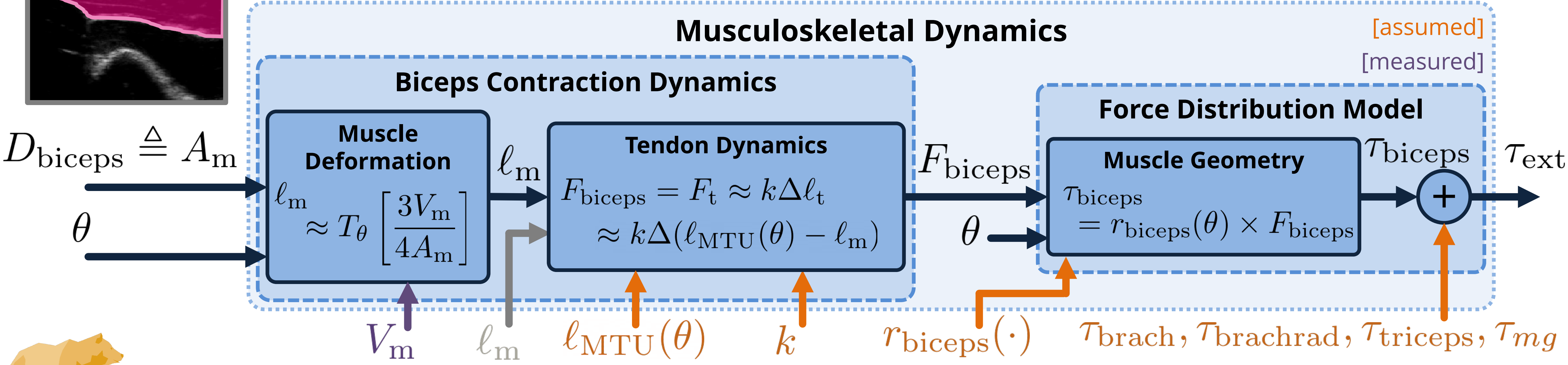


(Proposed) **Suite of Models**









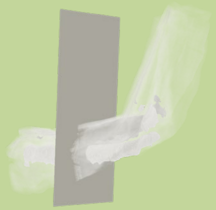
GRADUATE WORK: Advances in MSK Sensing & Modeling

neurological activation → **NEUROMUSCULAR DYNAMICS** *(cross-bridge cycle, etc.)* → musculoskeletal dynamics → **DEVICE CONTROL** → robot dynamics

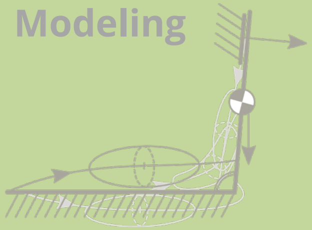
MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

Data Set Generation
(3D Deformation)



Systematic Force–Deformation Modeling



Force–Vibration Modeling

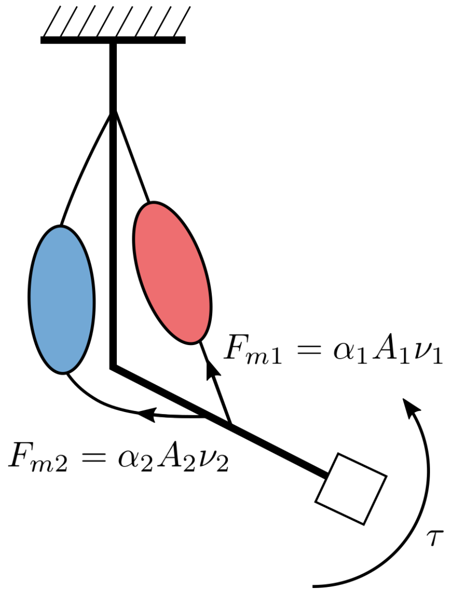
Preliminary AMG-Force Model

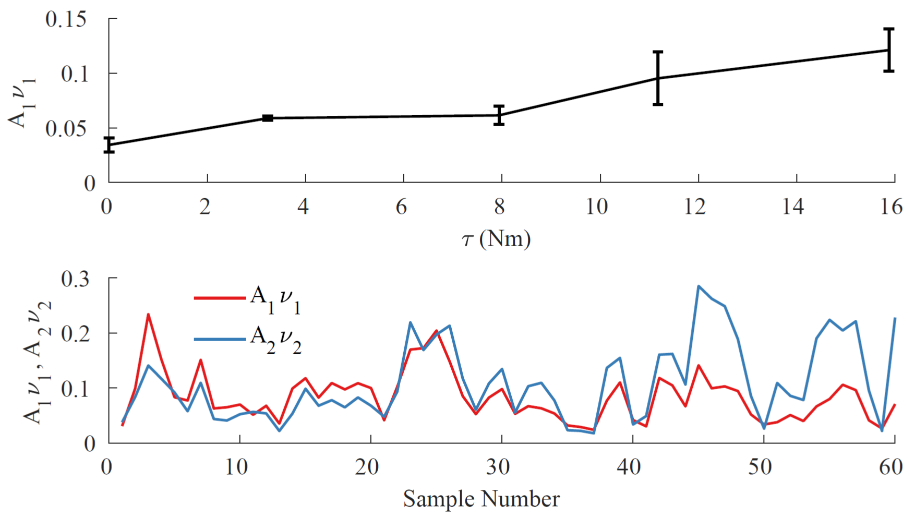
AMG amplitude $A \propto$ [# activated muscle fibers]

AMG frequency $\nu \propto$ [mean fiber force]

[Harrison 2018]

muscle force $F_m \propto A\nu$





- Preliminary data show **significant correlation of** $A\nu$ **quantity** with muscle output force
- Currently working to validate model and investigate its **spatial/temporal resolution**

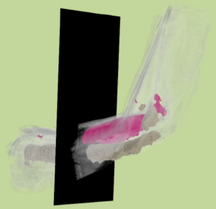
GRADUATE WORK: Advances in MSK Sensing & Modeling

neurological activation → **NEUROMUSCULAR DYNAMICS** *(cross-bridge cycle, etc.)* → musculoskeletal dynamics → **DEVICE CONTROL** → robot dynamics

MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

Data Set Generation
(3D Deformation)



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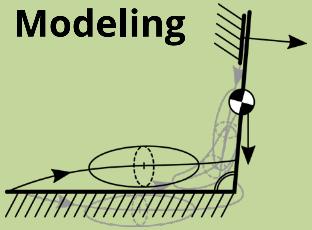
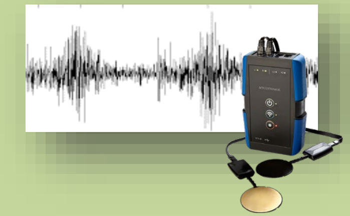


Force–Vibration Modeling



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GRADUATE WORK: Prototype Control

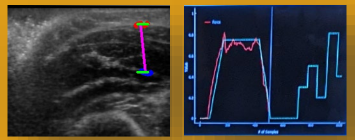
neurological activation

NEUROMUSCULAR DYNAMICS
(cross-bridge cycle, etc.)

musculoskeletal dynamics

DEVICE CONTROL

(Proof-of-Concept) Trajectory Tracking

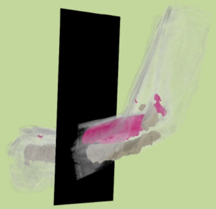


robot dynamics

MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

Data Set Generation
(3D Deformation)



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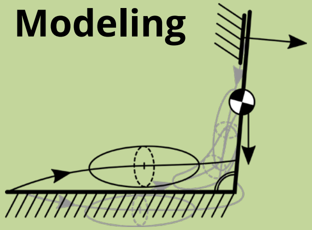

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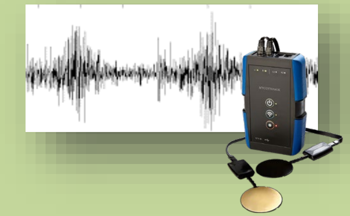

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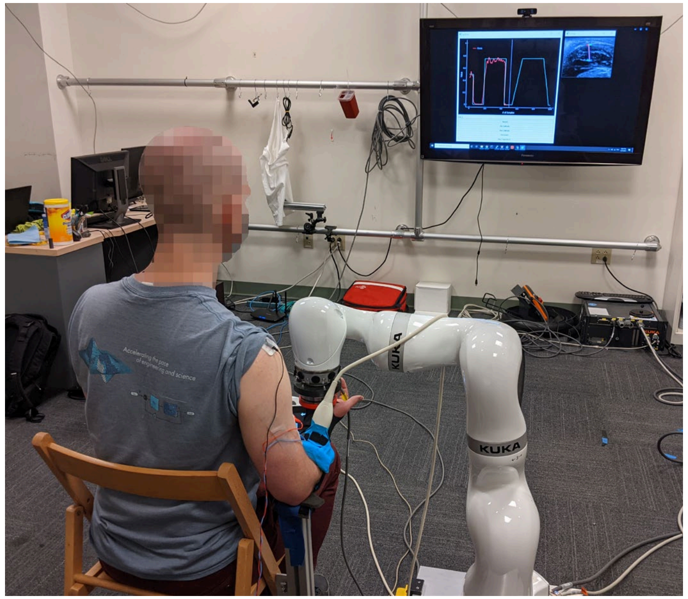
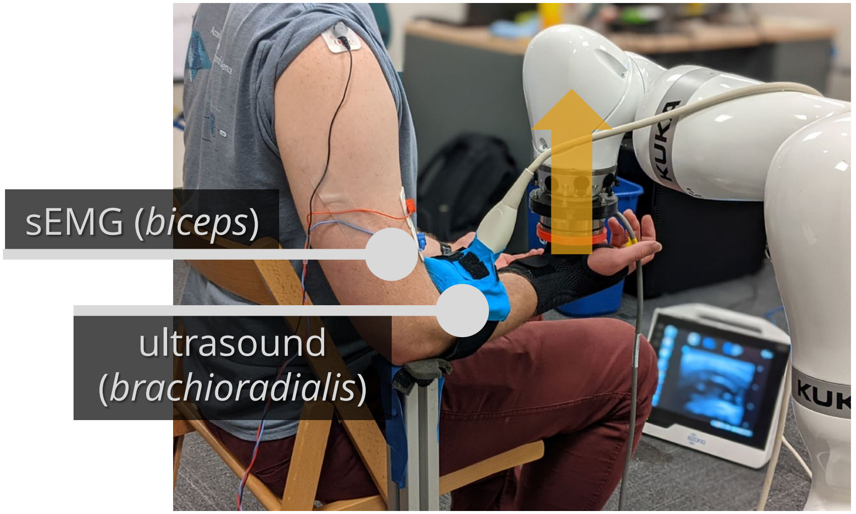
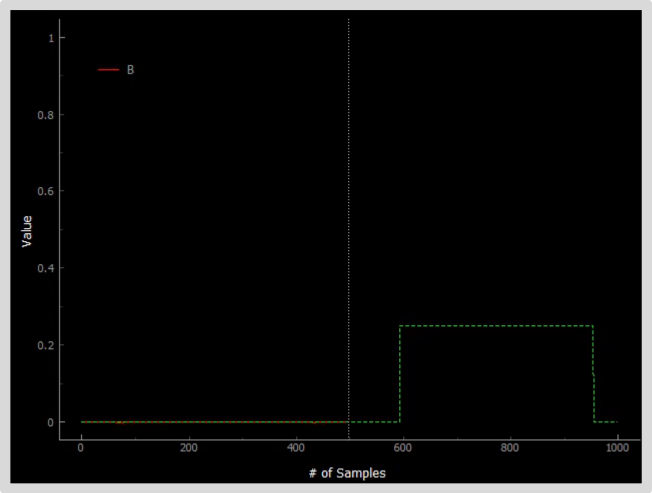
Prototype Deformation-based Control



