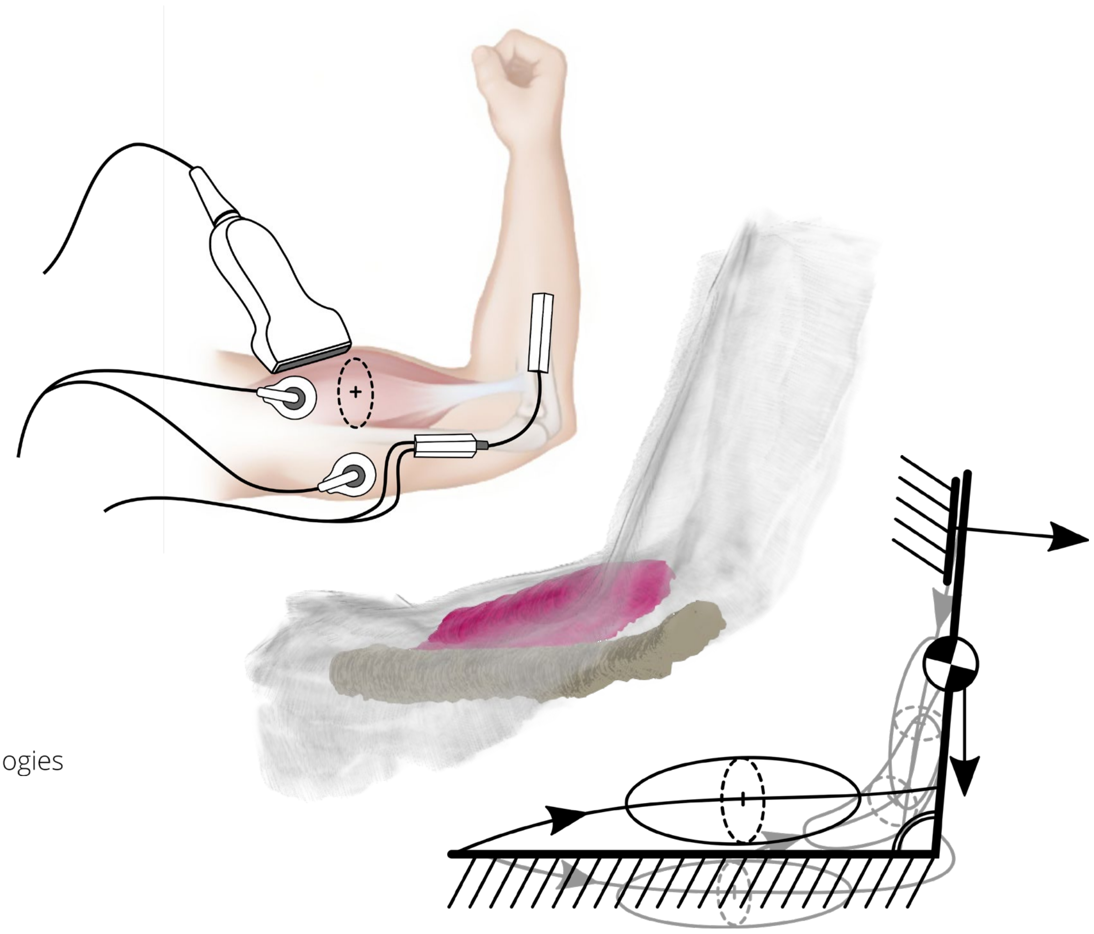
A systematic modeling framework for deformation-based muscle force inference

Laura Hallock

Sternad Group Meeting
Northeastern University
2019.12.06

HART Lab
Human-Assistive Robotic Technologies



Why measure individual muscle forces?

> *“Despite great scientific efforts, we have* ***no accurate, non-invasive, and simple way of measuring [or predicting] individual muscle forces*** *. . . during human movement. I believe [solving this problem] will* ***catapult our understanding of animal movements and locomotion into new and exciting dimensions****.”*

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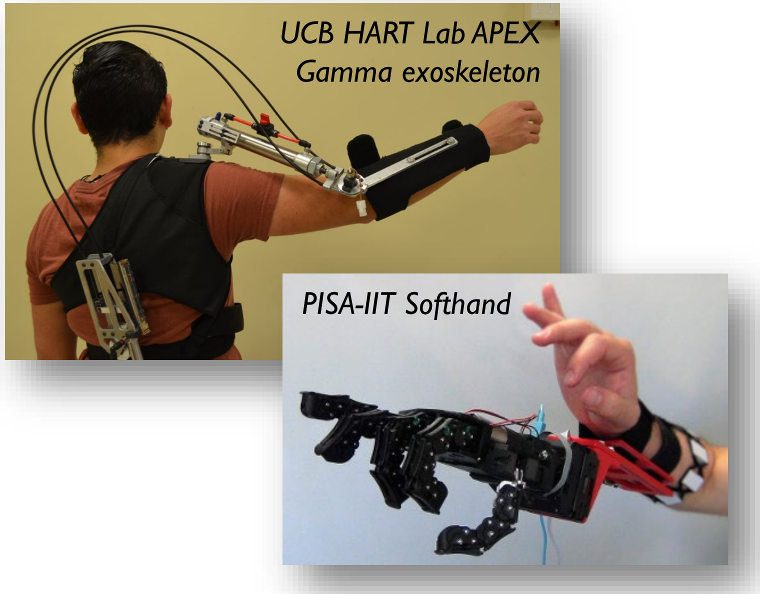
Safe and Expressive Device Control



UCB HART Lab APEX Gamma exoskeleton

PISA-IIT Softhand

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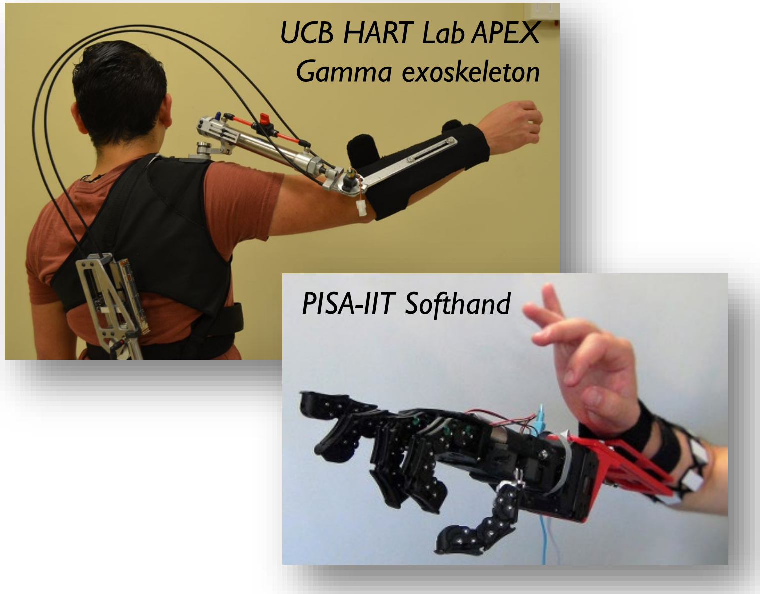

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Understanding of Highly Dexterous Movements

Contact juggling, GIPHY

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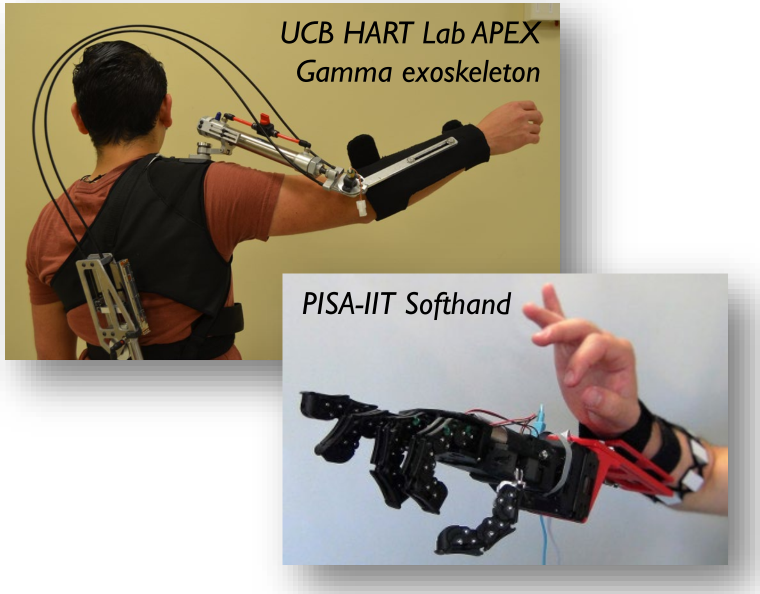

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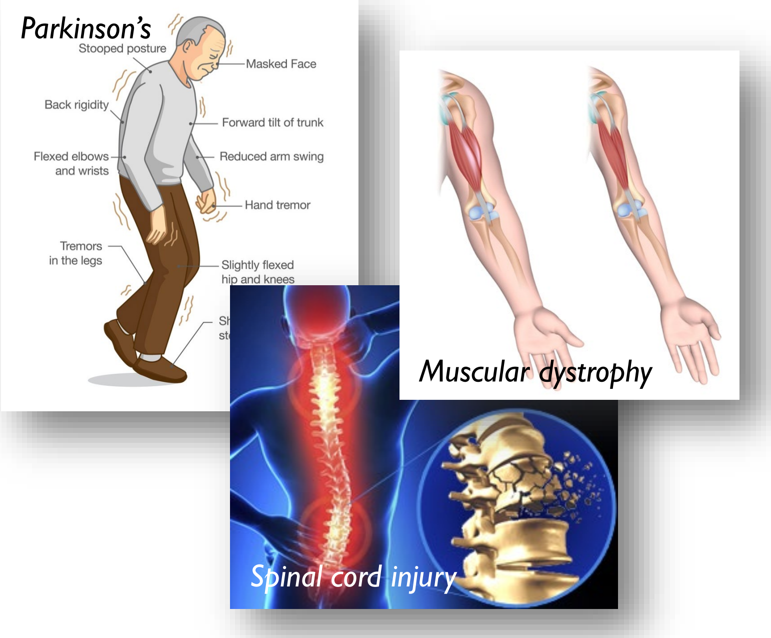
Diagnosis and Rehabilitation of Pathology



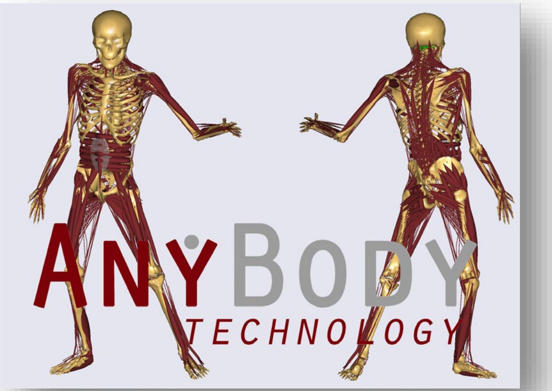
Parkinson's

Spinal cord injury

Muscular dystrophy

Muscle Force Inference: State-of-the-Art Shortcomings

[Delp et al. 2007]



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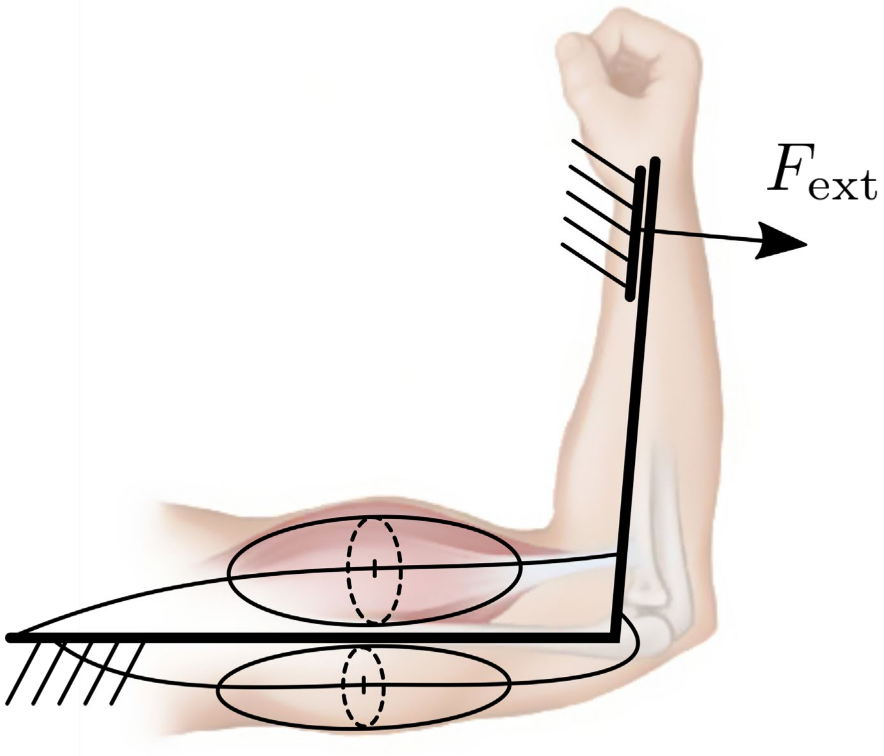

Humans are **highly over-actuated**, and existing modeling frameworks make **significant assumptions about muscle force distribution**.