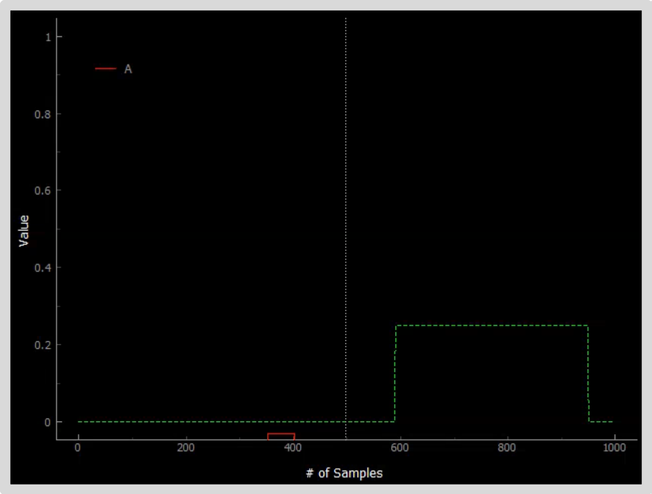


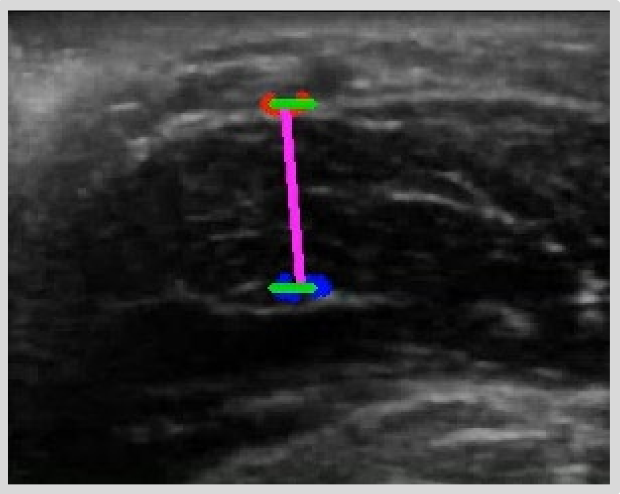
Prototype Deformation-based Control

(Normalized, Windowed)
Biceps sEMG

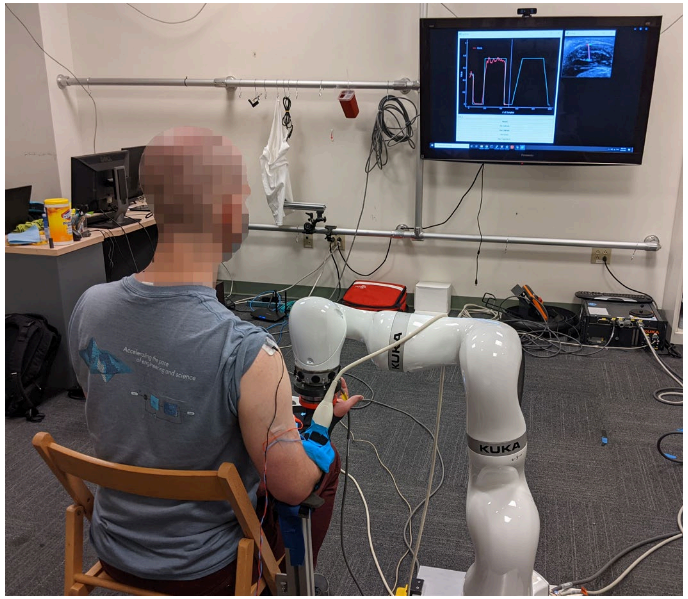


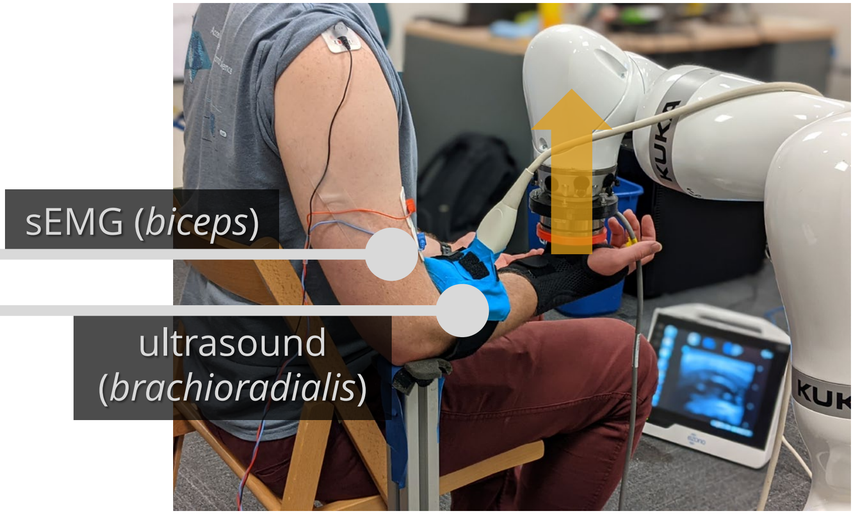
(Normalized)
Brachioradialis Thickness





(points tracked via Lucas–Kanade optical flow)

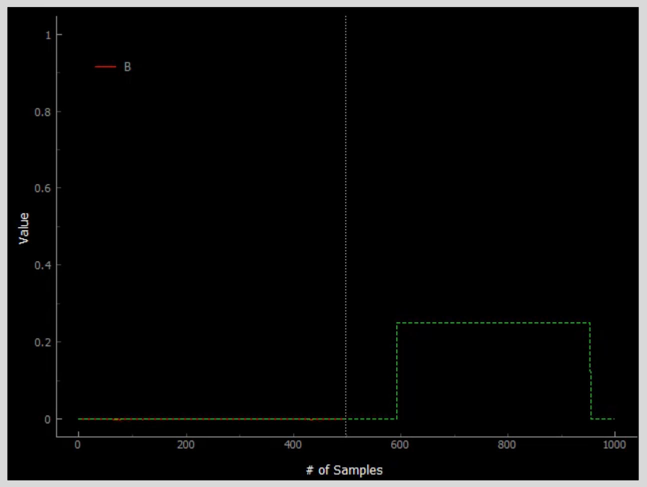




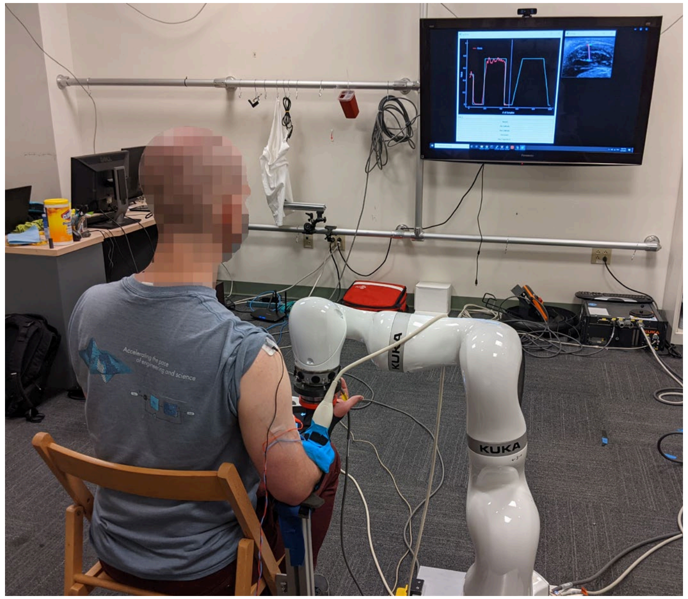
*[**Hallock**, Sud, Mitchell, Hu, Ahamed, Velu, Schwartz, Bajcsy, TNSRE 2021] (under review)*

Prototype Deformation-based Control

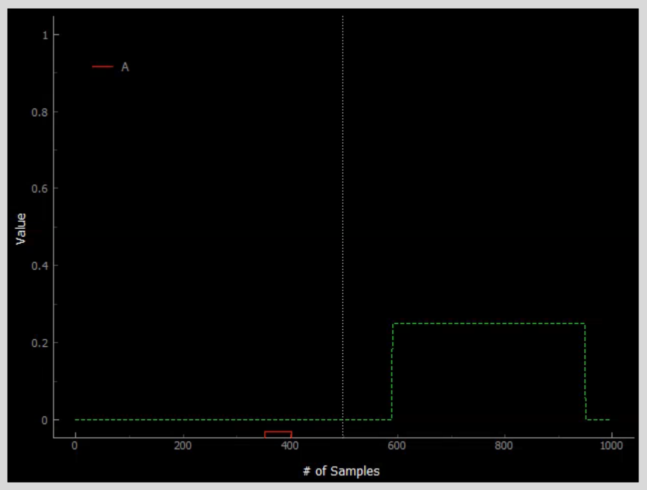
(*Normalized, Windowed*)
Biceps sEMG

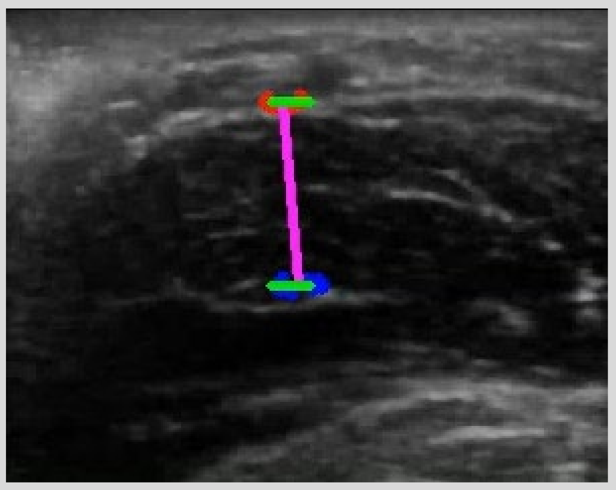


Subjects can track "forcelike" trajectories (exerting pressure during isometric elbow flexion) **via ultrasound-measured muscle thickness**.

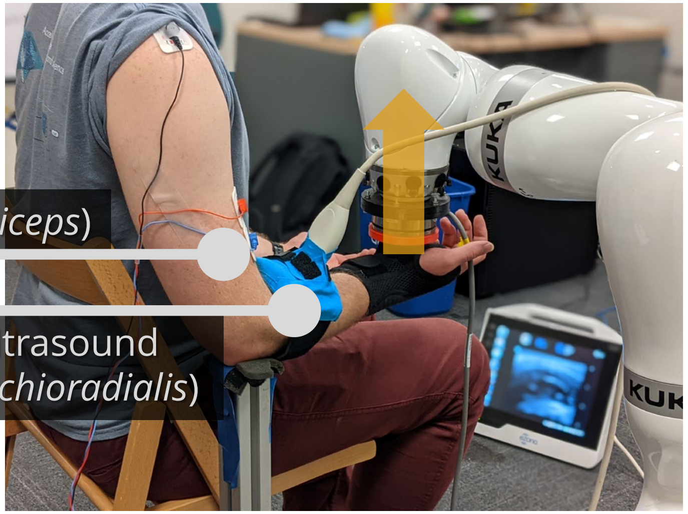


(*Normalized*)
Brachioradialis Thickness



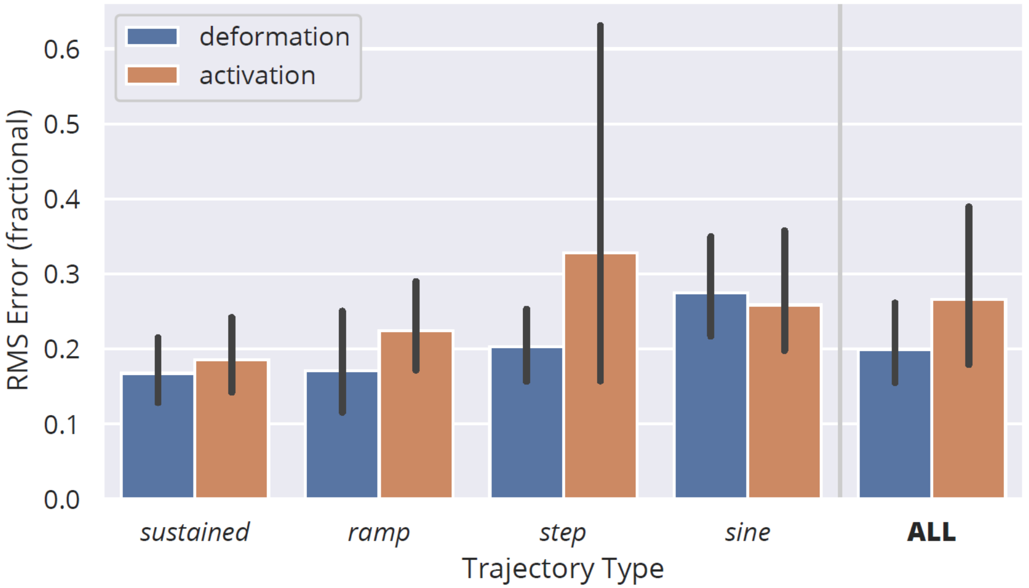


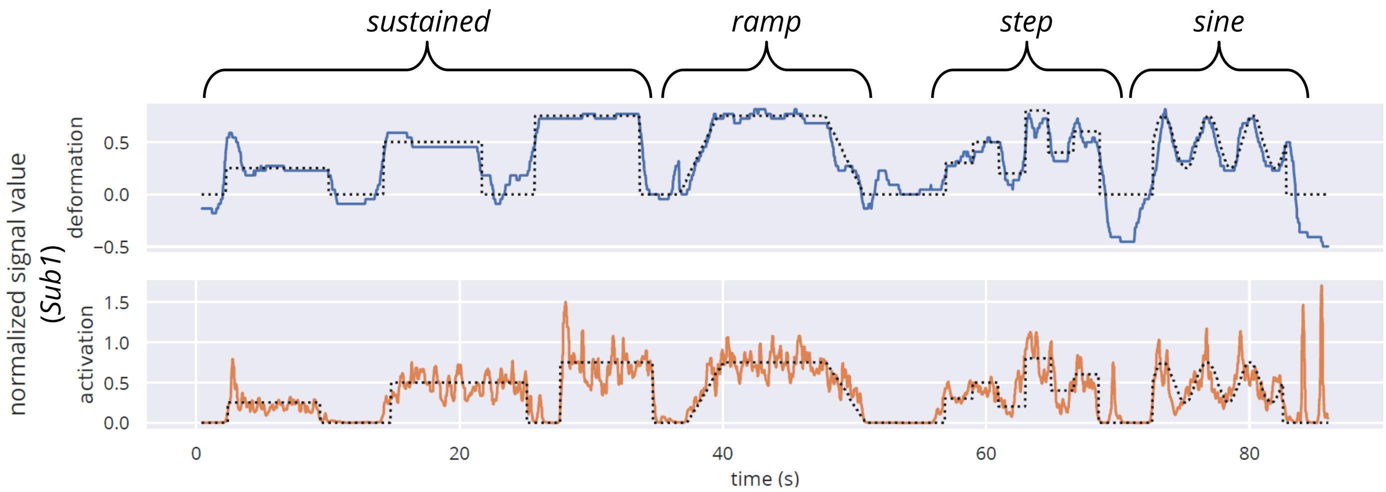
(*points tracked via Lucas–Kanade optical flow*)