Muscle Force Inference: State-of-the-Art Shortcomings

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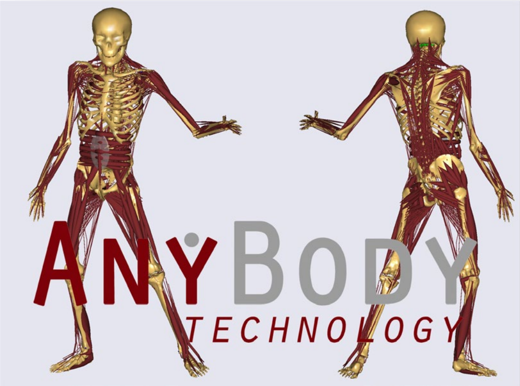

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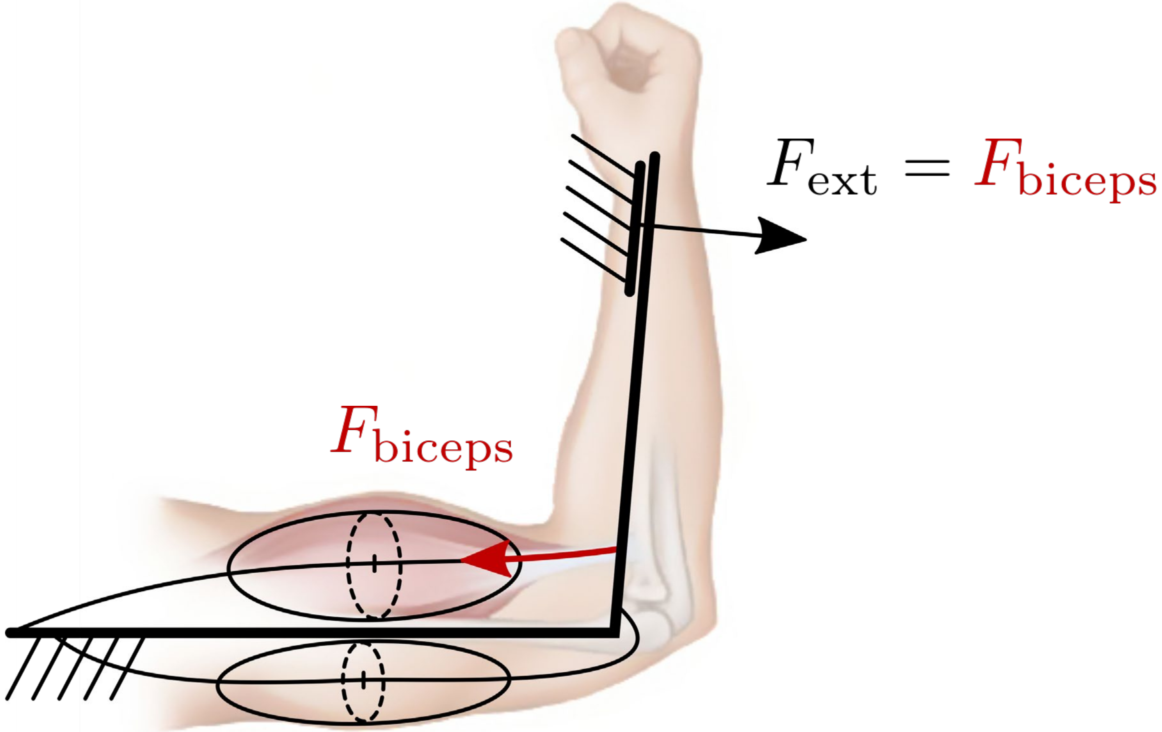

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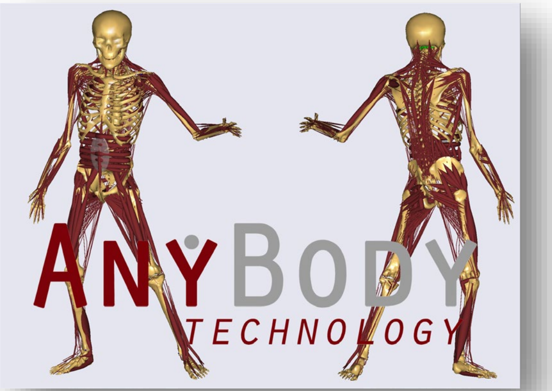

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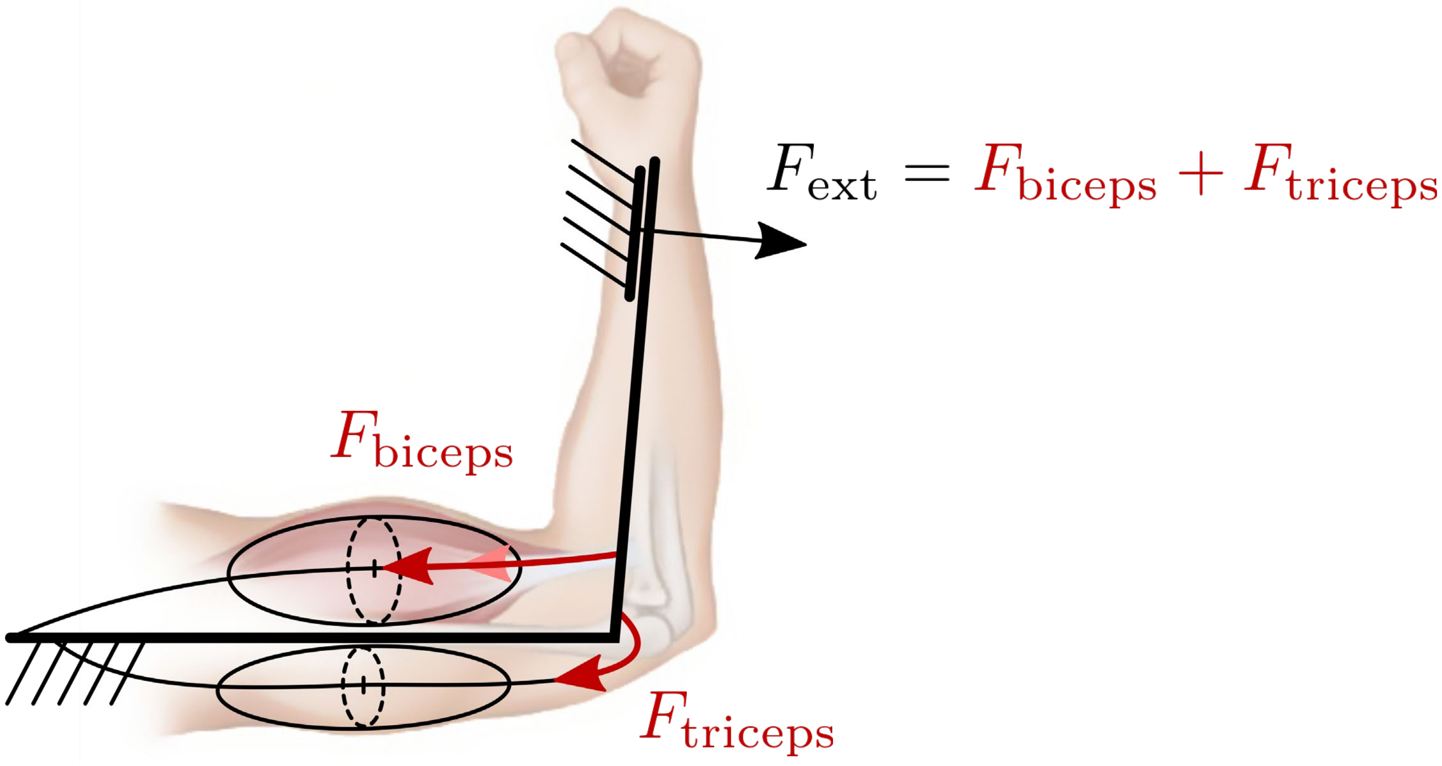

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Muscle Force Inference: State-of-the-Art Shortcomings

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

Contraction Dynamics
$f(\cdot)$

Muscle Output Force
$F_m = f(a)$

Muscle Force Inference

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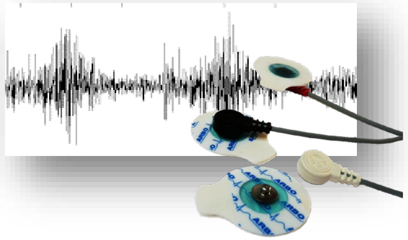

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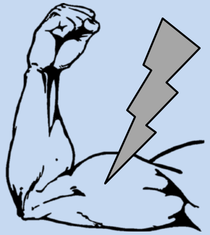


Deformation Dynamics

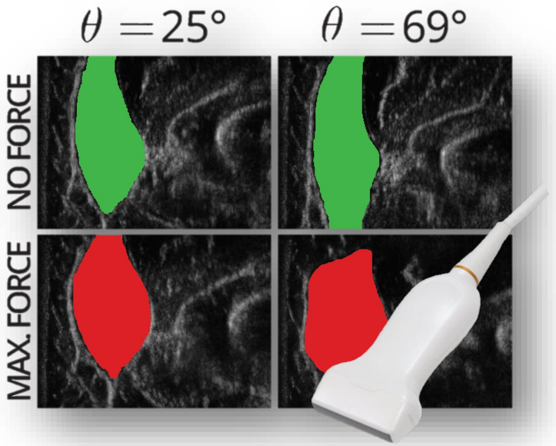
$g(\cdot)$

Muscle Output Force

$$F_m = f(a)$$

Muscle Deformation

$$D = g(F_m)$$



via ***ultrasound***

Muscle Force Inference: Our Approach

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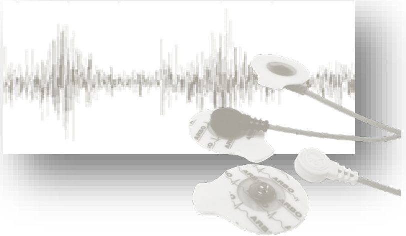

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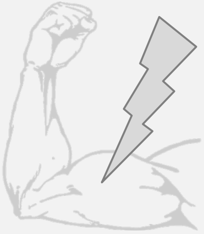

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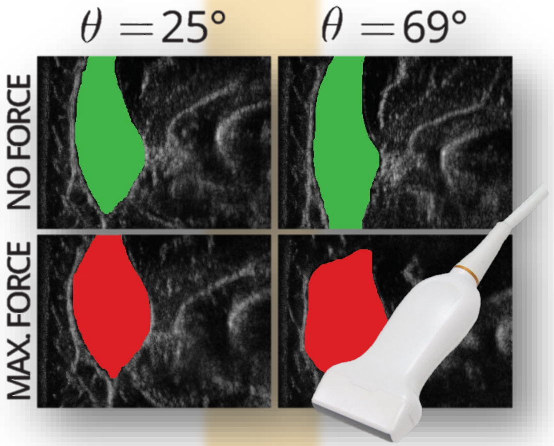

via ***ultrasound***

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

Roadmap

CORE OBJECTIVE

We seek to measure **individual muscle forces** in vivo via **ultrasound** based on **shape changes** under loading.

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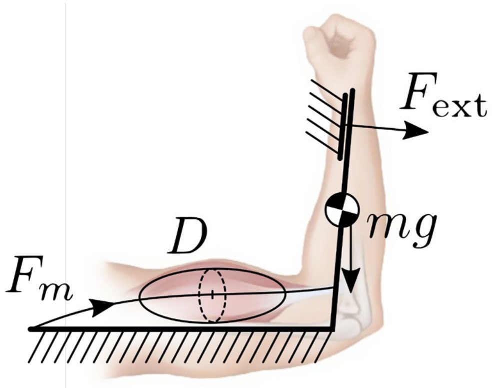

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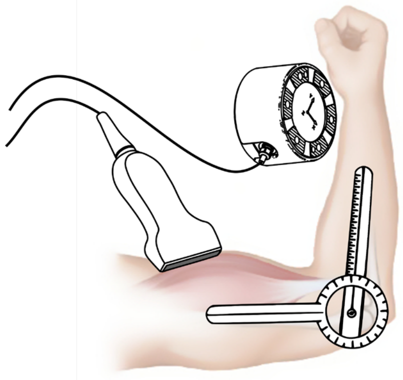

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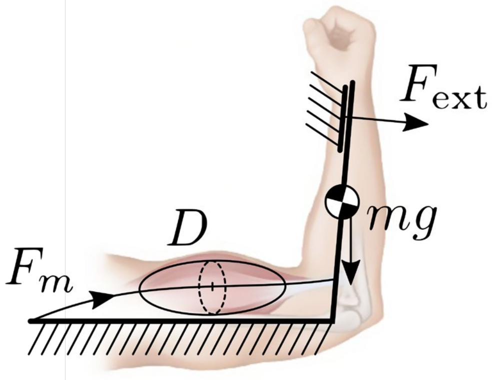

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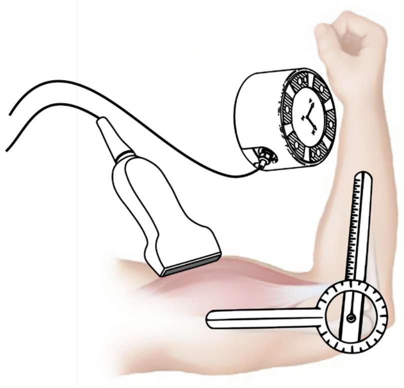

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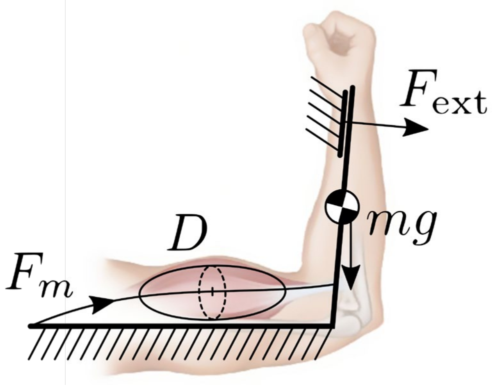
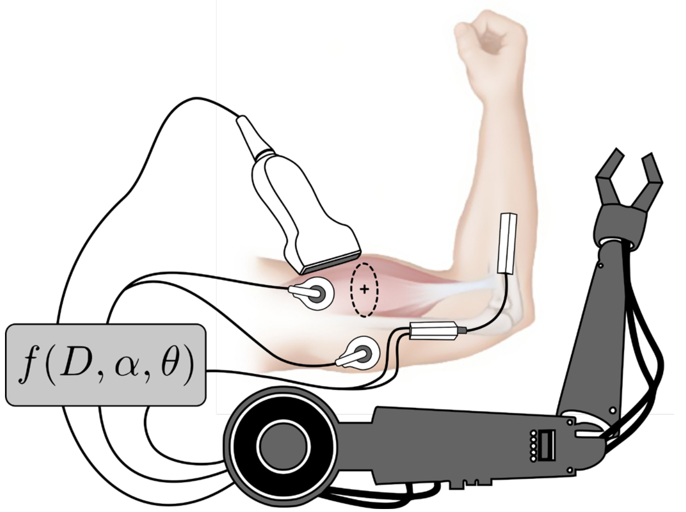


III Proof-of-Concept Applications



Alternate Modalities & Conclusions

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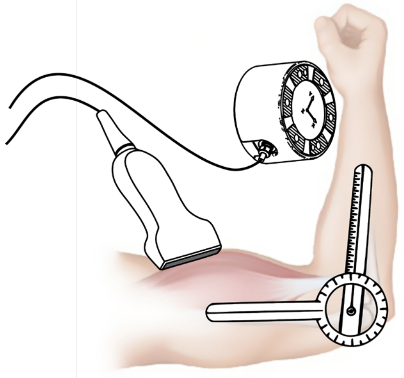

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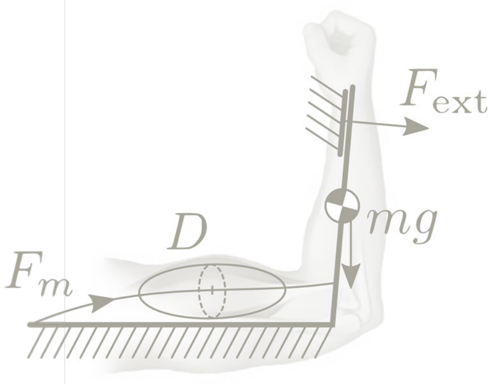

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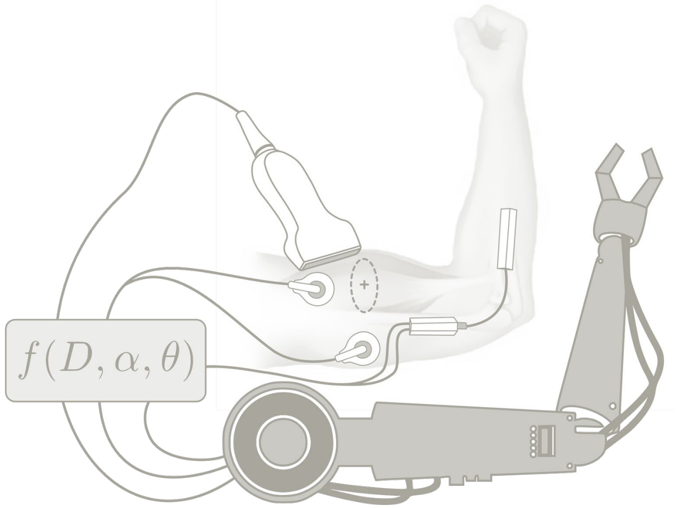

Alternate Modalities & Conclusions

Muscle Force Inference: Our Approach

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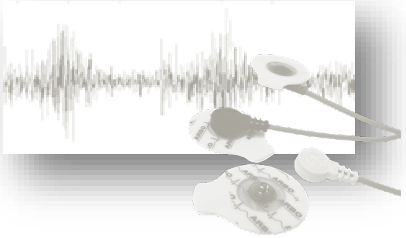

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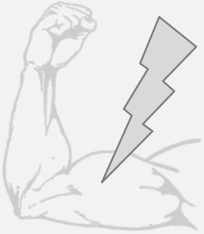

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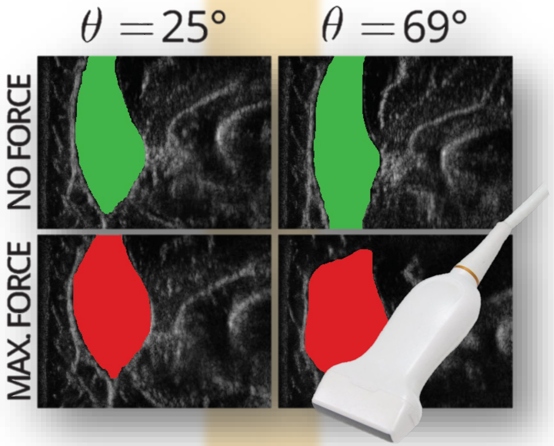

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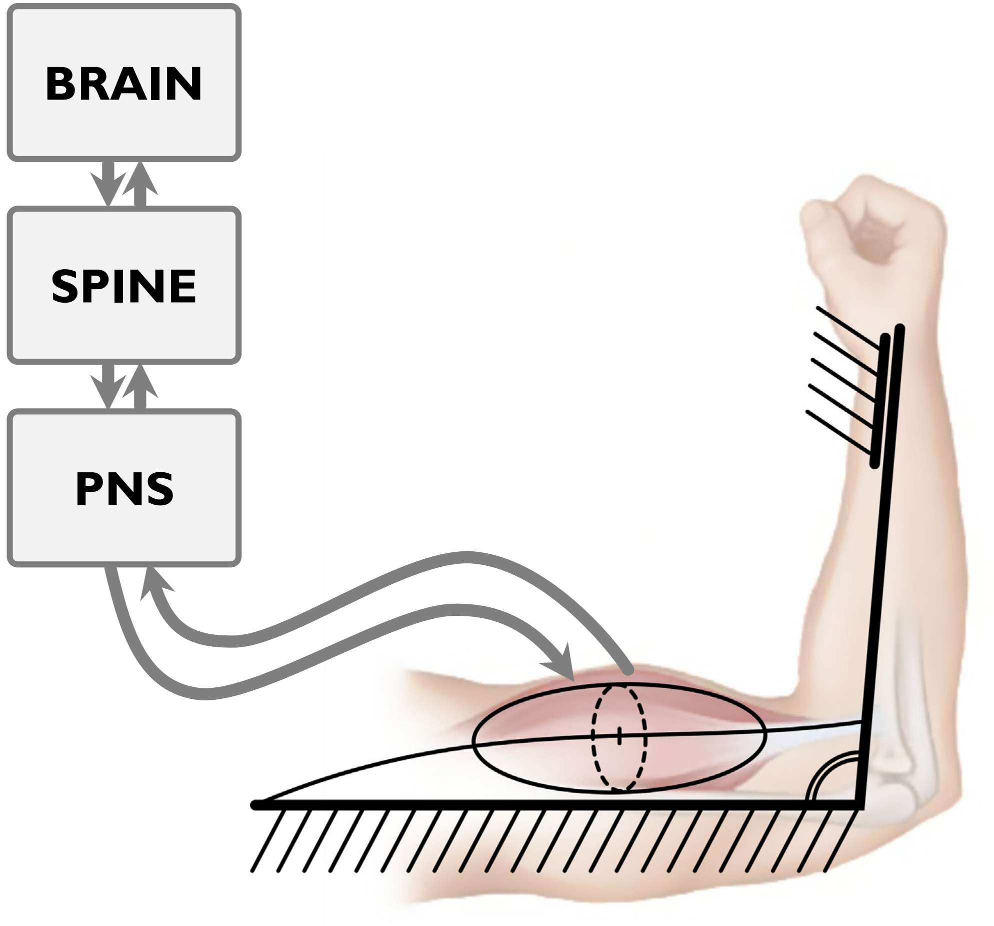
What should this model look like?

(Simplified) **Biological Mechanism**



When muscles are activated by the nervous system, they contract, extending springlike **tendons**, which impart force to the skeleton.

Muscles are **isovolumetric**, so **decreases in muscle length** result in **increases in cross-sectional area** that should be visible in our data set.

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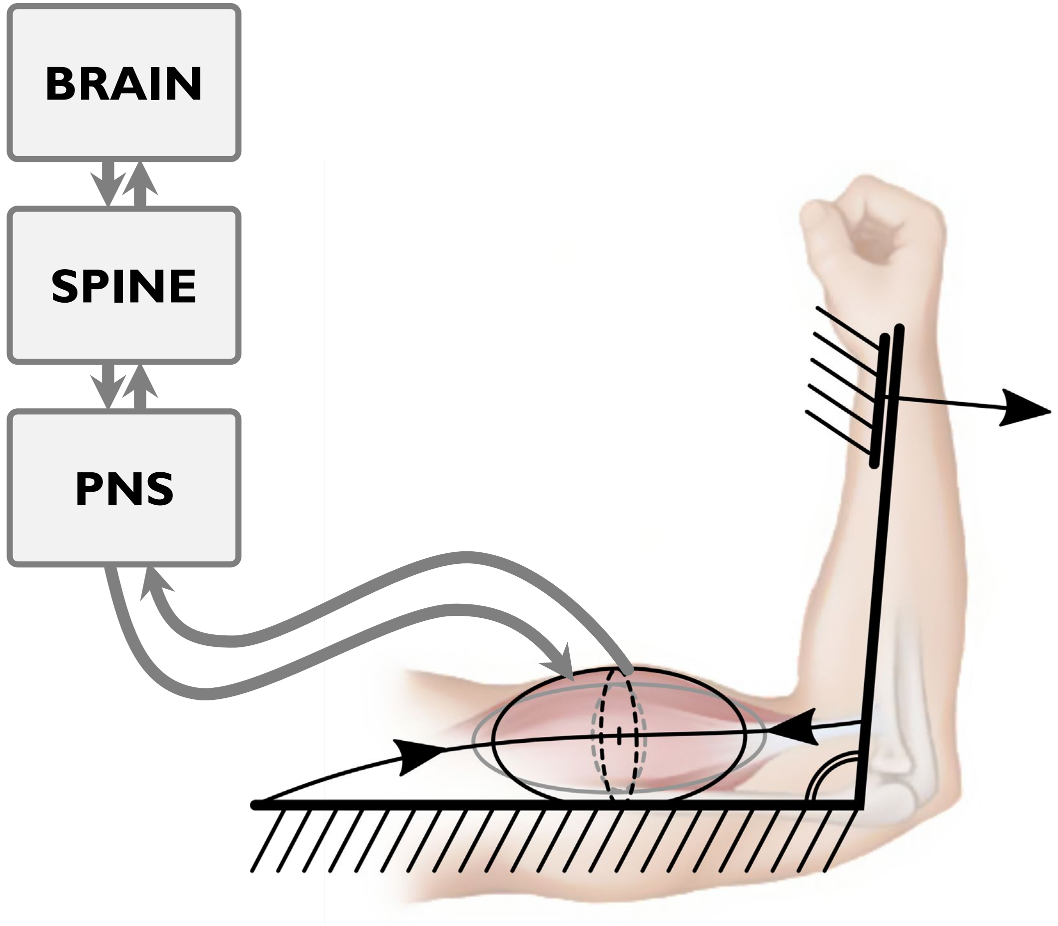

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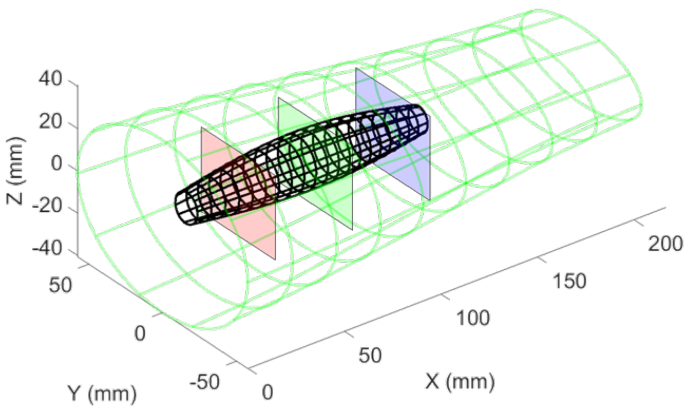
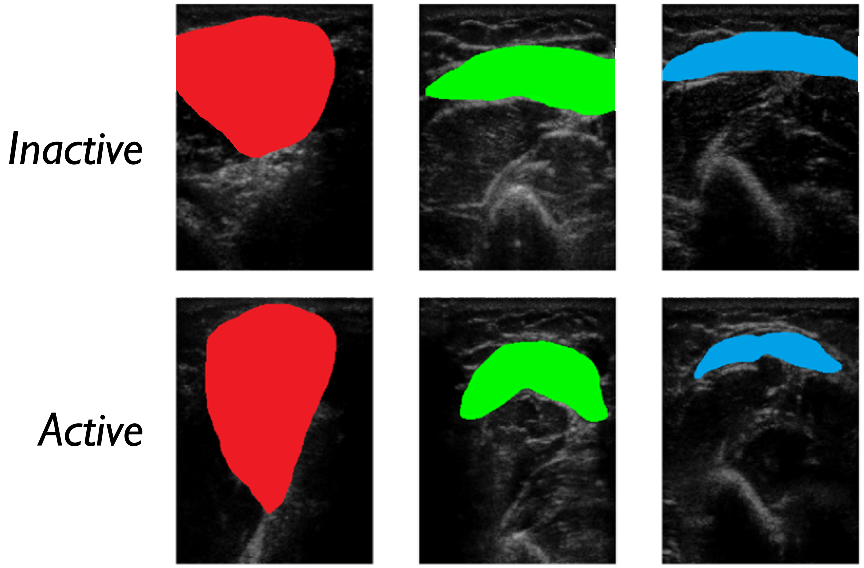
Deformation Modeling Challenges

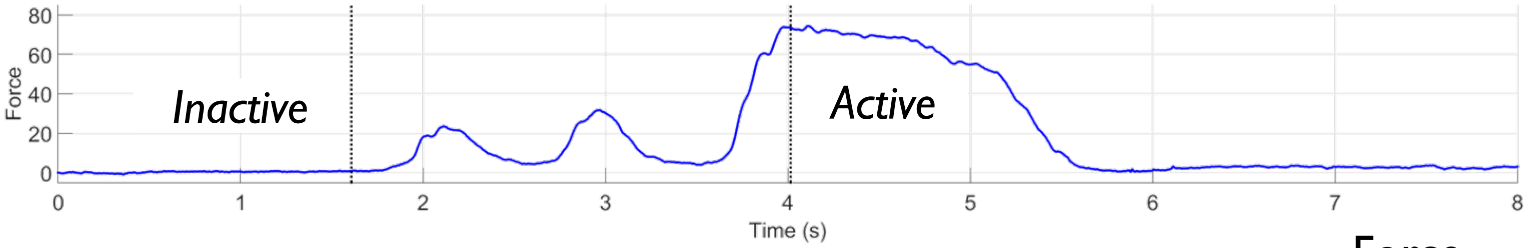
1. Observed deformation **varies substantially with sensor location**.