[***Hallock**, Sud, Mitchell, Hu, Ahamed, Velu, Schwartz, Bajcsy, TNSRE 2021] (under review)*

Prototype Deformation-based Control: Performance





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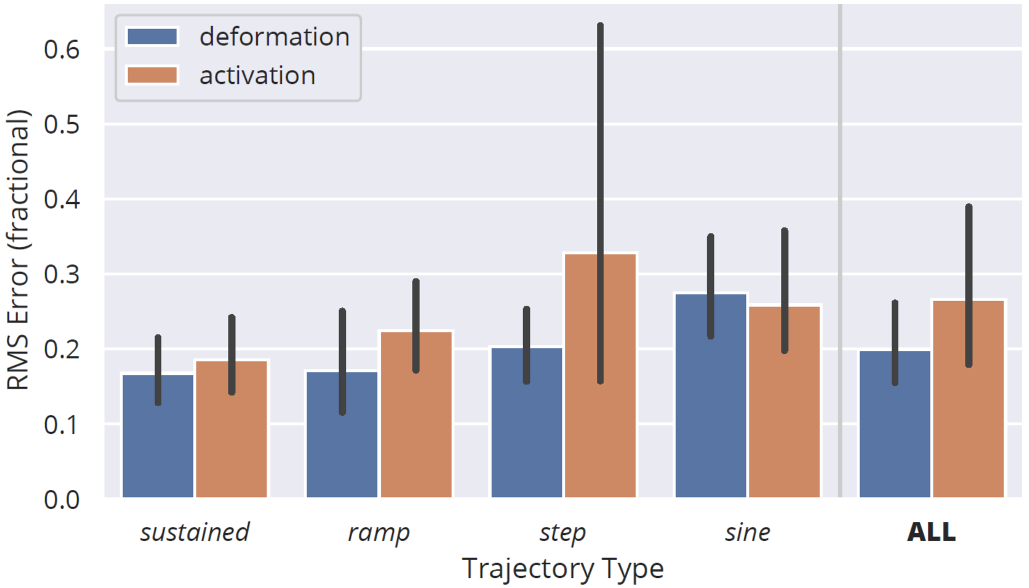
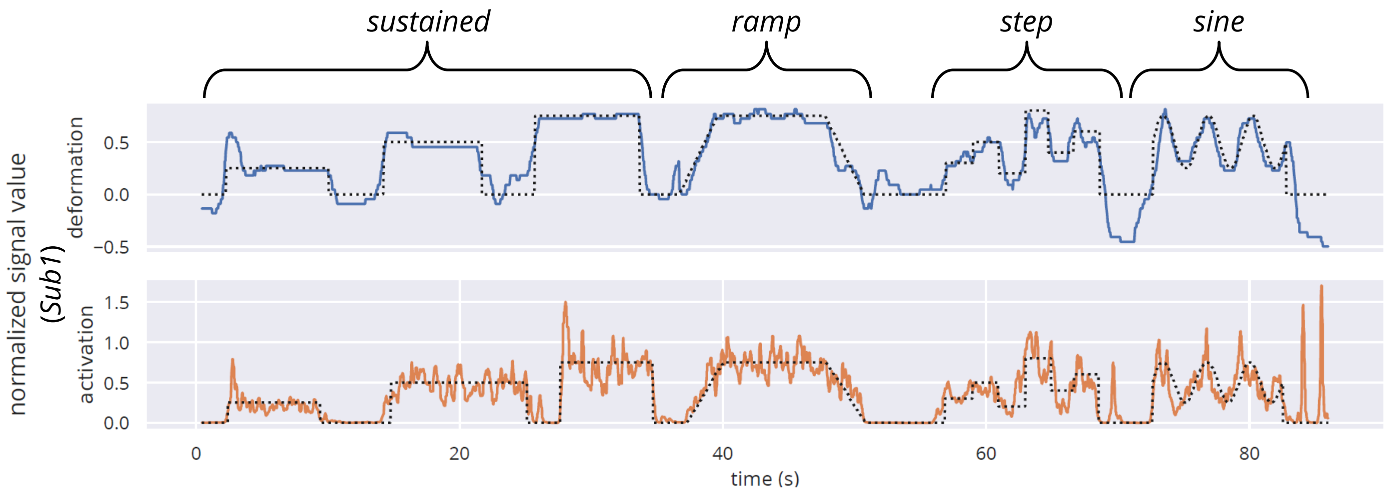
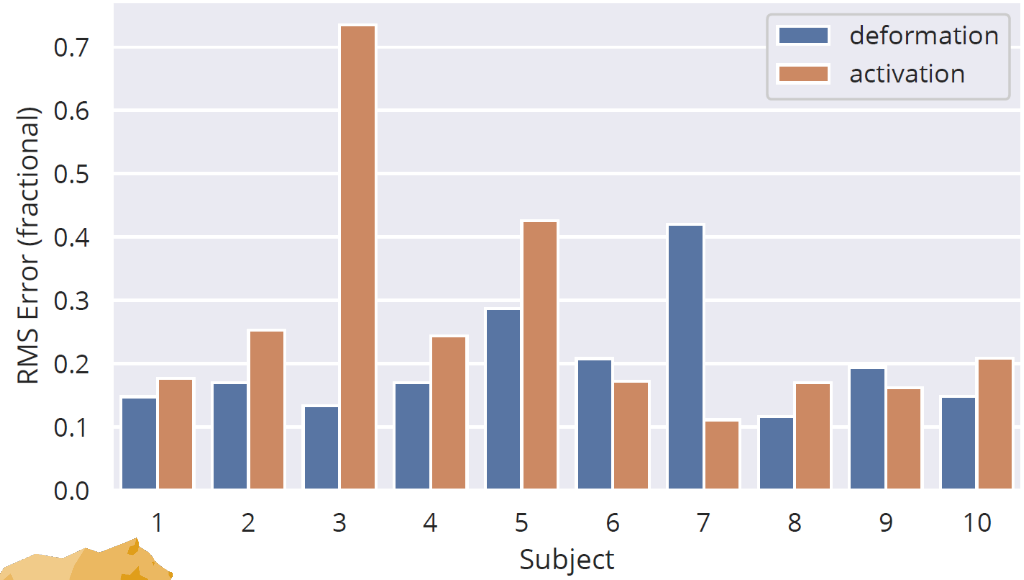
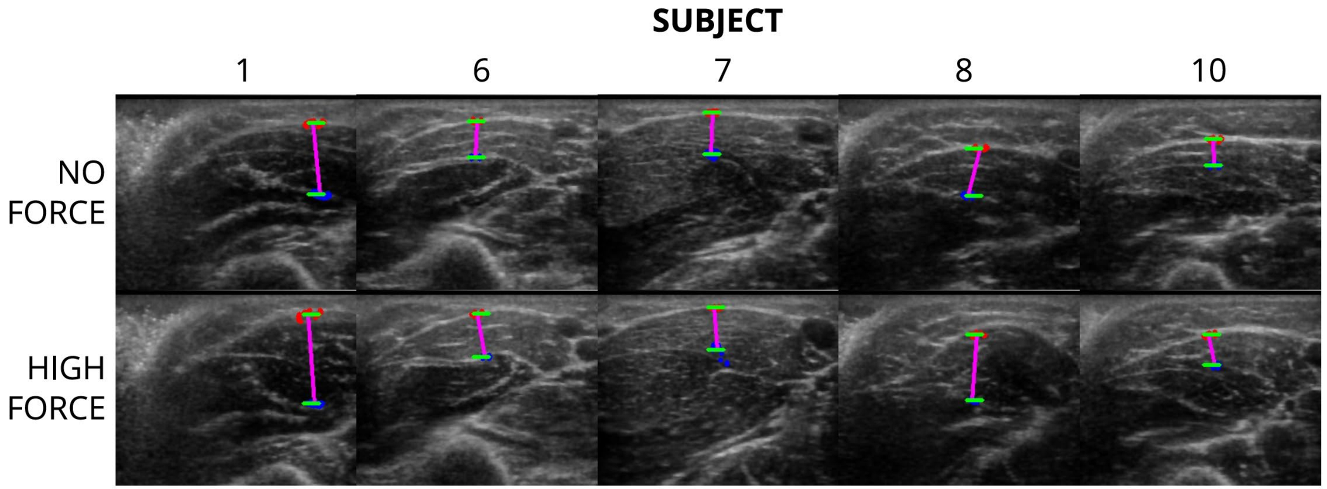