3D View



Muscle Cross-Section *(Brachioradialis)*





Force

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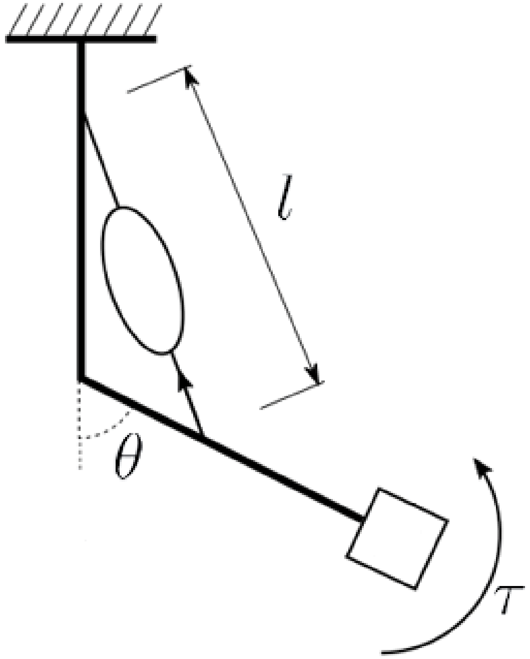
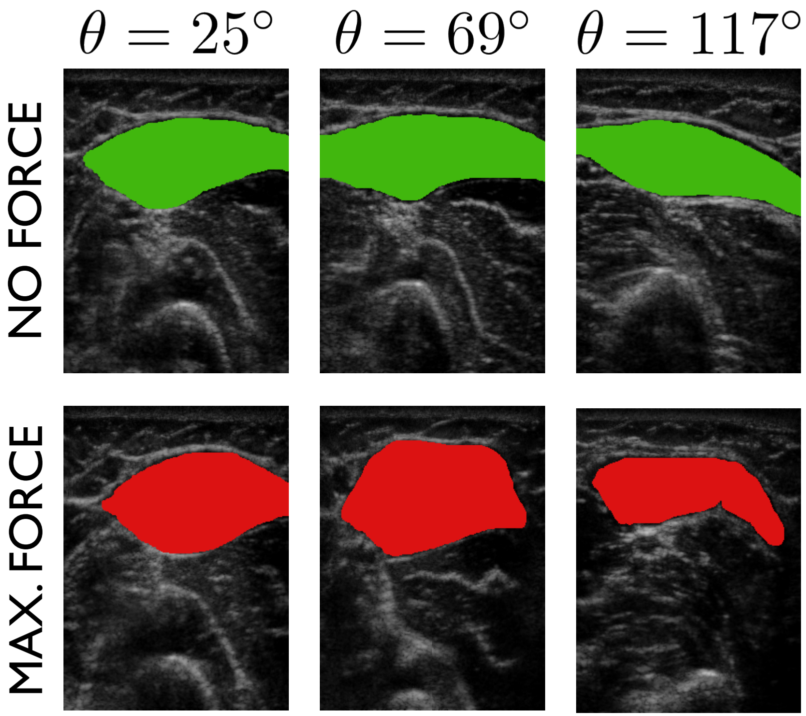
2. Deformation occurs under changes in both **kinematic configuration** and **force output**.





Deformation Modeling Challenges

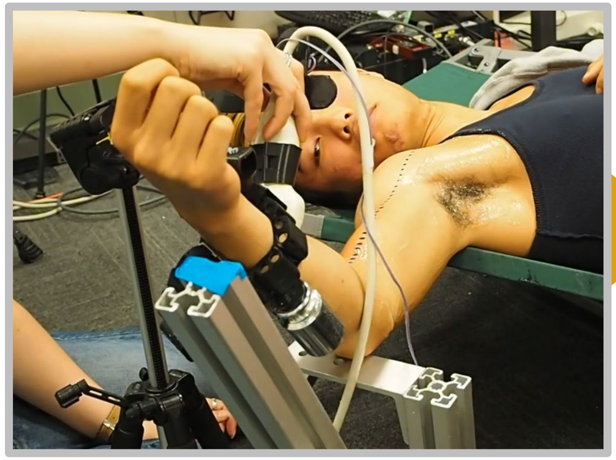
1. Observed deformation **varies substantially with sensor location**.

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

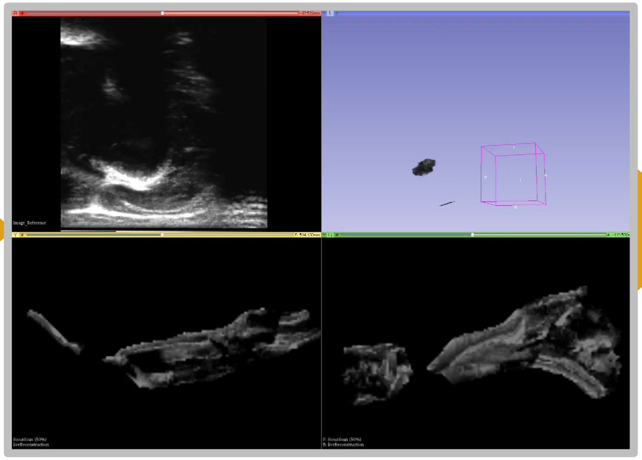
To build a model that can robustly infer muscle force, we need to observe the **entire muscle** under **multiple** (ideally, factorial) **joint positions** and **loading conditions**.

Data Collection Setup: Ultrasound + Motion Capture

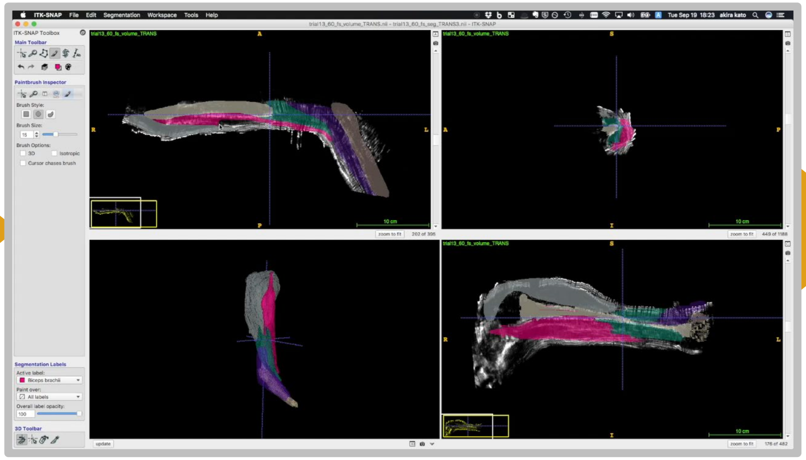
Raw Data Collection
via Ultrasound & Motion Capture



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**.

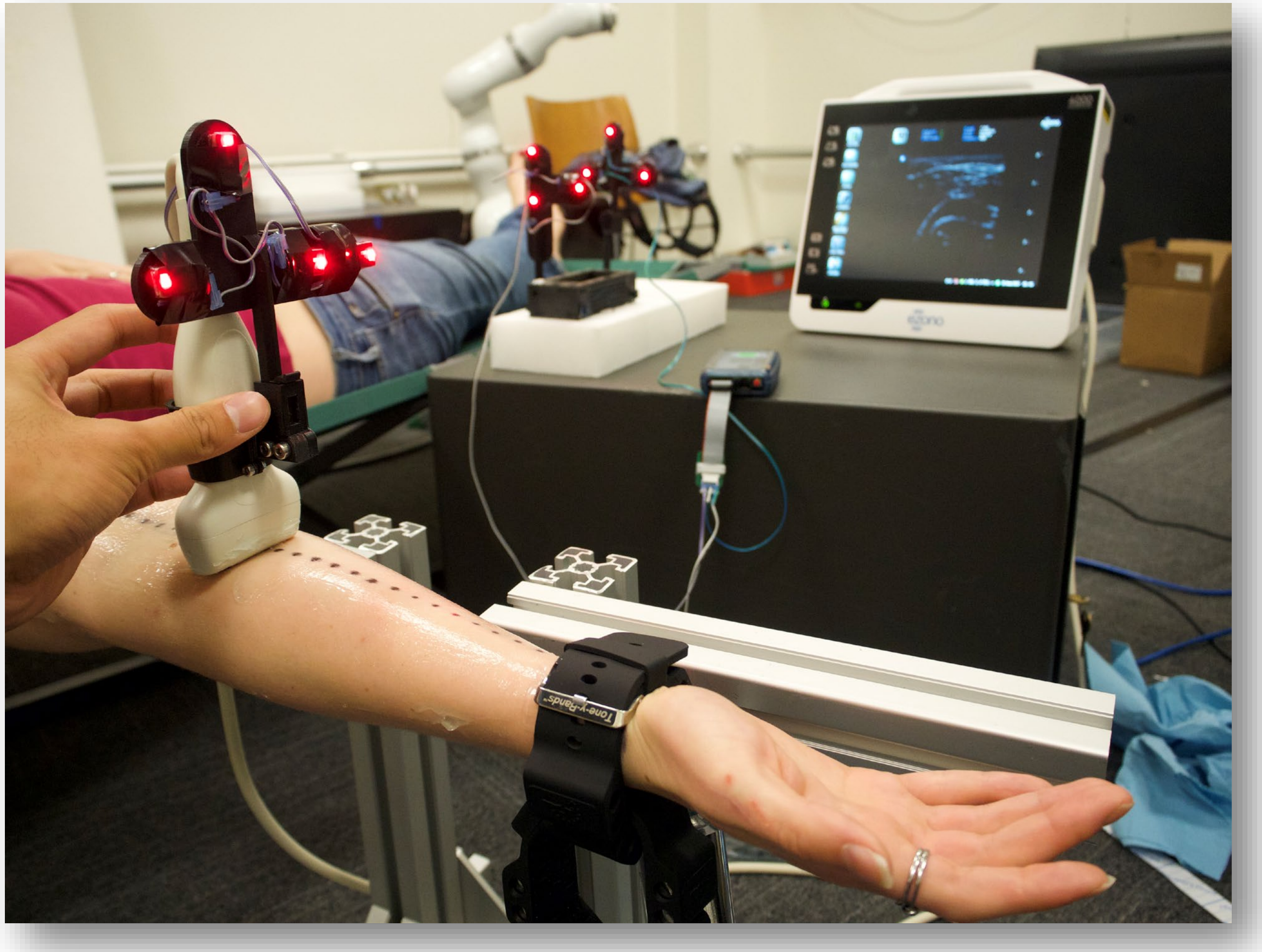
*[**Hallock**, Kato, Bajcsy, ICRA 2018]*

Preliminary Data Set

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

Data set:

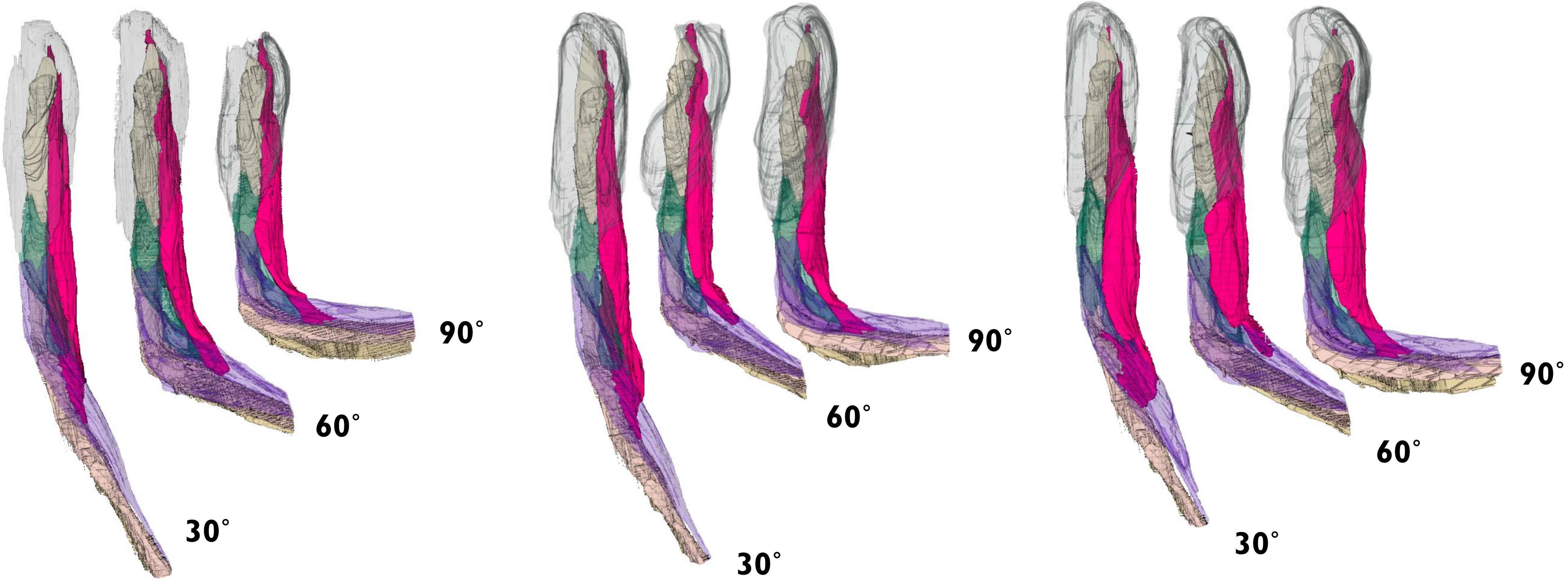
- 3 subjects (1 F, 2 M)
- full arm ultrasound volumetric scan
- 4 elbow flexion angles, 0–90°
- 5 loading conditions
  - ***FS***: fully supported
  - ***GC***: gravity compensation only
  - ***LF***: light wrist weight (~225g)
  - ***MF***: medium wrist weight (~725g)
  - ***HF***: heavy wrist weight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