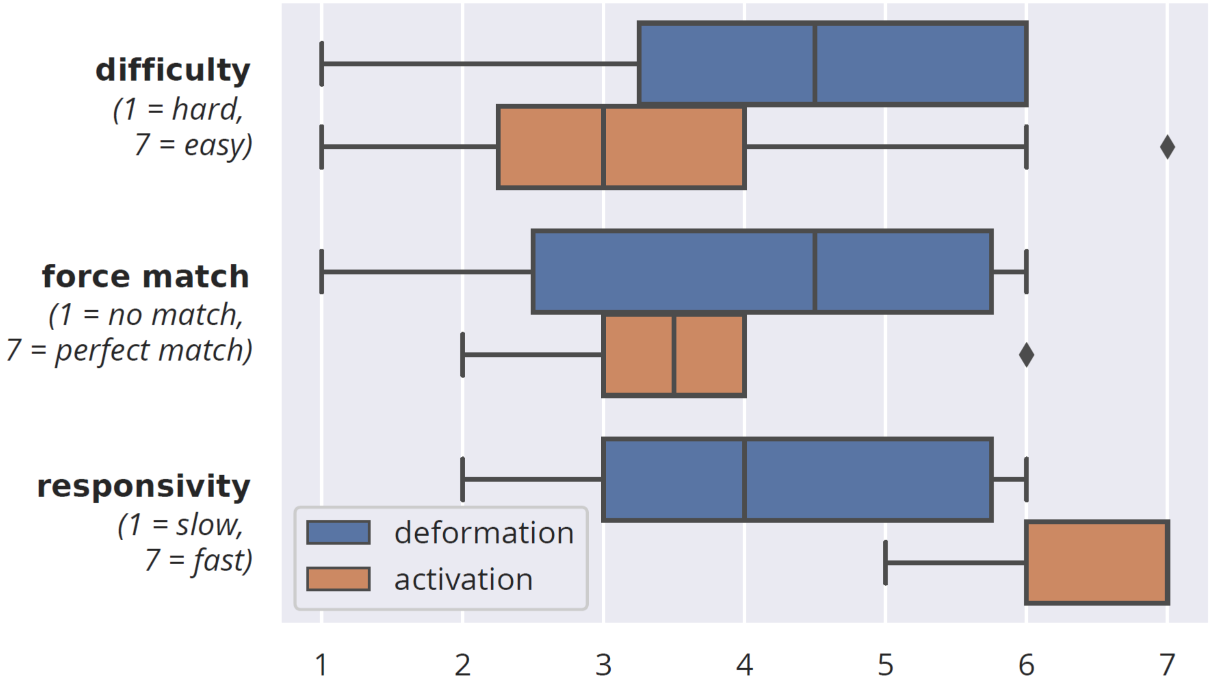


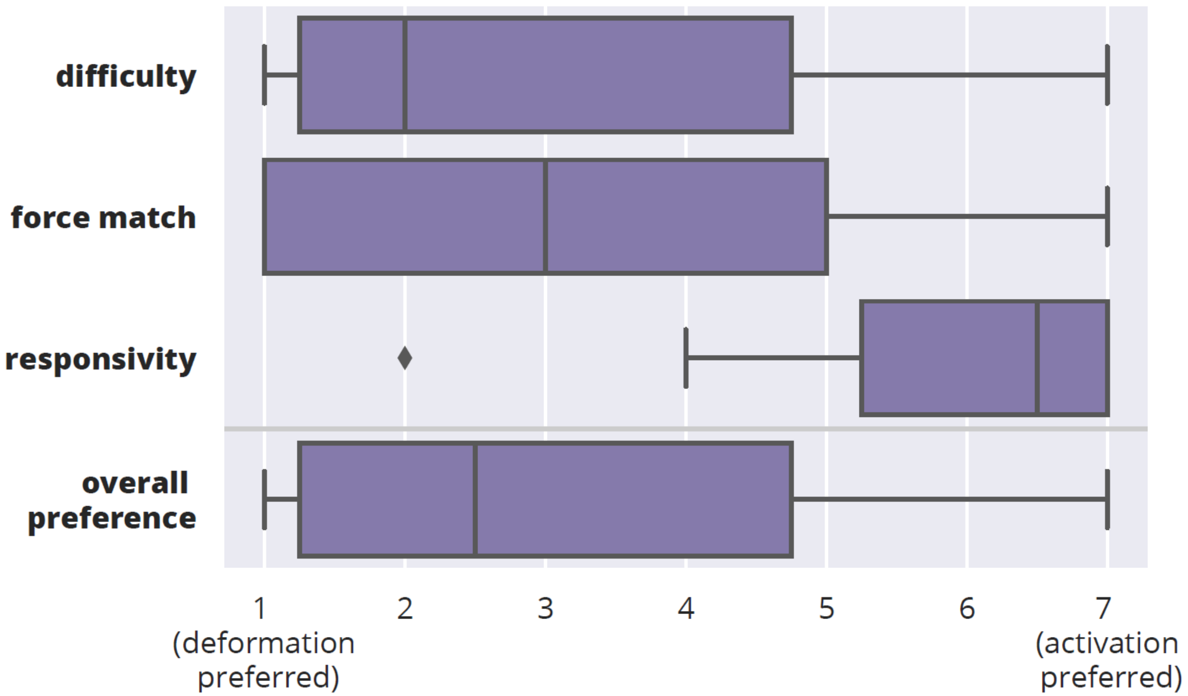




[***Hallock***, *Sud, Mitchell, Hu, Ahamed, Velu, Schwartz, Bajcsy, TNSRE 2021] (under review)*

Prototype Deformation-based Control: Preferences





GRADUATE WORK: Prototype Control

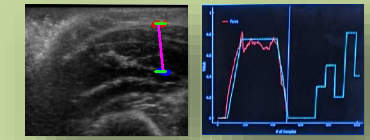
neurological activation

NEUROMUSCULAR DYNAMICS
(cross-bridge cycle, etc.)

musculoskeletal dynamics

DEVICE CONTROL

(Proof-of-Concept) Trajectory Tracking

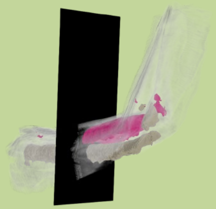


robot dynamics

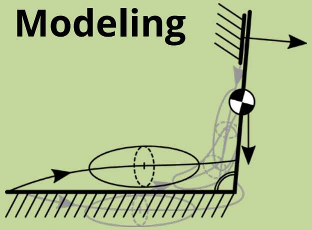
MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

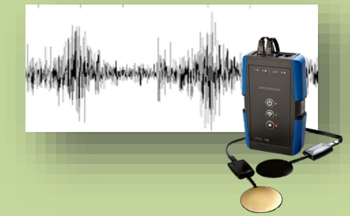
Data Set Generation
(3D Deformation)



Systematic Force–Deformation Modeling



Force–Vibration Modeling



Roadmap

GOAL:

Build safe, capable assistive devices that grant the human user full control authority.

FUNDAMENTAL CHALLENGE: Insufficient Models

Current musculoskeletal modeling approaches don't sufficiently capture human dynamics to ensure safety and capability.

THESIS CONTRIBUTION: New Modeling Paradigms & Prototype Control

By directly measuring muscle movement (as deformation/vibration), we can build and use new classes of control-ready musculoskeletal models that represent human dynamics with greater fidelity.

VISION: Safe and Capable Systems for Assistance & Rehabilitation

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VISION: Safe and Capable Systems for Assistance & Rehabilitation

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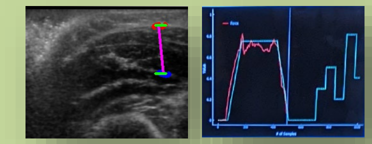
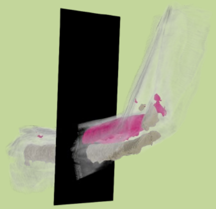


robot dynamics

MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

Data Set Generation
(3D Deformation)



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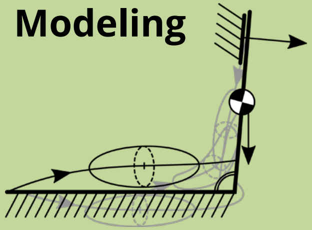
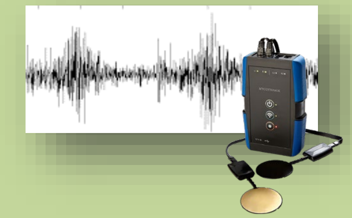


Force–Vibration Modeling



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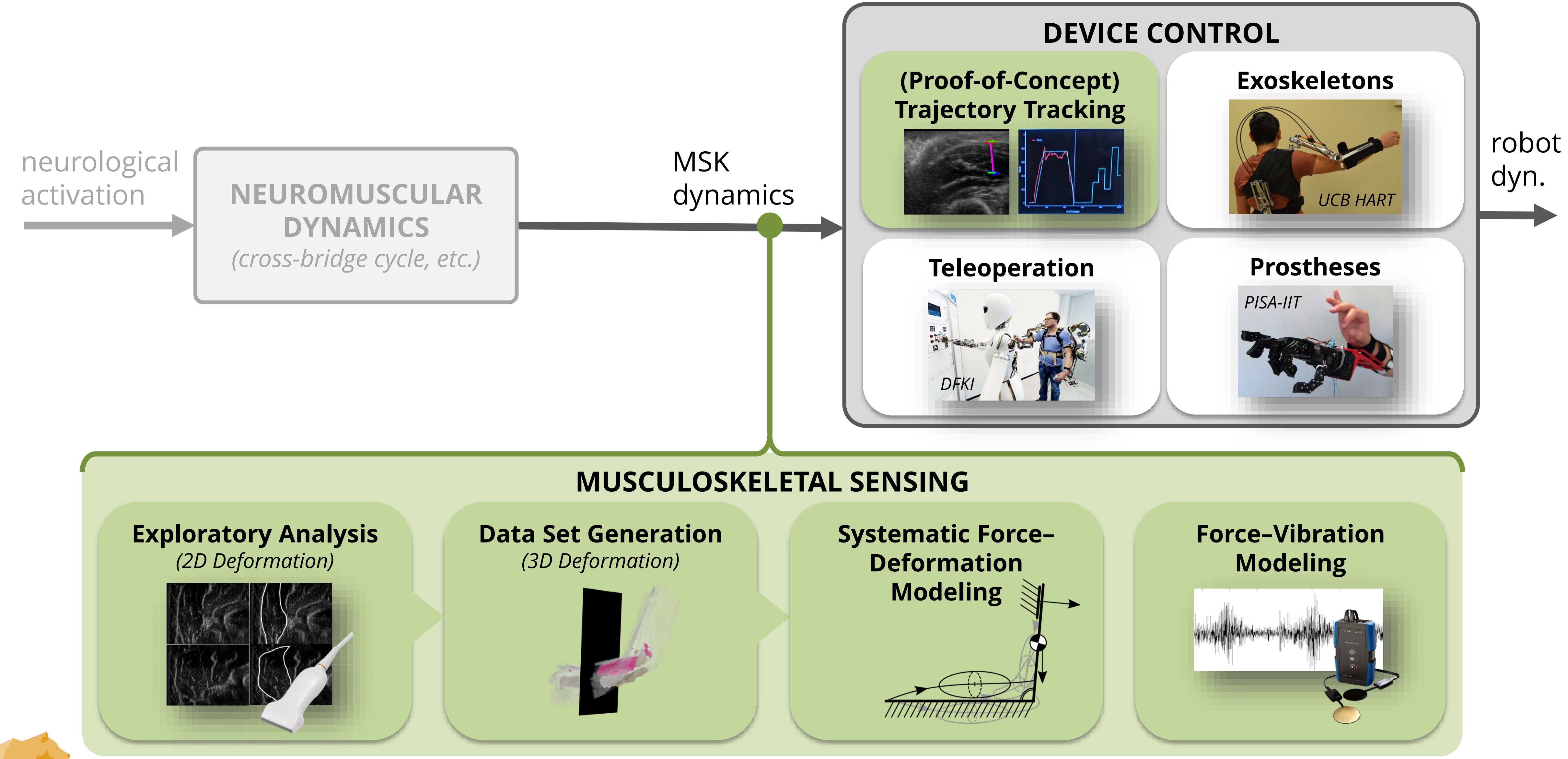
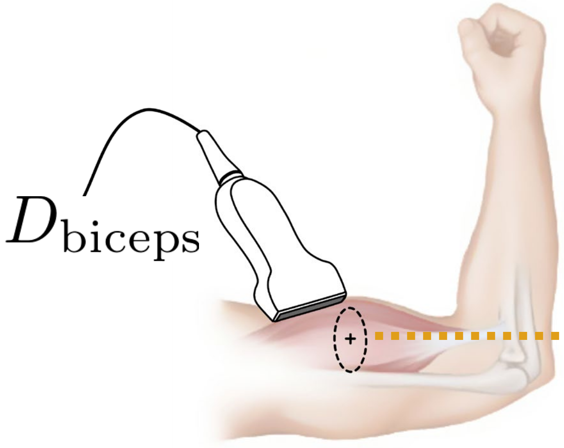
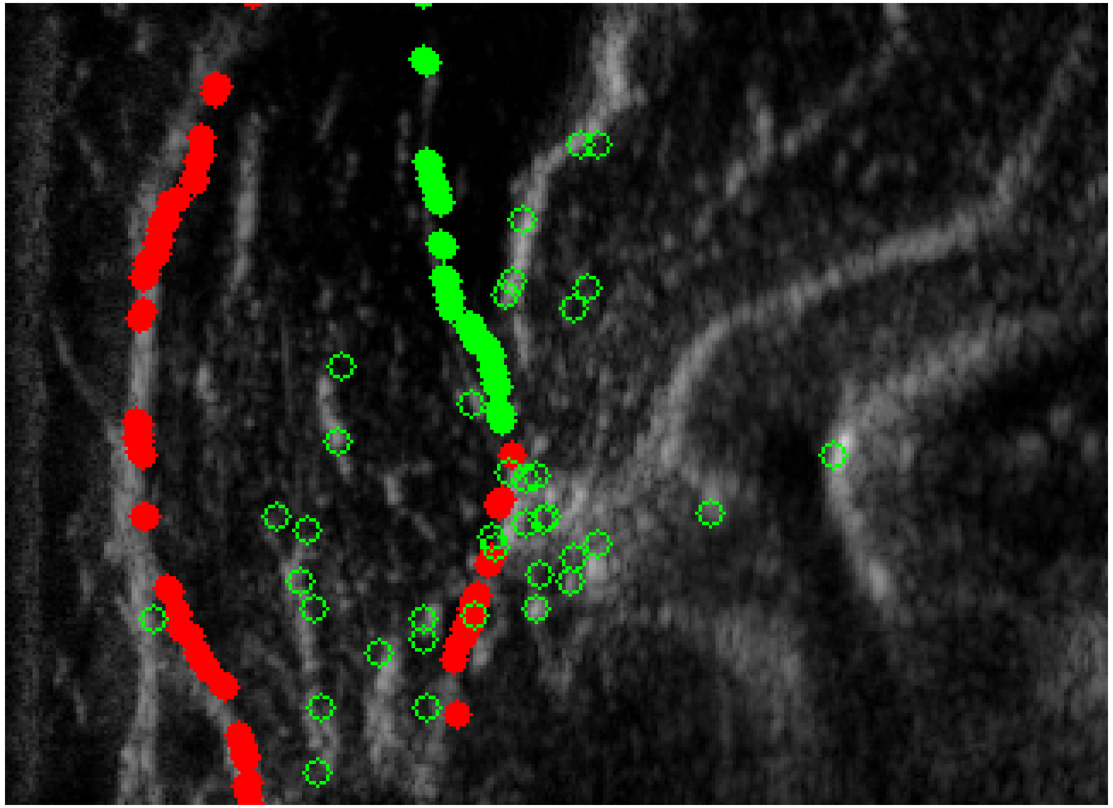
UNIVERSITY OF CALIFORNIA

VISION: Advances in Assistive Device Control



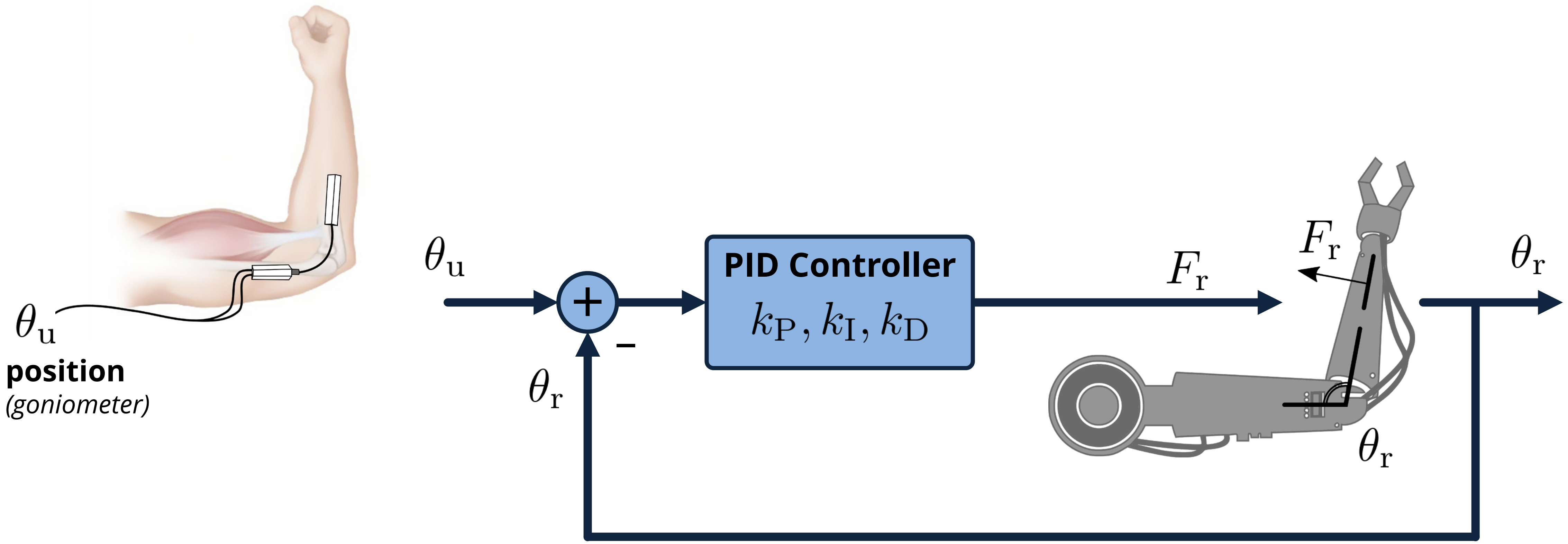
Device Control: Expanded Deformation Tracking



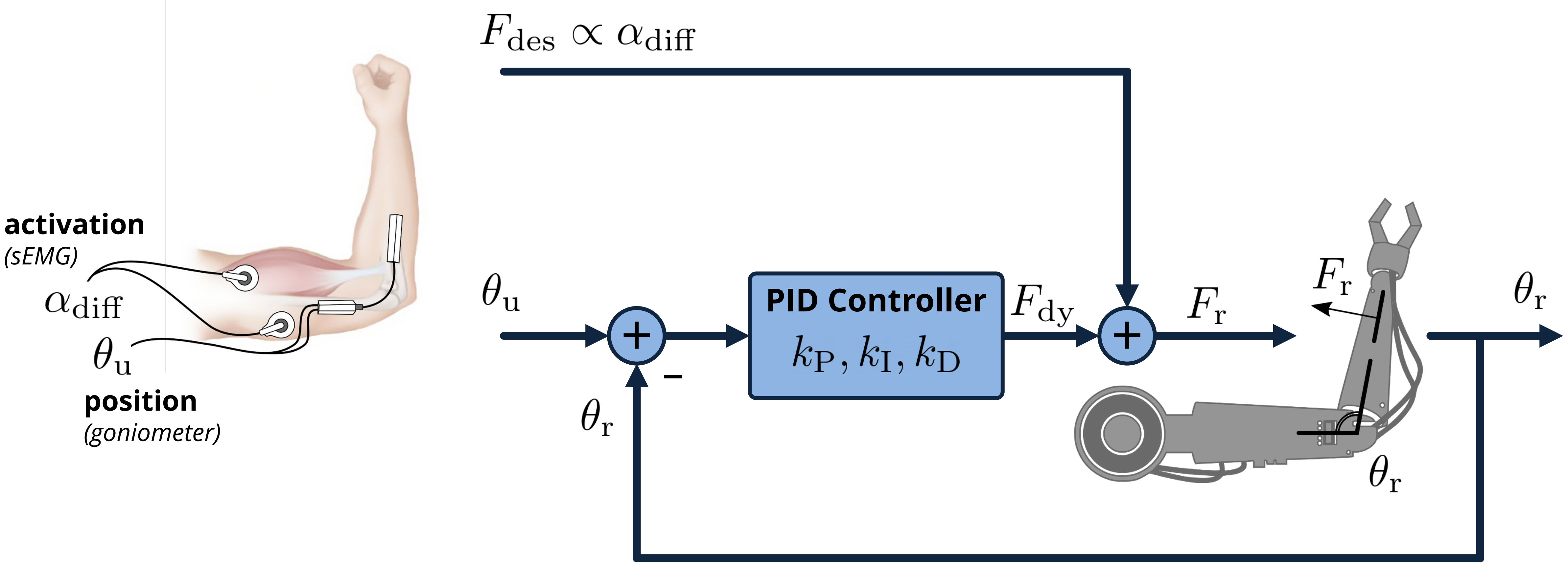


Points along the muscle fascia can be **reliably tracked in real time** via Lucas–Kanade optical flow-based methods.

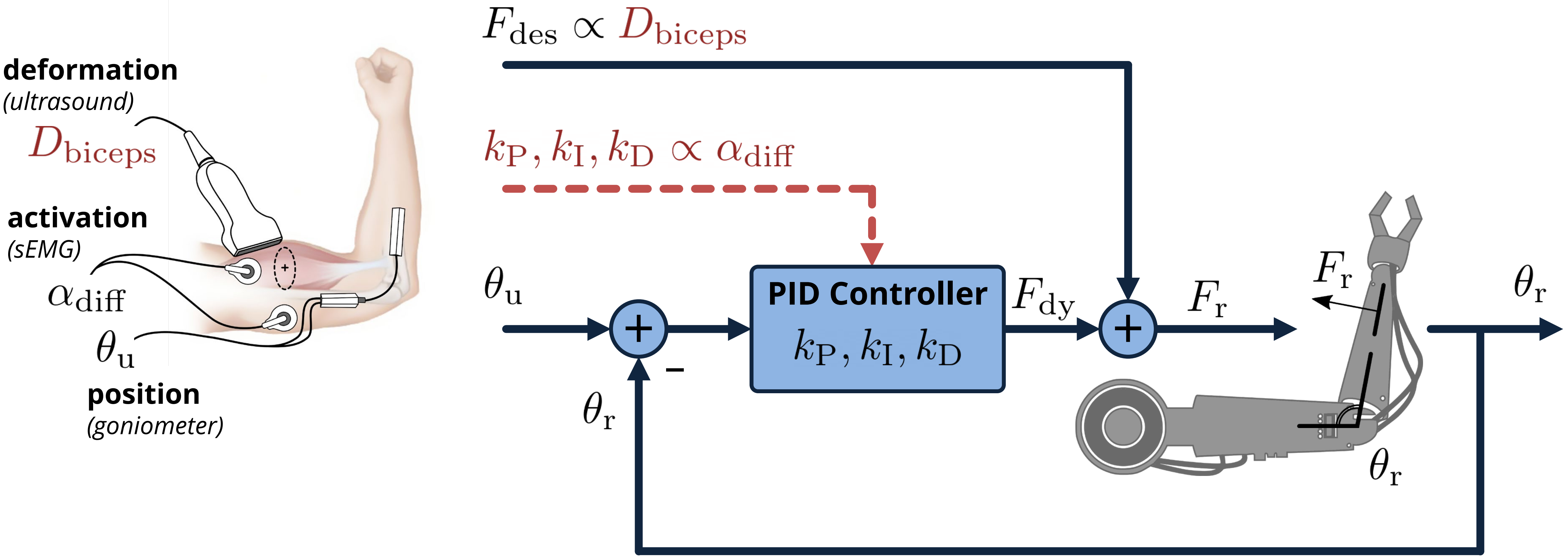
Device Control: Robot Teleoperation



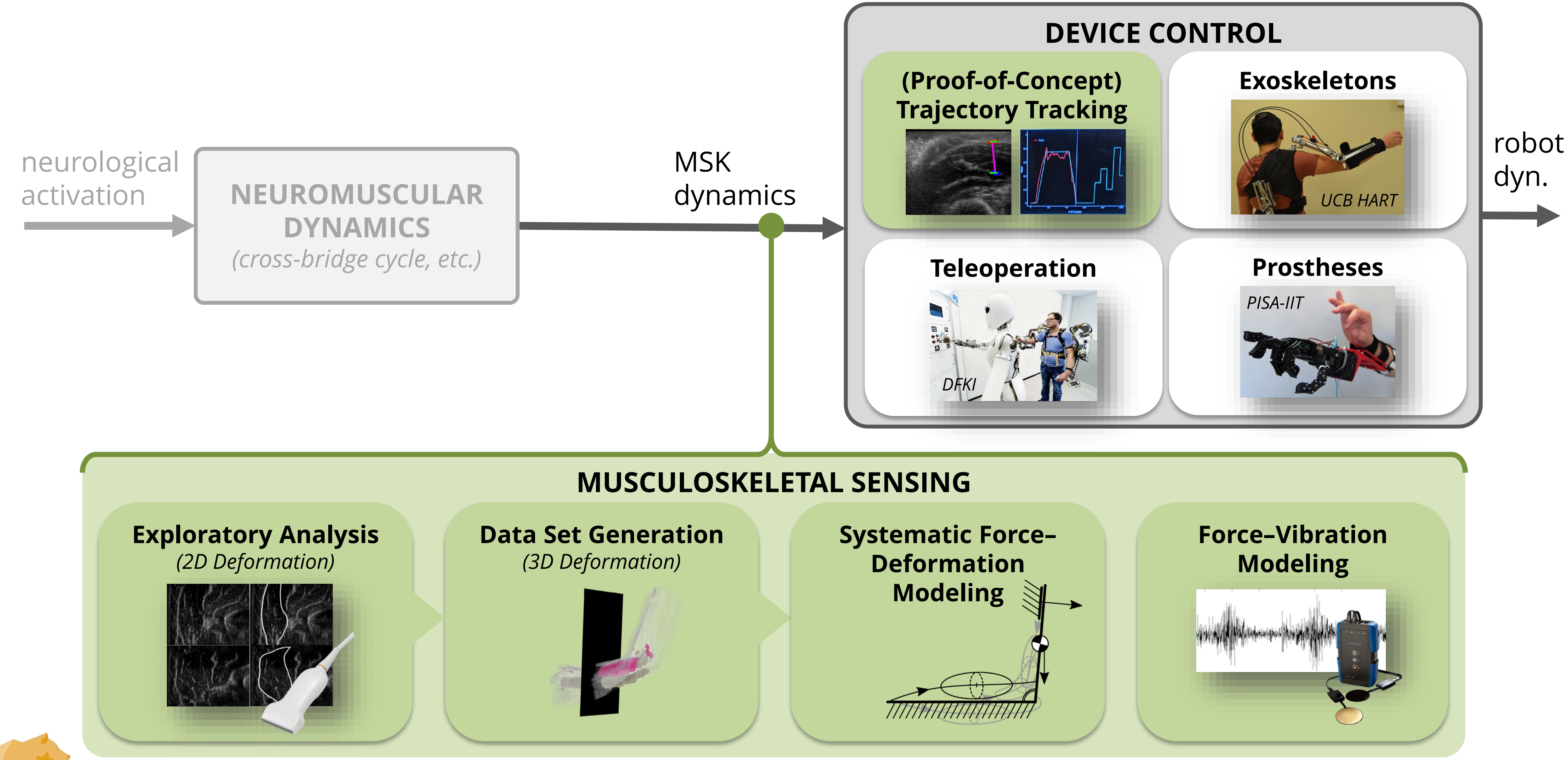
Device Control: Baseline sEMG Control



Device Control: Proposed Augmented Control



VISION: Advances in Assistive Device Control



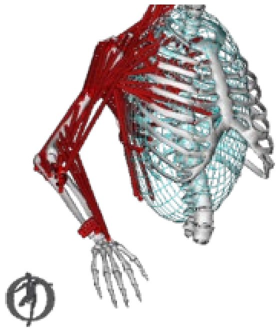
VISION: Advances in Motor Control Science

neuro. activ.