Ultrasound volumetric data collection, HART Lab 2017

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

Preliminary Results: Qualitative



FS
("Fully Supported")

LF
("Low Force")

HF
("High Force")

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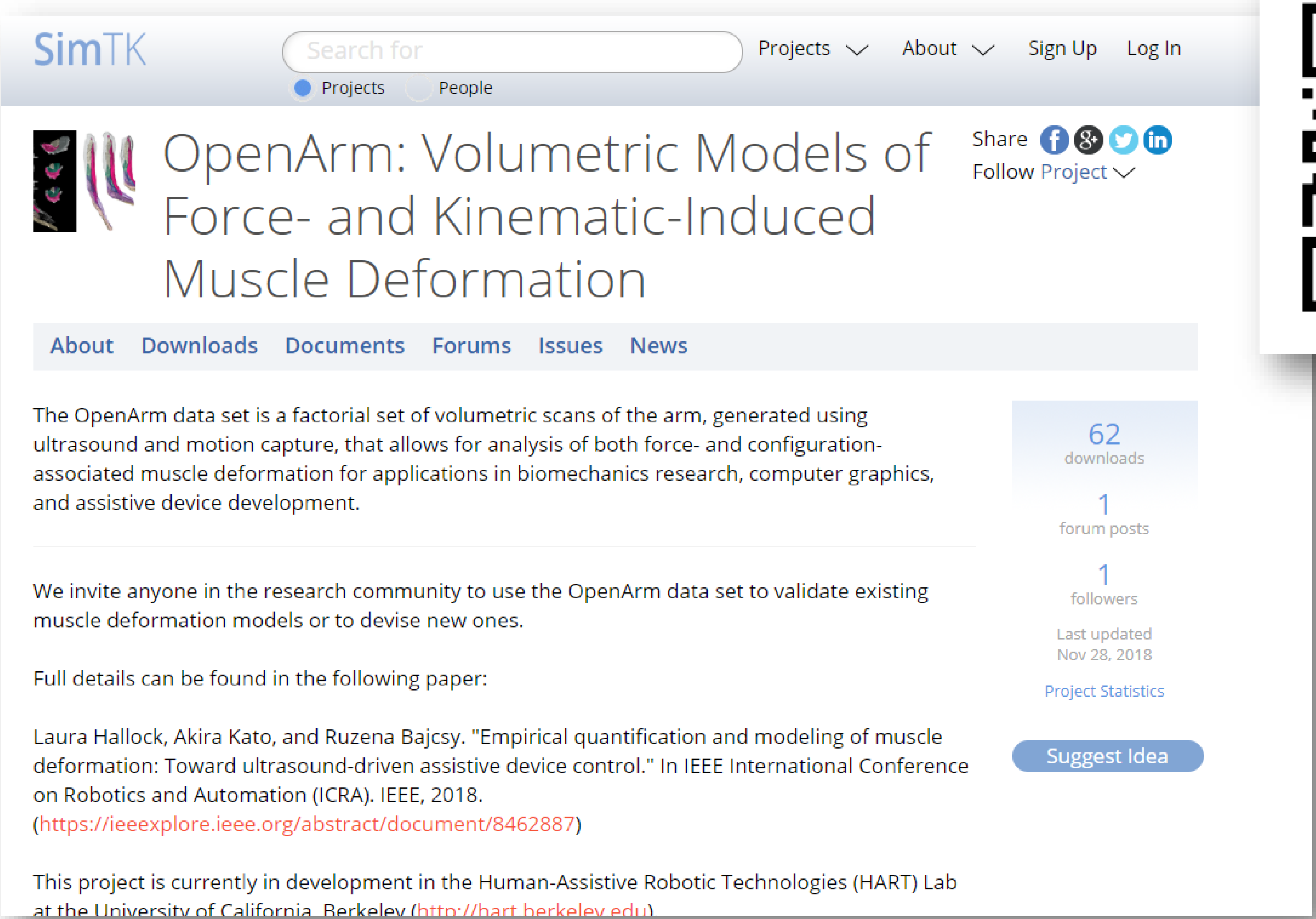
Data Set Release: OpenArm 1.0



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

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)

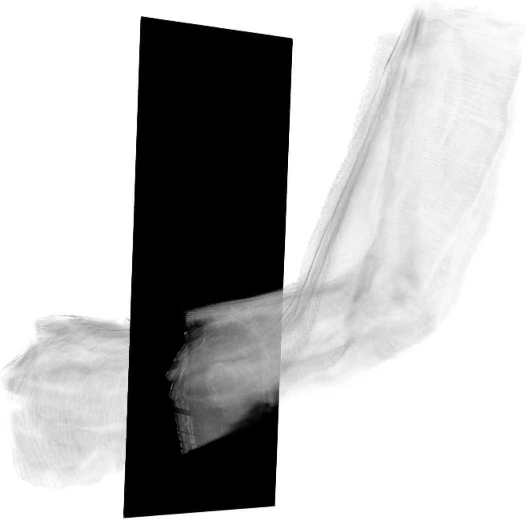
This project is currently in development in the Human-Assistive Robotic Technologies (HART) Lab at the University of California, Berkeley (http://hart.berkeley.edu)

Last updated
Nov 28, 2018

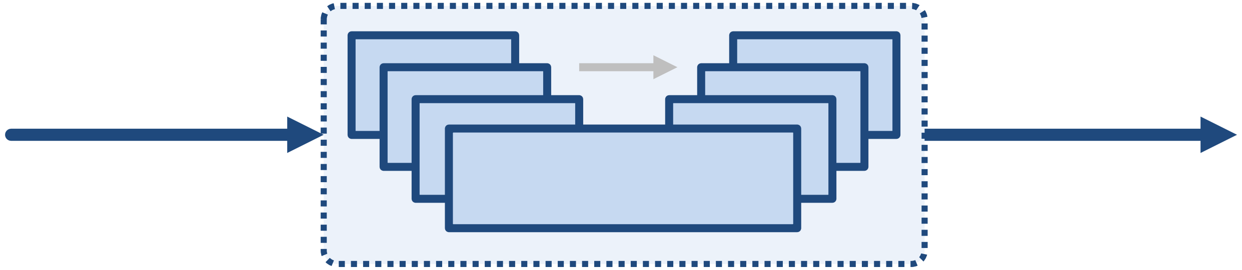
*[**Hallock**, Kato, Bajcsy, ICRA 2018]*

Automated Tissue Segmentation: U-Net

intensity map (2D slice)

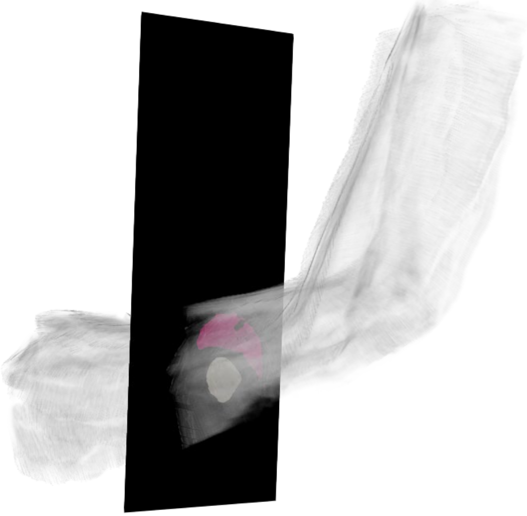


(2D) **U-Net**



[Ronneberger et al. 2015]

output segmentation (2D slice)



[Nozik, **Hallock***, Ho, Mandava, Mitchell, Li, Bajcsy, EMBC 2019]*

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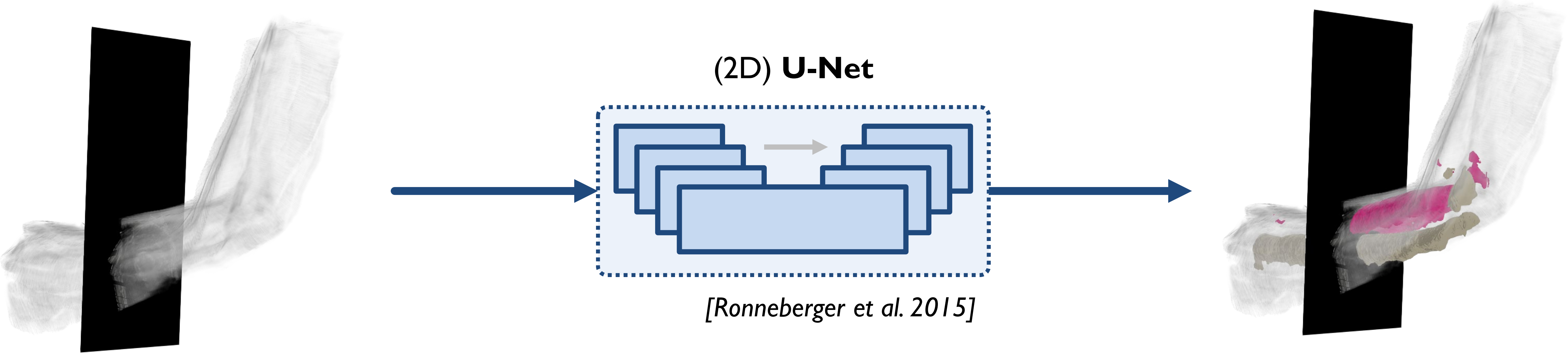

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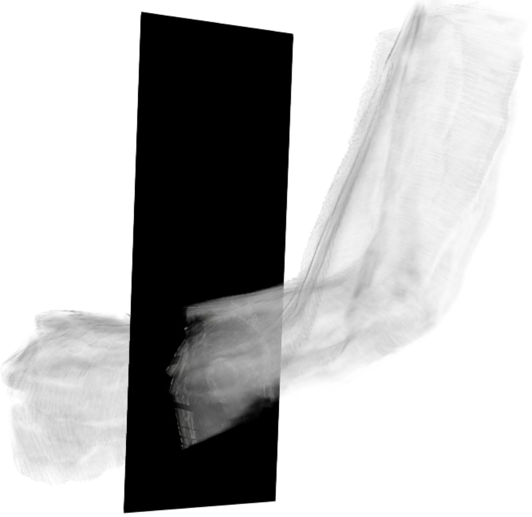

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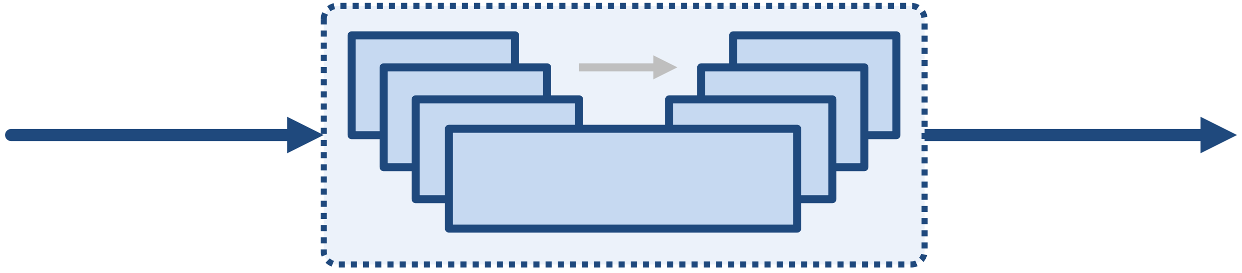

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CNN-based segmentation performs better than classical registration on the **center of the muscle**, where we focus our modeling analyses.

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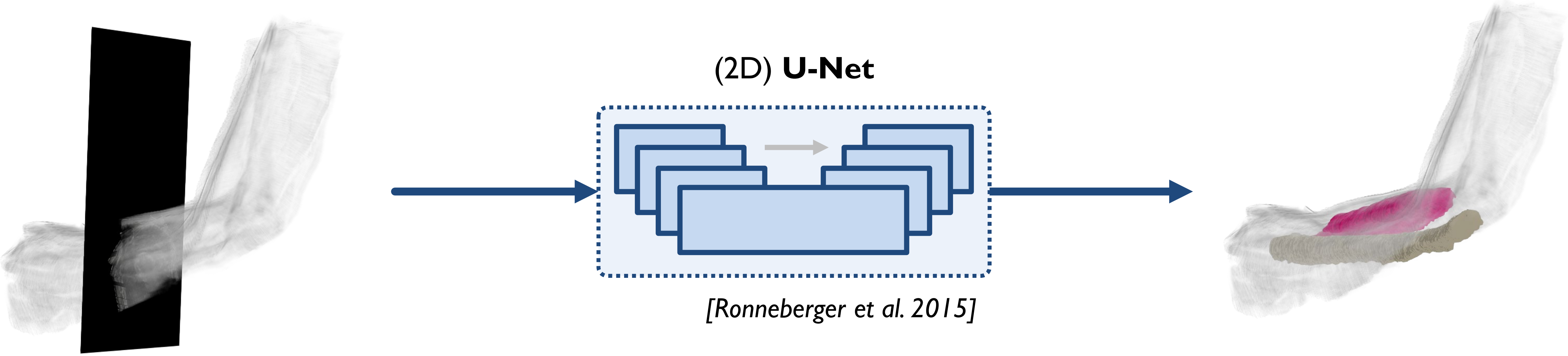