NEUROMUSCULAR DYNAMICS

Force–Activation Modeling

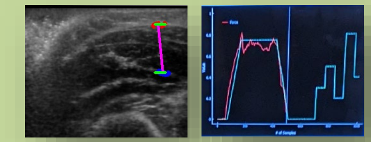
Modeling Synergies
(evaluating software)



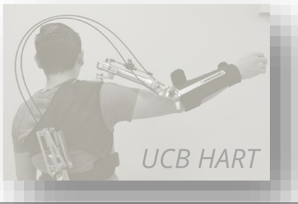
MSK dyn.

DEVICE CONTROL

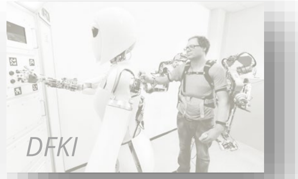
(Proof-of-Concept) Trajectory Tracking



Exoskeletons



Teleoperation



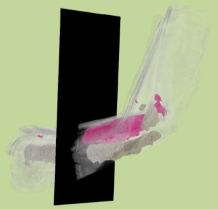
Prostheses

robot dyn.

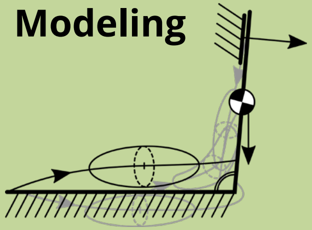
MUSCULOSKELETAL SENSING

Exploratory Analysis
(2D Deformation)

Data Set Generation
(3D Deformation)

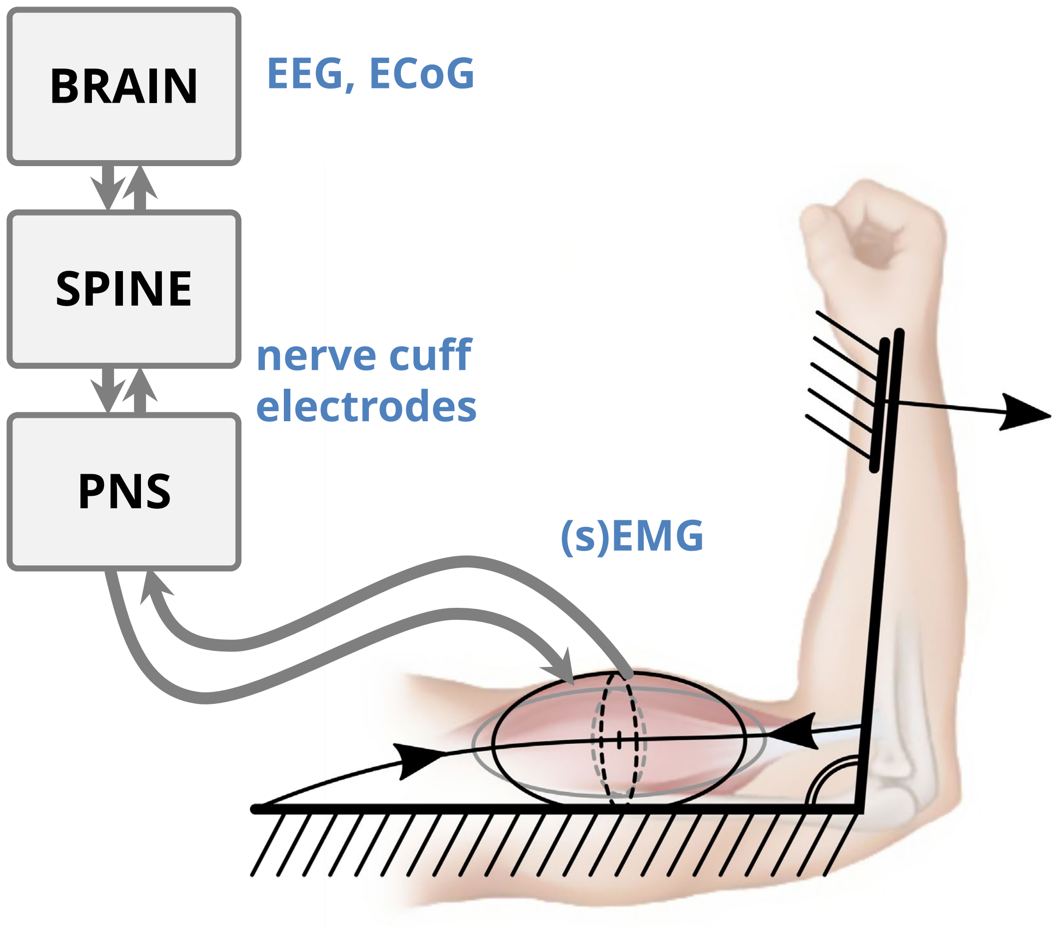


Systematic Force–Deformation Modeling



Force–Vibration Modeling

Force–Activation Modeling: "Closing the Loop"



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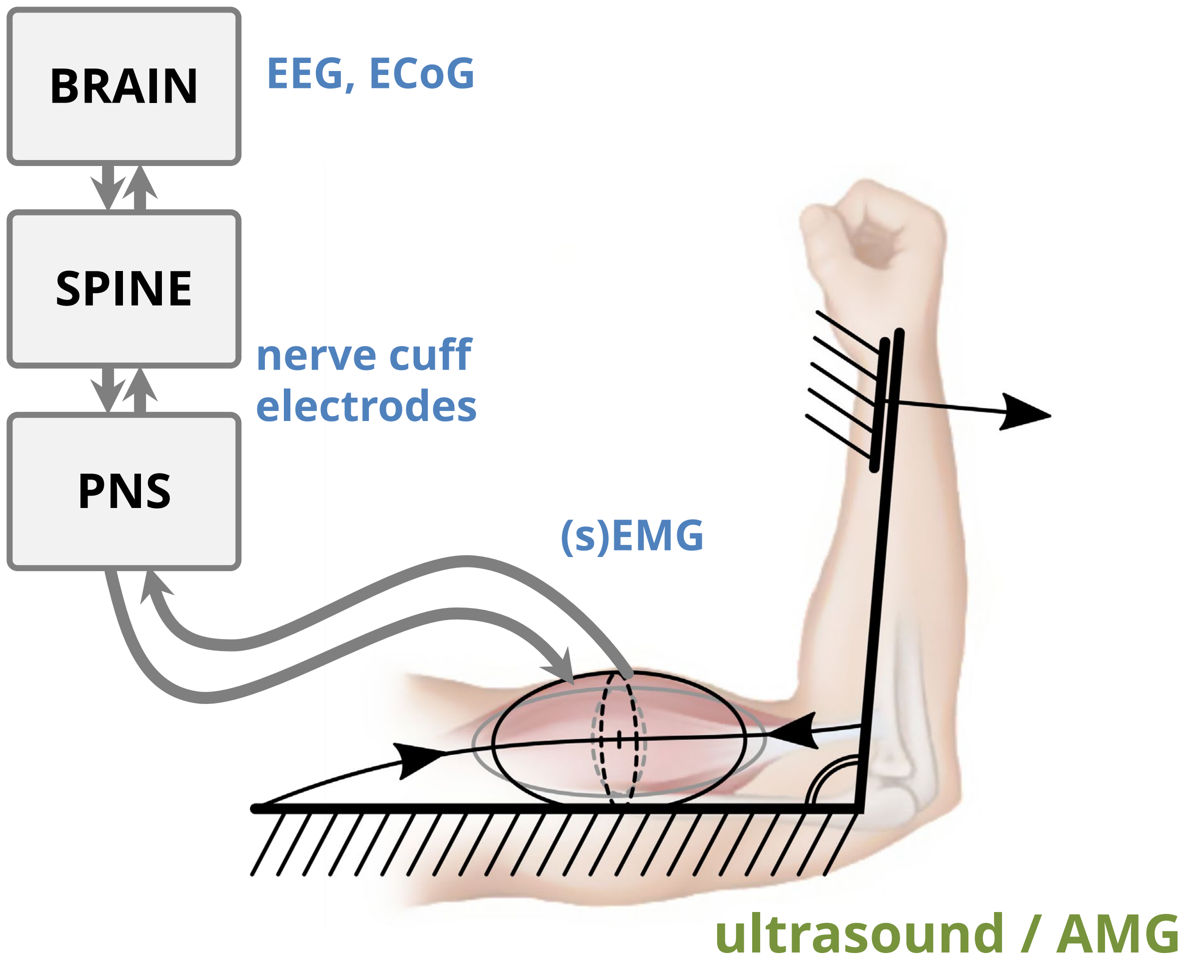


Measuring muscle output force directly would allow for **improved interpretation of existing sensing modalities**.

Modeling Synergies: State-of-the-Art

Joint Angles / Velocities

$\{\theta, \dot{\theta}\}$ → **INVERSE DYNAMICS** →

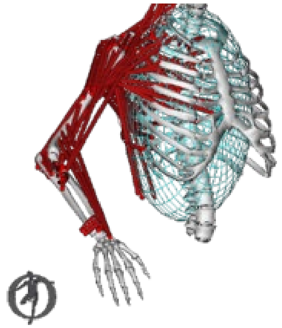
Joint Torques

$\{\tau\}$ → **COST FUNCTION** (e.g., minimum total energy, sEMG matching) →

Muscle Output Forces

$\{F_{\mathrm{m}}\}$

[e.g., OpenSIM, AnyBody]



Modeling Synergies: Cost Function Evaluation

Joint Angles / Velocities

$\{\theta, \dot{\theta}\}$

→ **INVERSE DYNAMICS** →

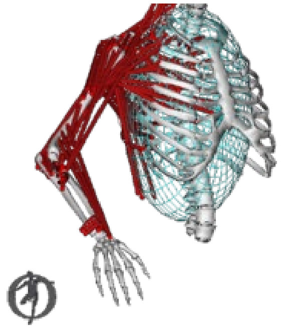
Joint Torques

$\{\tau\}$

→ **COST FUNCTION** (e.g., minimum total energy, sEMG matching) →

Muscle Output Forces

$\{F_{\mathrm{m}}\} = \{\ldots, F_{\mathrm{biceps}}, \ldots\}$



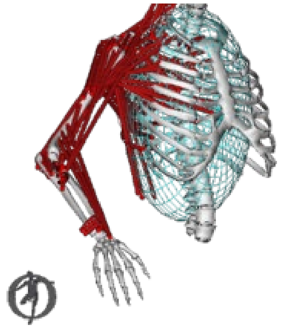
[e.g., OpenSIM, AnyBody]

Measuring individual muscle forces allows for **probing / validating current ID inference**.

Modeling Synergies: Novel Systems

Joint Angles / Velocities $\{\theta, \dot{\theta}\}$ → **INVERSE DYNAMICS** → **Joint Torques** $\{\tau\}$ → **COST FUNCTION** (e.g., minimum total energy, sEMG matching) → **Muscle Output Forces** $\{F_{\mathrm{m}}\} = \{\ldots, F_{\mathrm{biceps}}, \ldots\}$

[e.g., OpenSIM, AnyBody]



Muscle Output Forces $\{F_{\mathrm{m}}\}$ → **FORWARD DYNAMICS** → **Joint Angles / Velocities** $\{\theta, \dot{\theta}\}$

Measuring individual muscle forces allows for **probing / validating current ID inference models** and **developing FD measurement systems** with reasonable behavior.

VISION: Advances in Motor Science & Device Control

neuro. activ.

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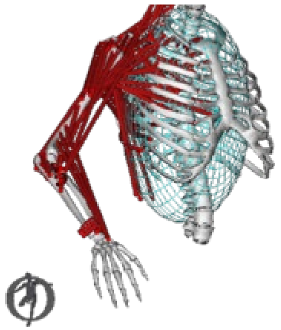
Modeling Synergies

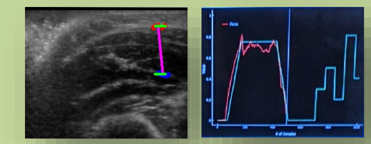
(evaluating software)



MSK dyn.

DEVICE CONTROL

(Proof-of-Concept) Trajectory Tracking



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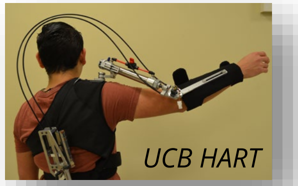
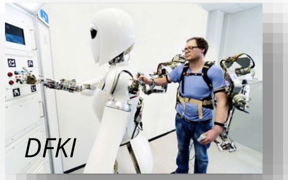
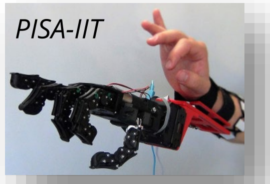


Teleoperation



Prostheses



robot dyn.

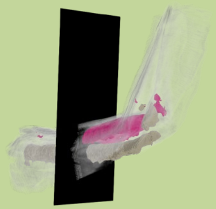
MUSCULOSKELETAL SENSING

Exploratory Analysis

(2D Deformation)

Data Set Generation

(3D Deformation)



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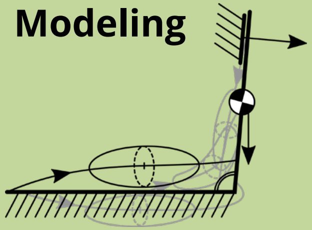

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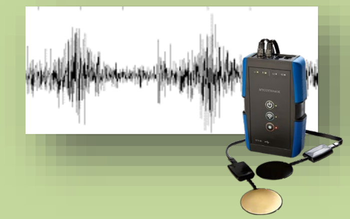
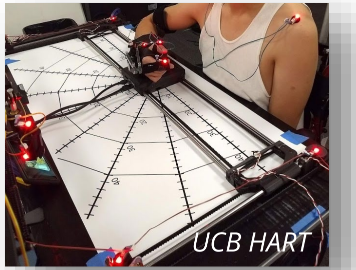


VISION: Advanced Human–Robot Systems

JOINT HUMAN–ROBOT SYSTEM

Addressing Pathology
(quantifying, rehabilitating, tracking)



neuro. activ. →

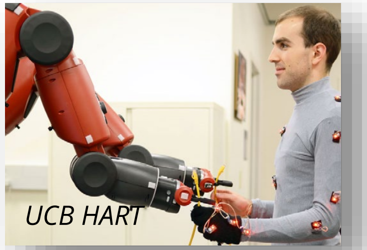
NEUROMUSCULAR DYNAMICS
(cross-bridge cycle, etc.)

MSK dyn. →

DEVICE CONTROL

robot dyn. →

Human–Robot Collaboration



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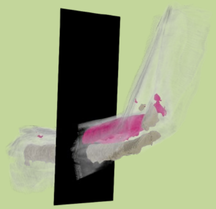

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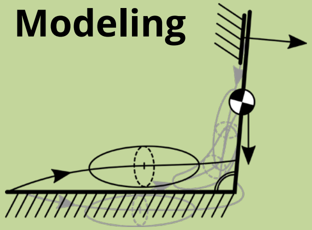

Force–Vibration Modeling

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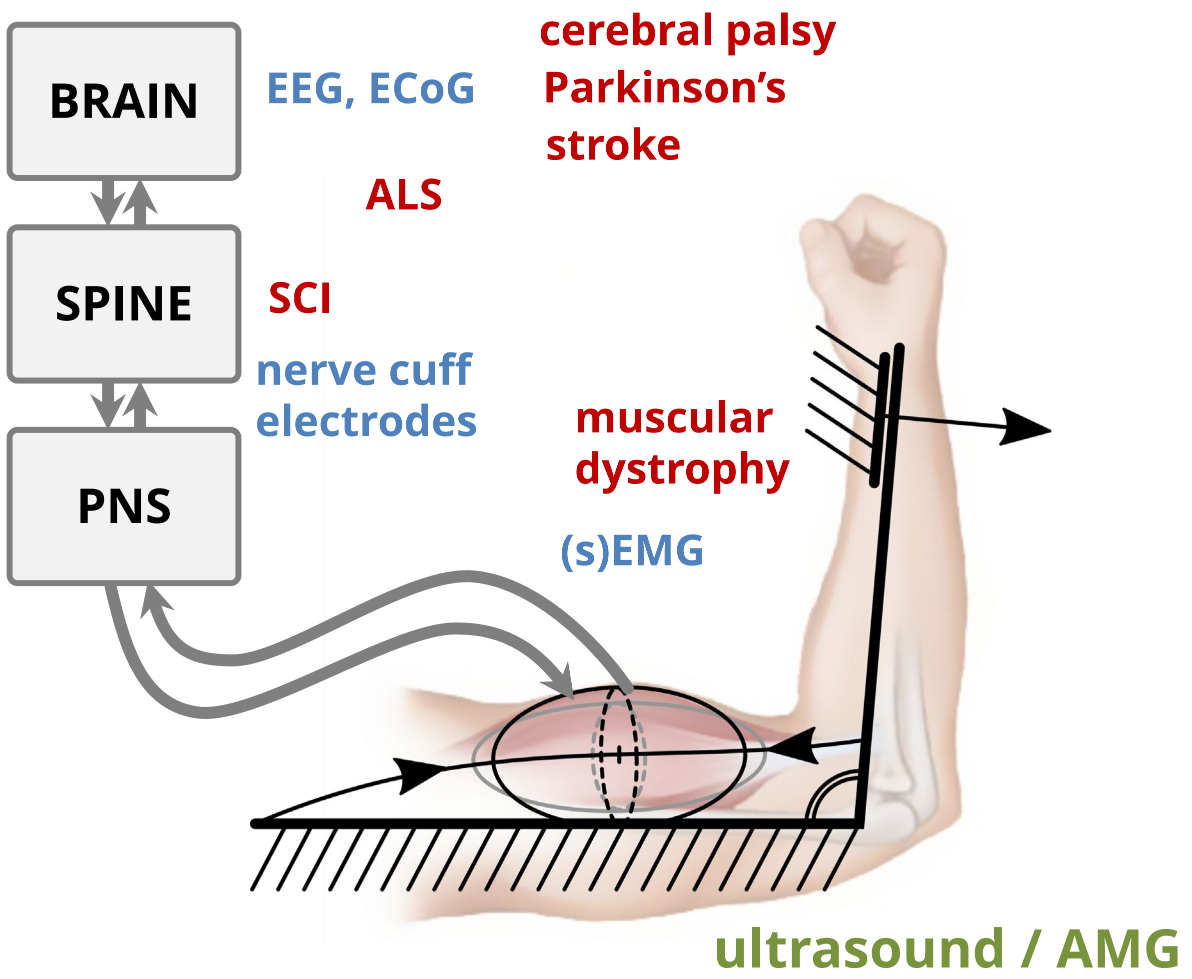

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VISION: Safe and Capable Systems for Assistance & Rehabilitation

Better musculoskeletal models will enable not only safe and capable human–robot systems, but enhanced understanding of neurological motor control and diagnosis and treatment of pathology.

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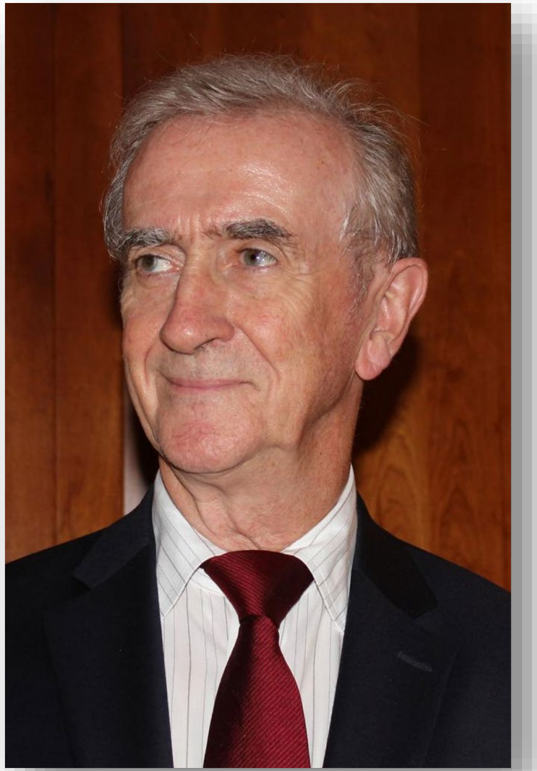
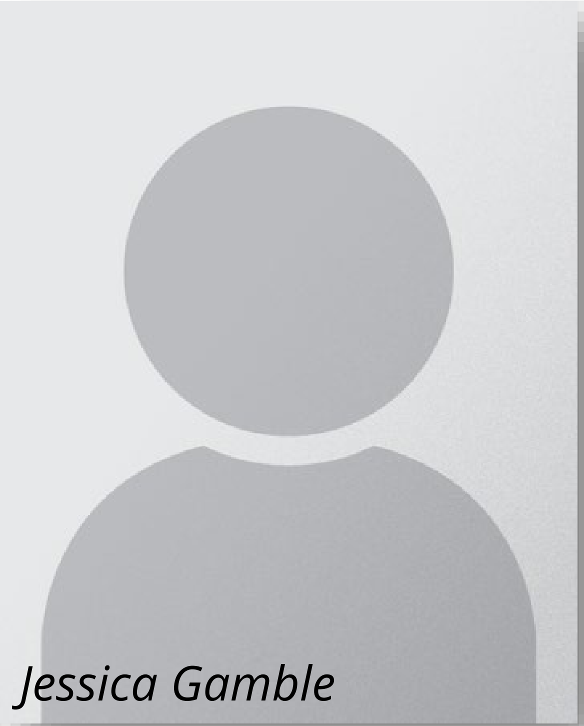
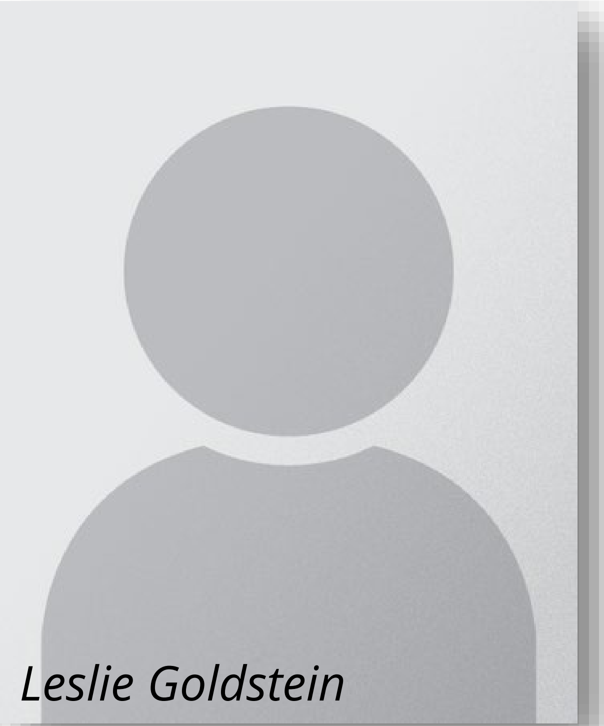