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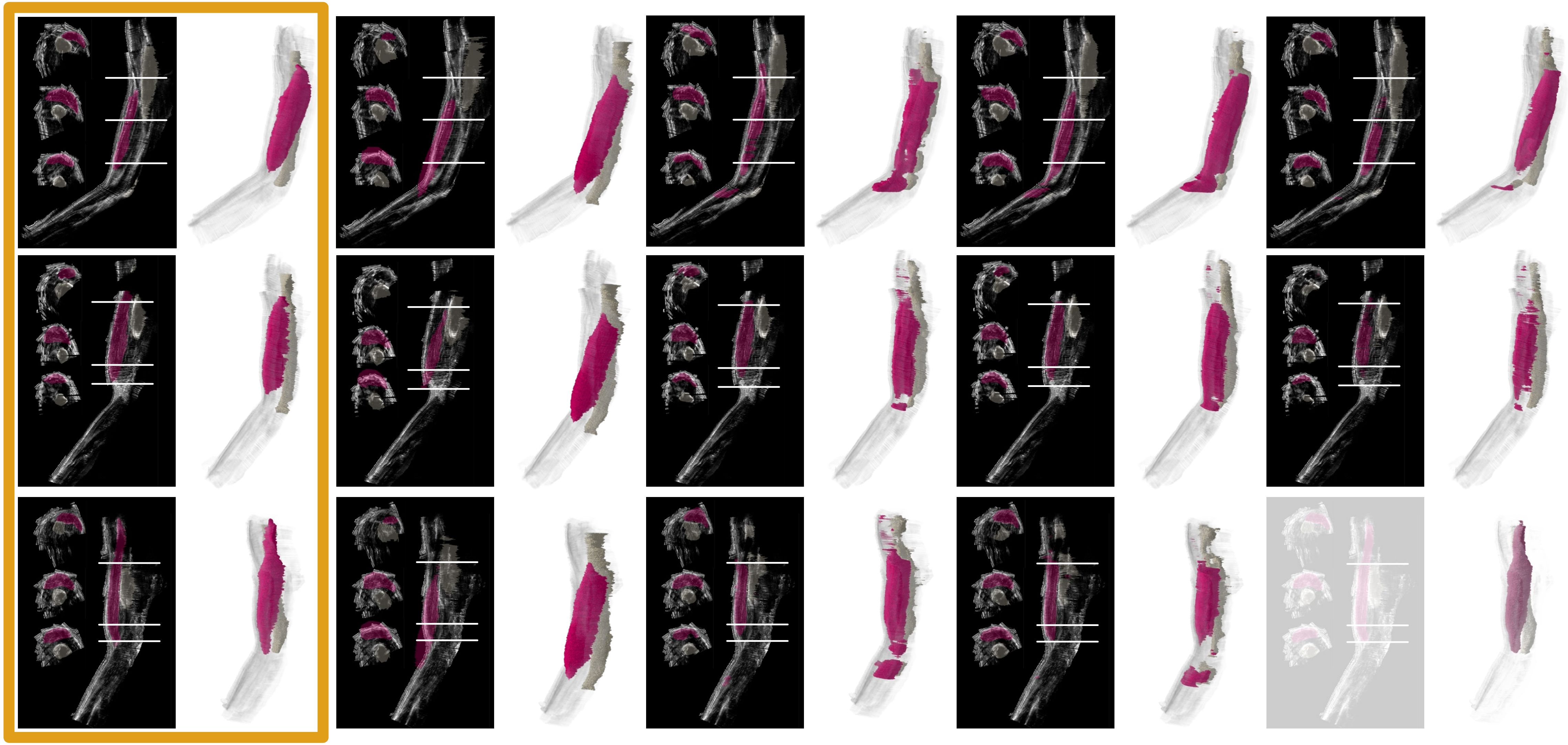
Automated Tissue Segmentation: Preliminary Results

Ground Truth | Registration | U-NET | U-NET+EA | Multi-Subject U-NET+EA

new angle, same force, same subject (*Sub1, 60°, FS*)

same angle, **new** force, same subject (*Sub1, 30°, P3*)

same angle, same force, **new** subject (*Sub2, 30°, FS*)



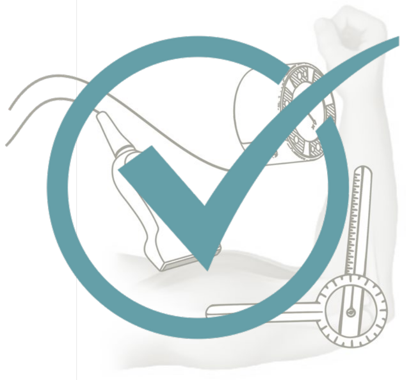
[Nozik, **Hallock***, Ho, Mandava, Mitchell, Li, Bajcsy, EMBC 2019]*

Roadmap

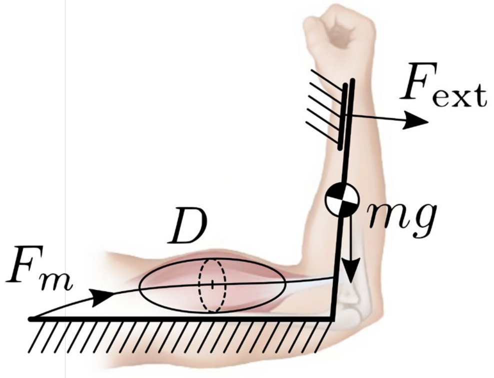
CORE OBJECTIVE

We seek to measure **individual muscle forces** in vivo via **ultrasound** based on **shape changes** under loading.

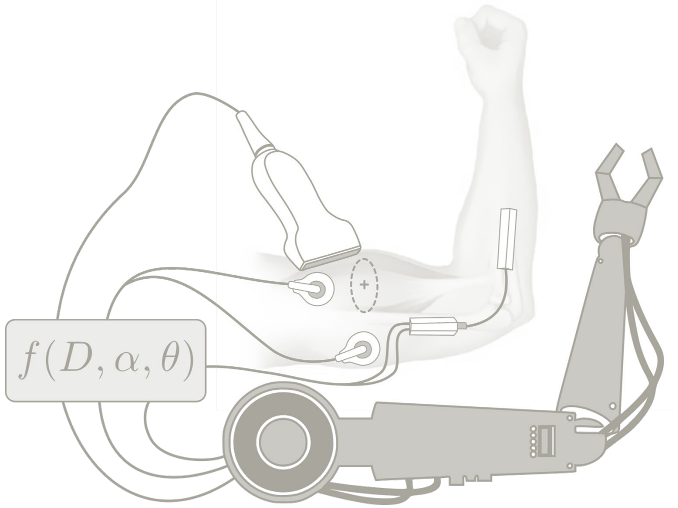
I Exploratory Data Set Generation



II Model Development & Validation

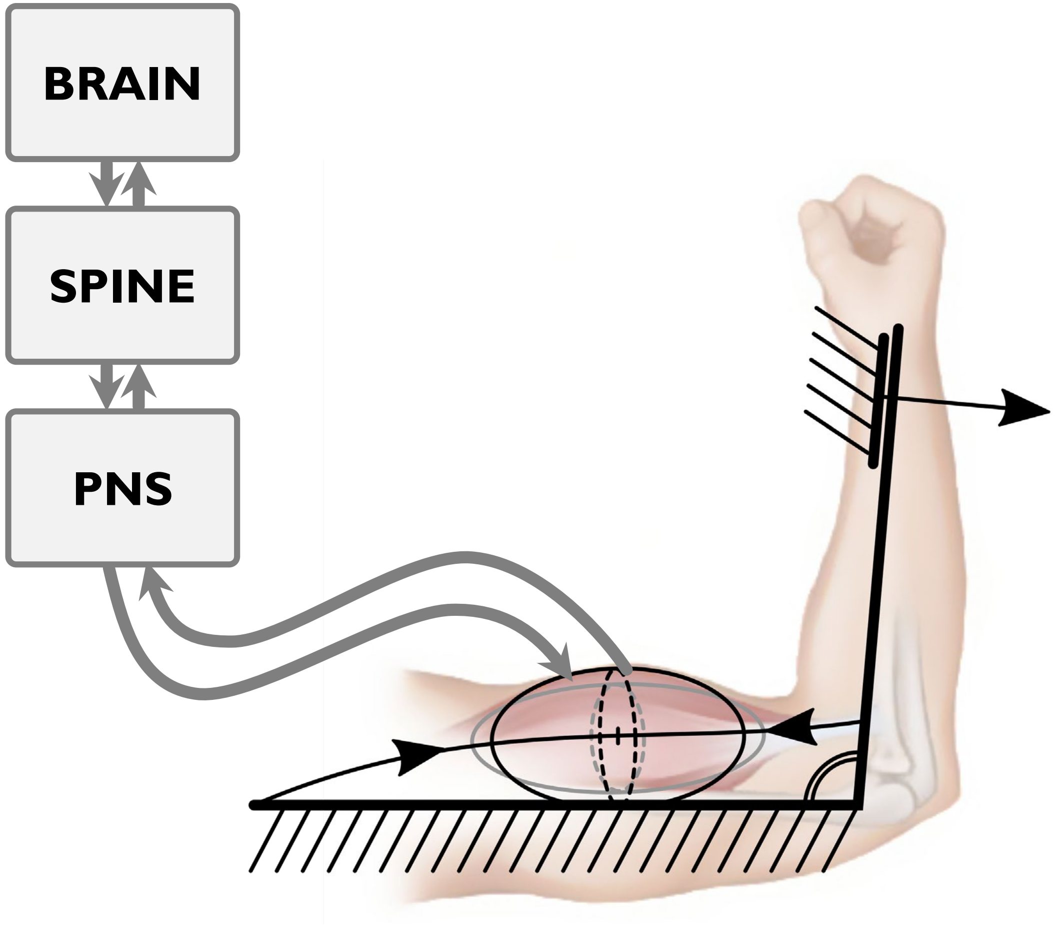


III Proof-of-Concept Applications



Alternate Modalities & Conclusions

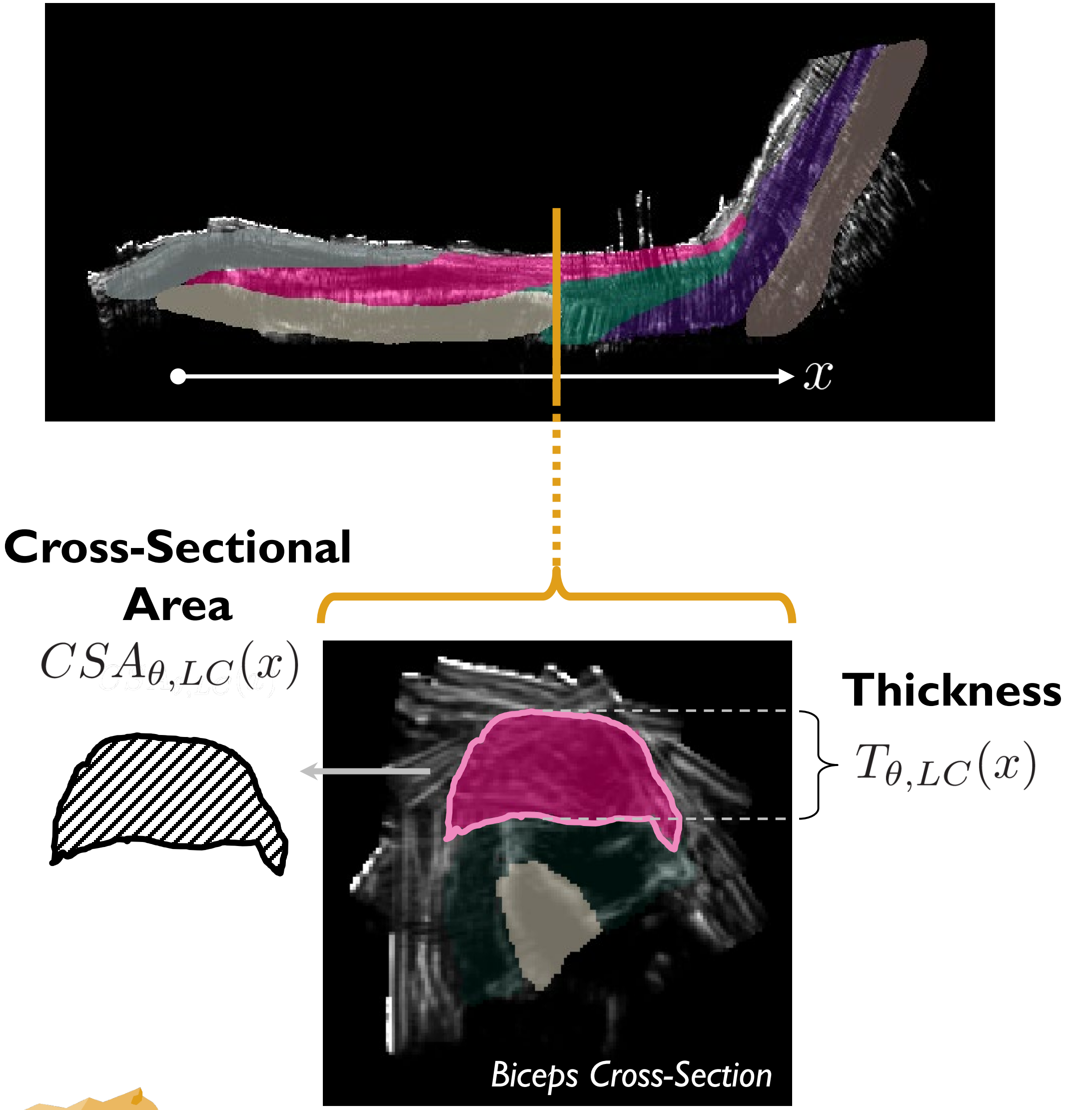
(Simplified) **Biological Mechanism**



How close is what we observe to the simplified model?