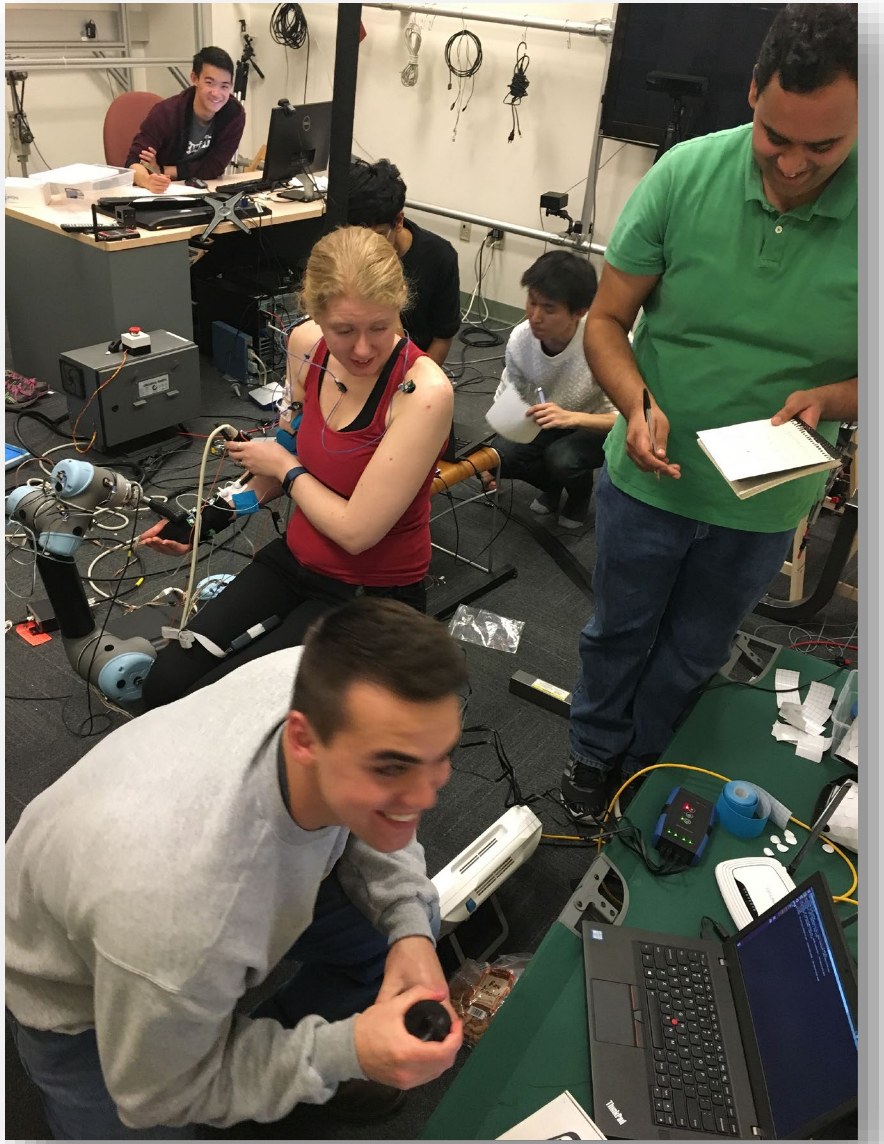


Jessica Gamble


Leslie Goldstein


HART Lab
Human-Assistive Robotic Technologies
Berkeley


Cal


AntiWork



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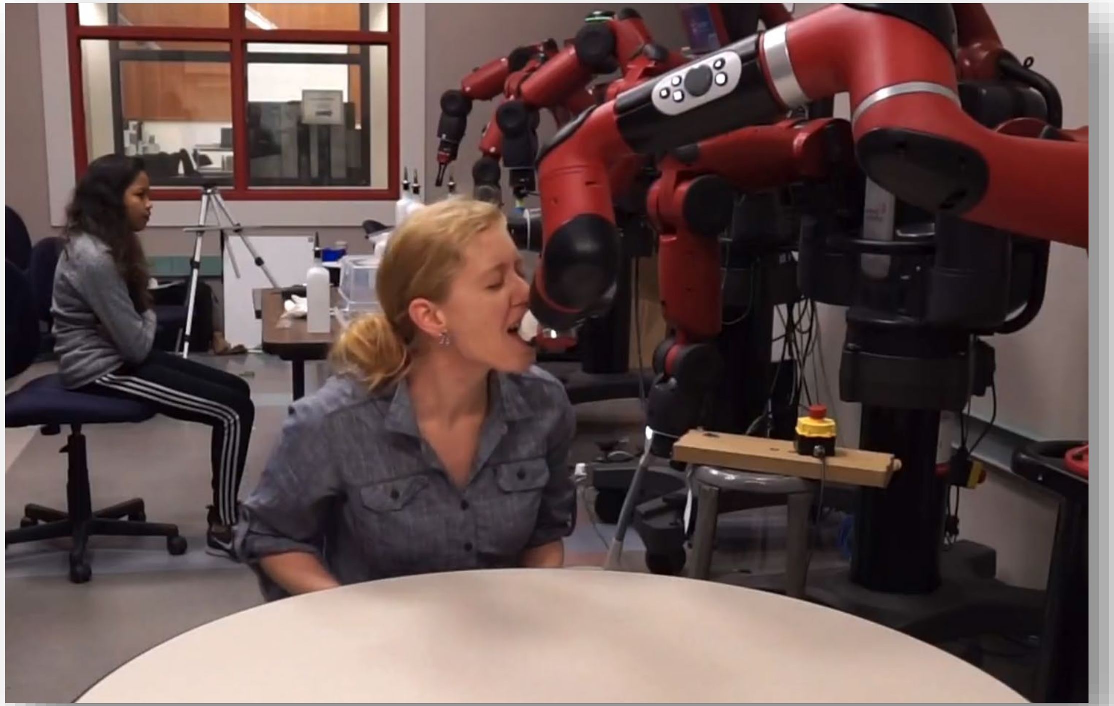


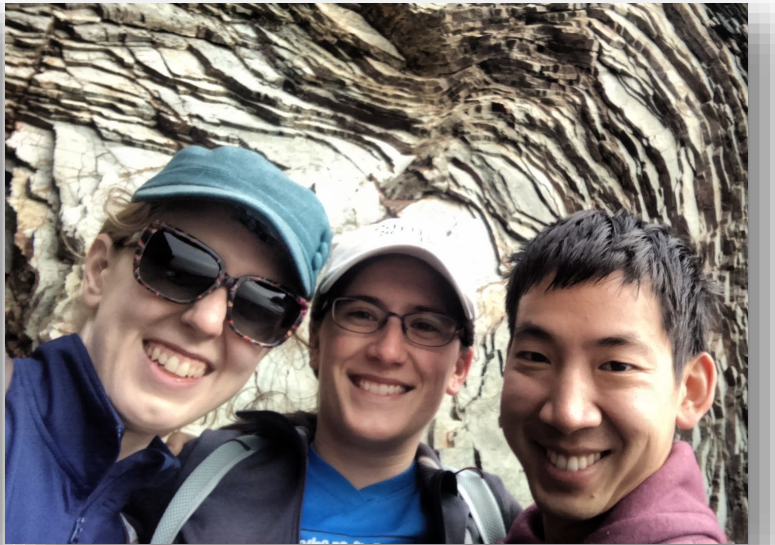
the teaching teams — and students! — of EECS 106A and 127


Google


AXEVENTURES
AXE THROWING


Kristen Cotner (she/her)
David Mcpherson
Victoria Tuck


MT WHITNEY
14508

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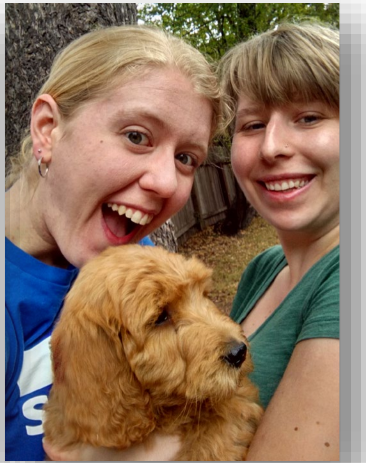
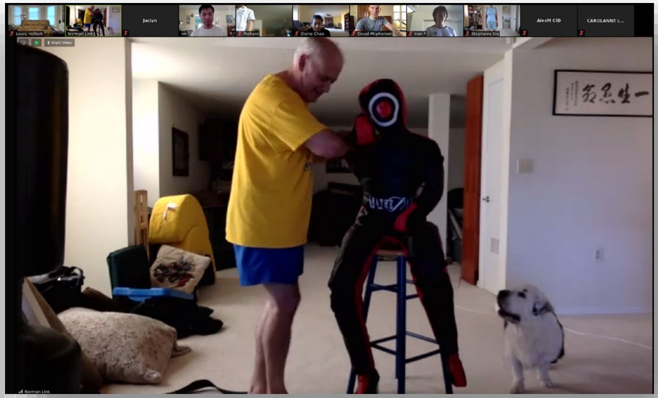
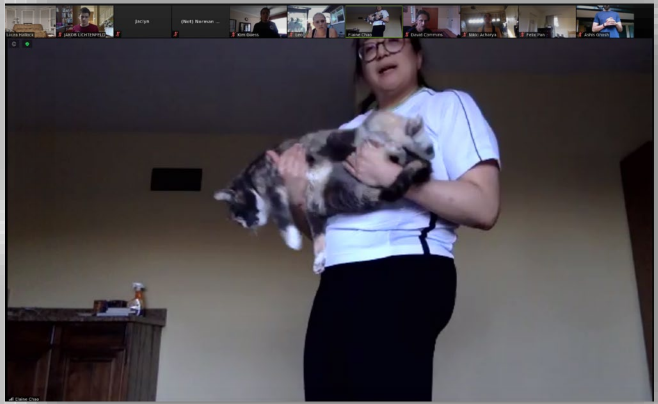
59


GO
AARON!!

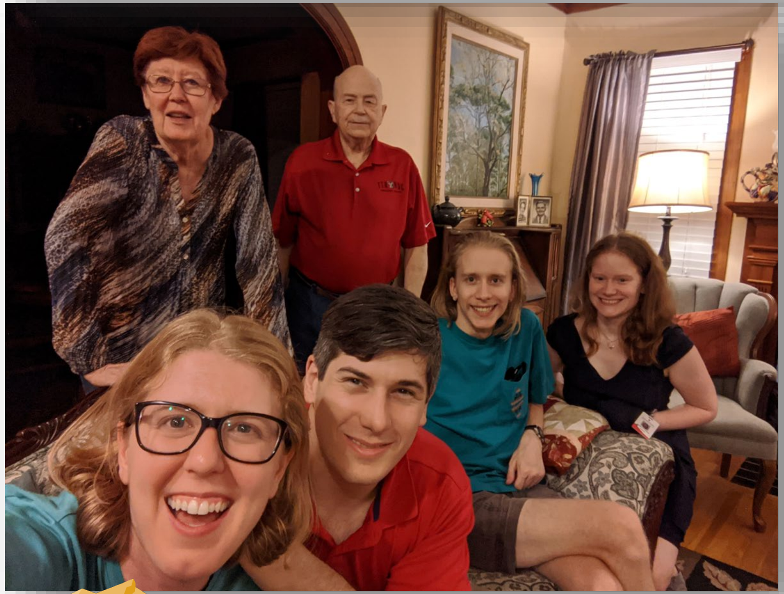




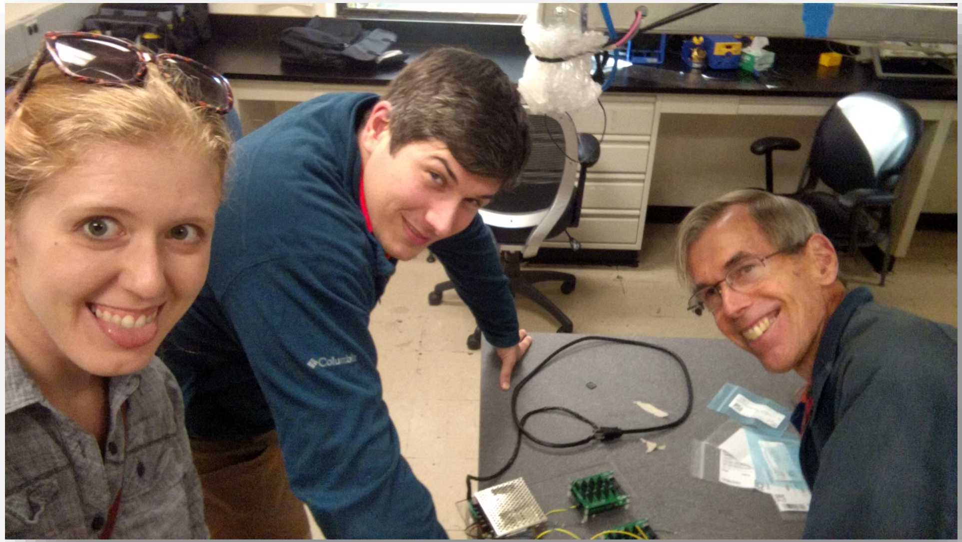


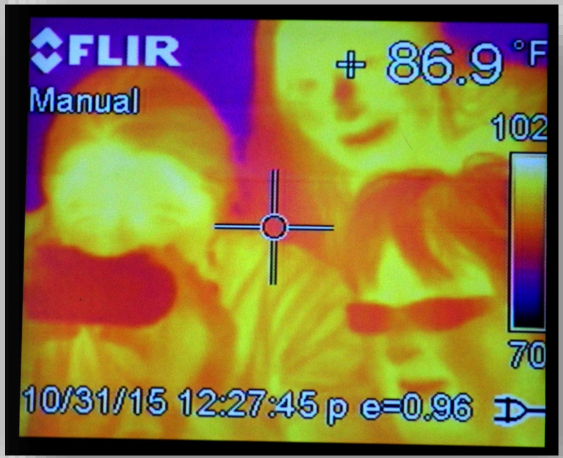

BISTRO • BAR • DESSERT


Laura Hallock
Gary A Hallock
Kelsey Hallock
katherinevollenweider
Patricia Hallock
Terry
Corey
Doreen Hallock
Andrea Dacka




CALTOPIA
20 19




FLIR
Manual
+ 86.9 °F
102
70
10/31/15 12:27:45 p e=0.96






Great minds like a think.





Someone brought their dog to lab 😍