Exploratory Data Analysis: OpenArm 1.0

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

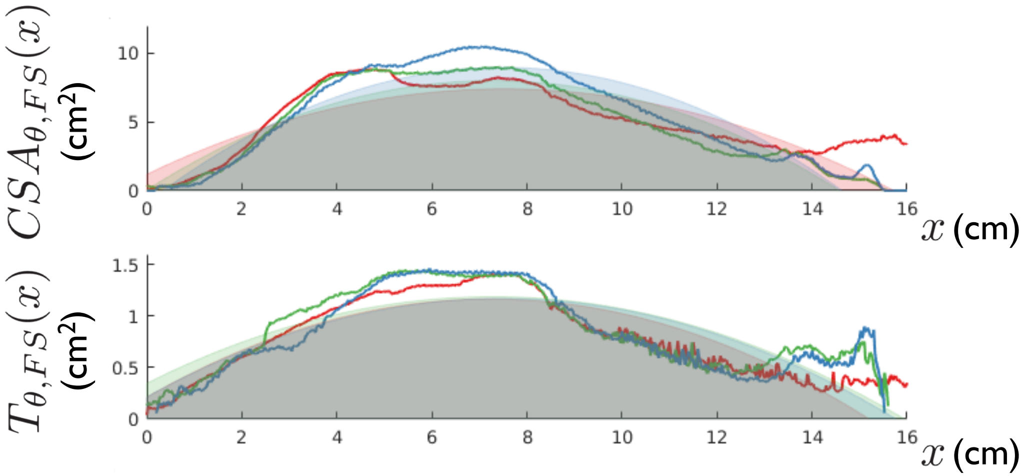


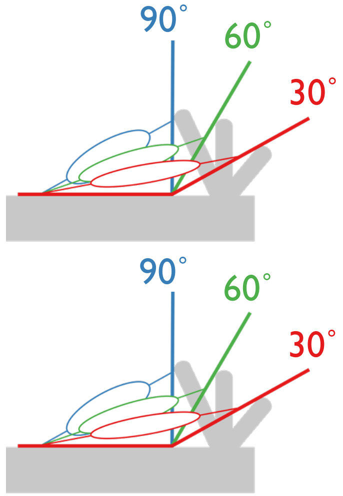
Cross-Sectional Area

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

Thickness

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





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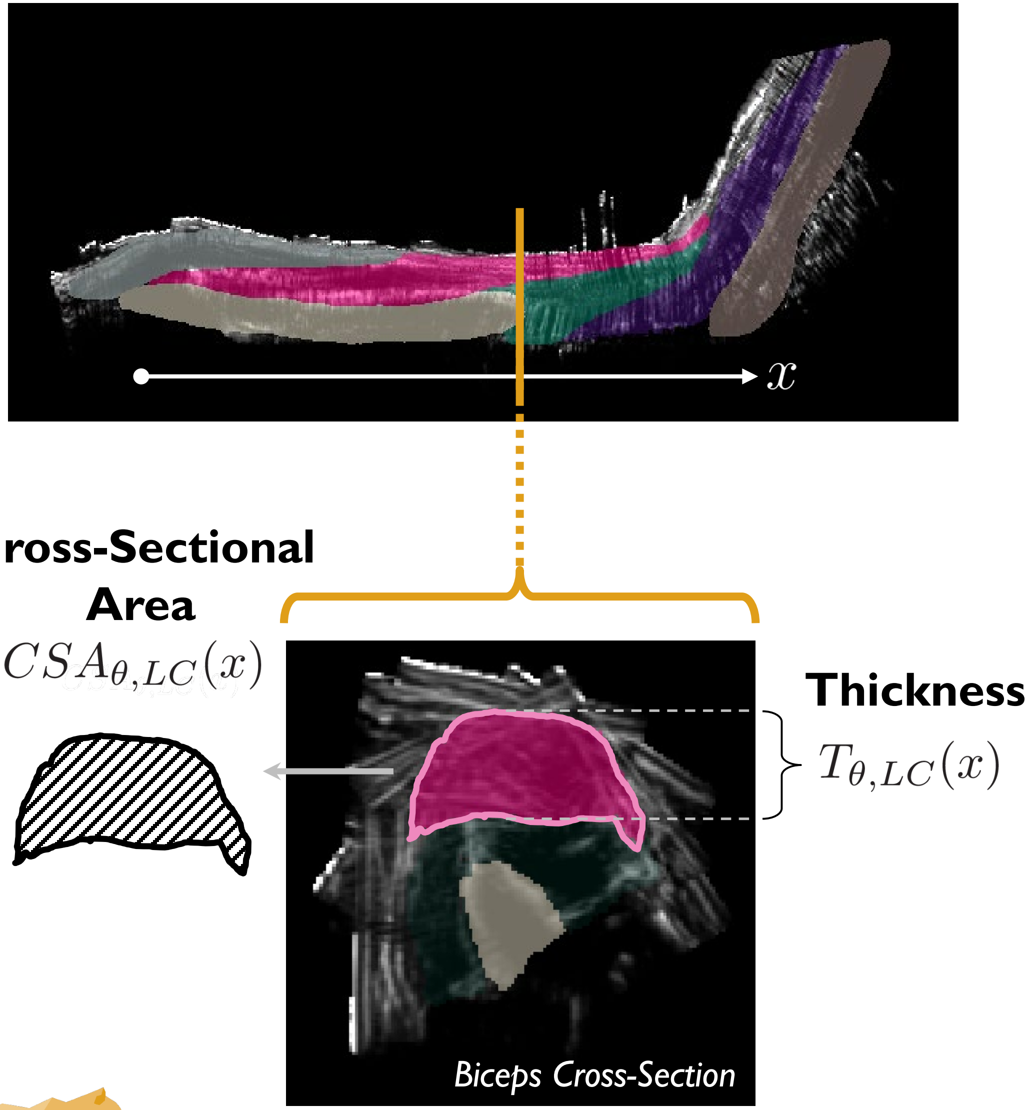

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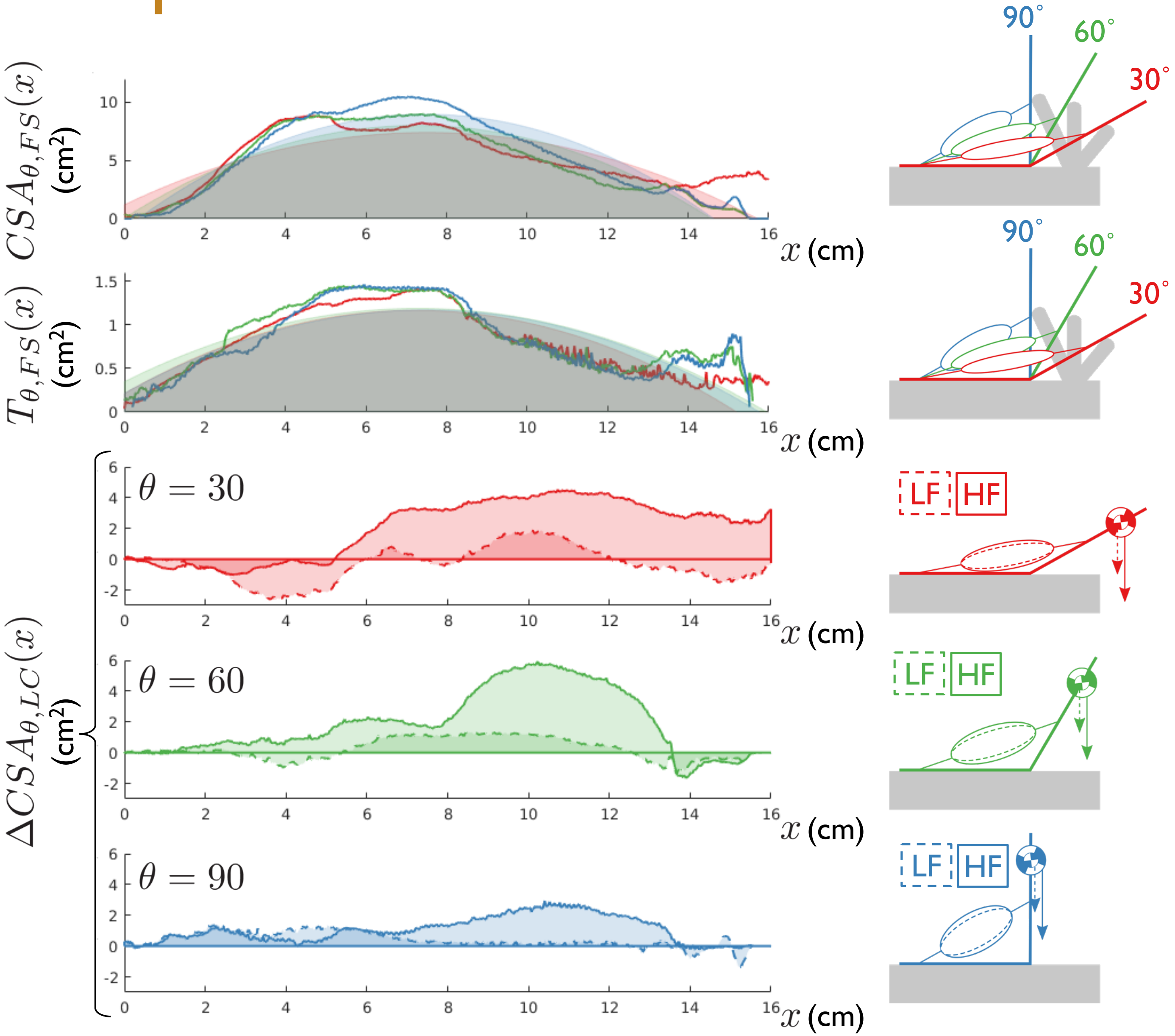

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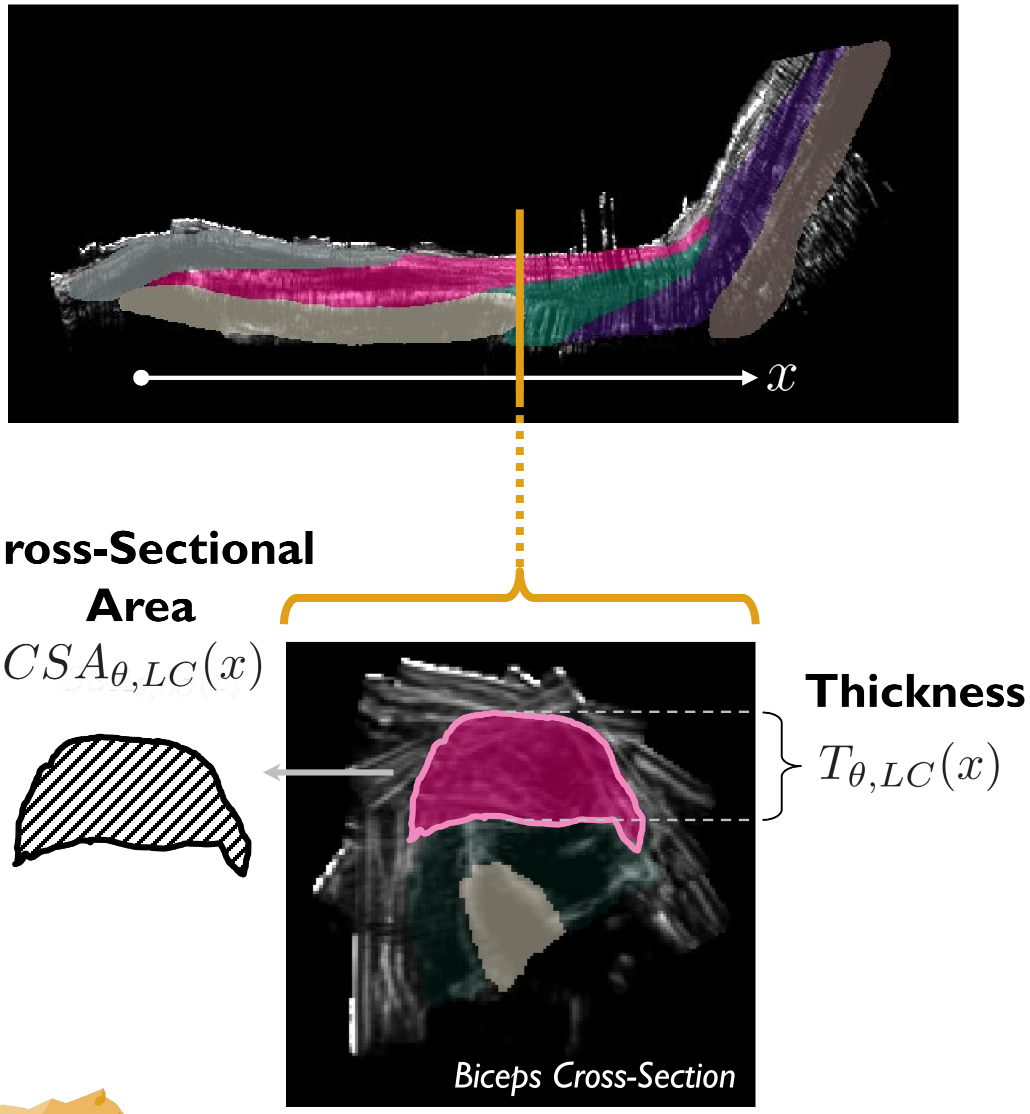

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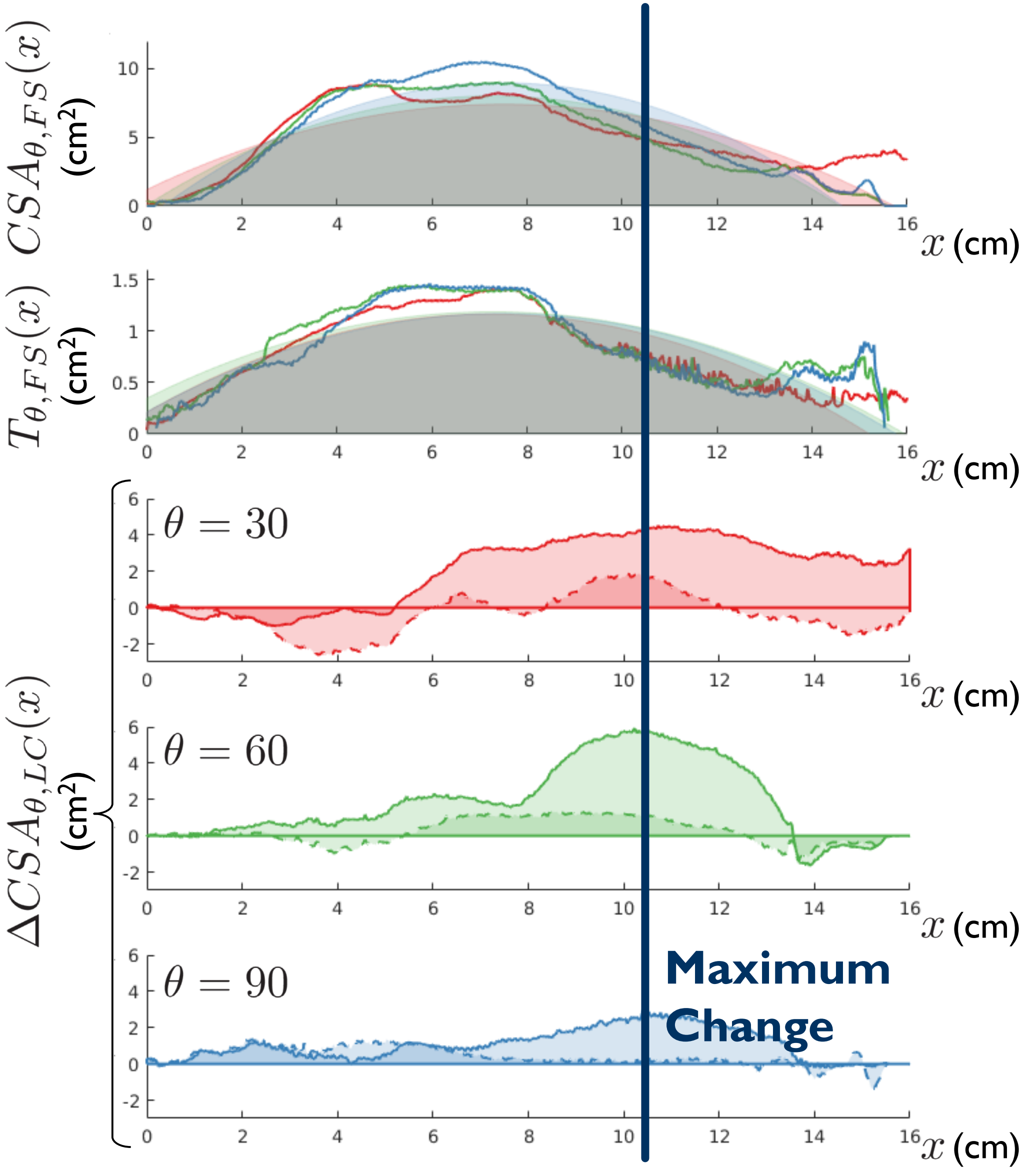

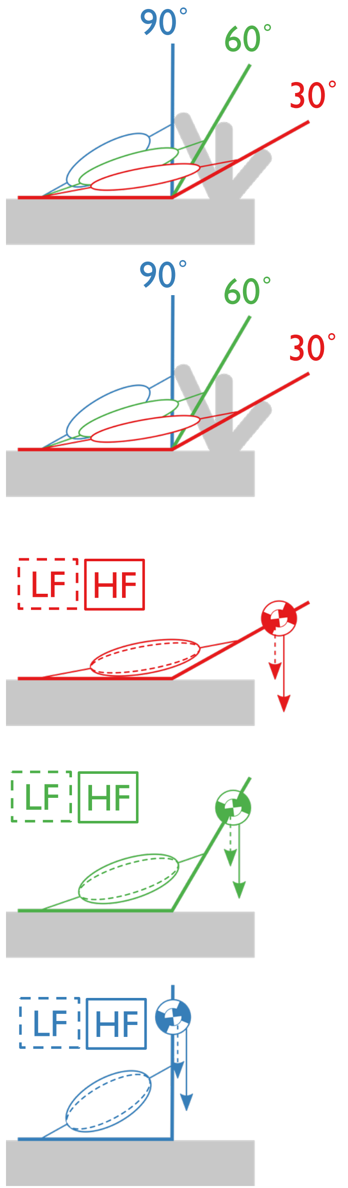

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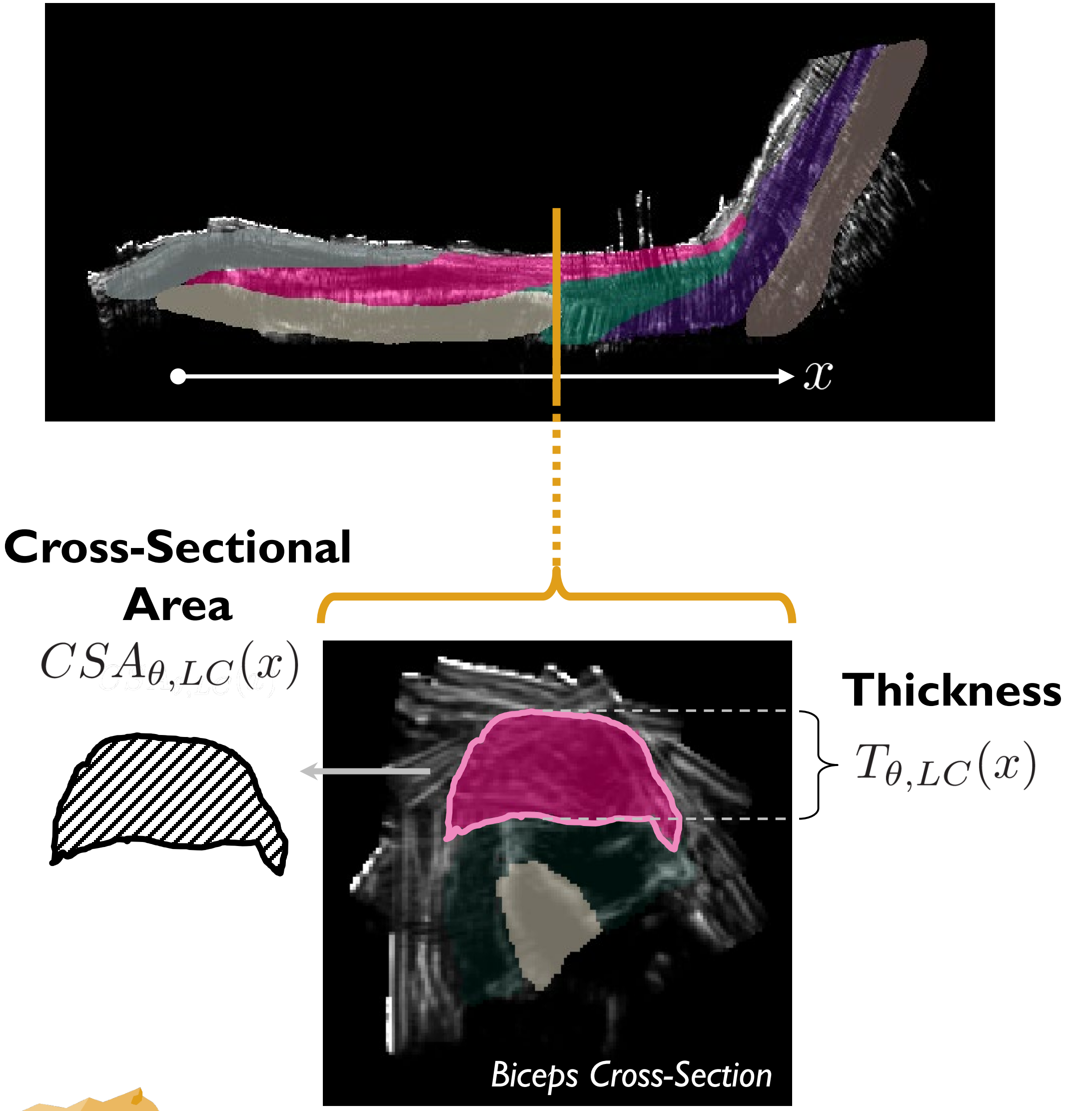
[**Hallock**, Kato, Bajcsy, ICRA 2018]



Cross-Sectional Area
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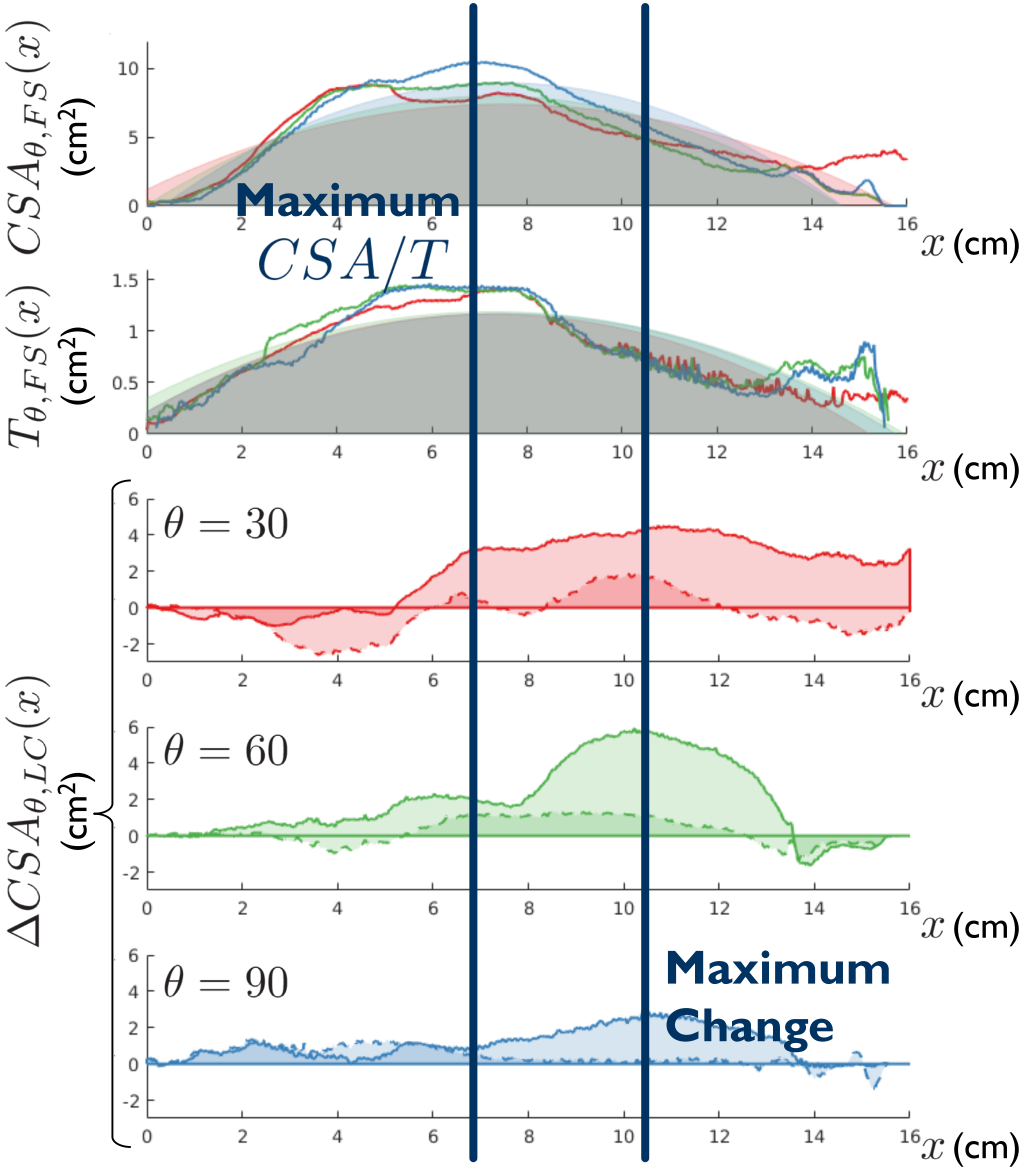
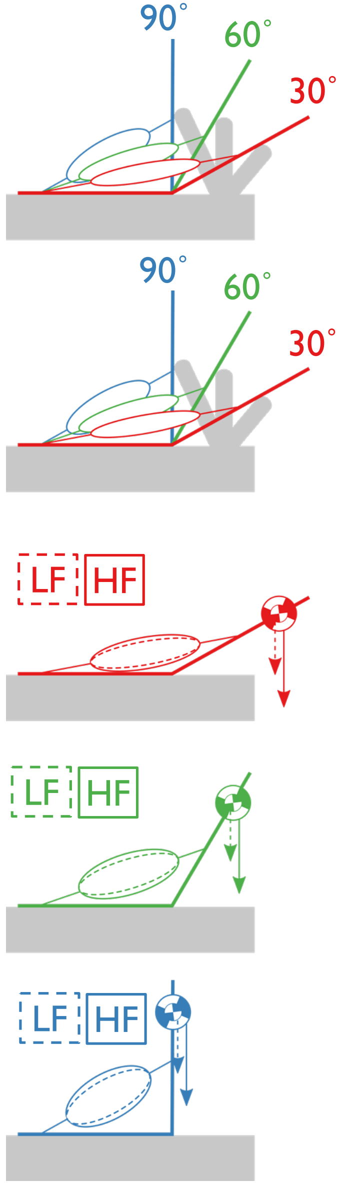
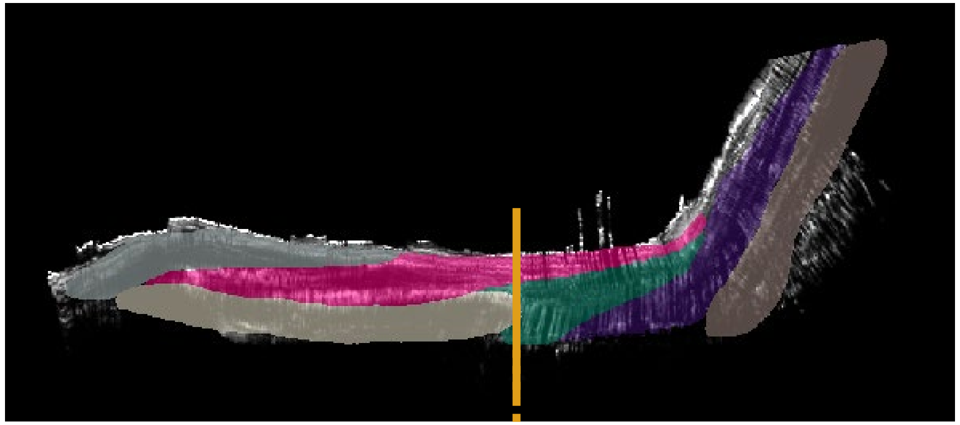


Maximum
CSA/T

Maximum Change

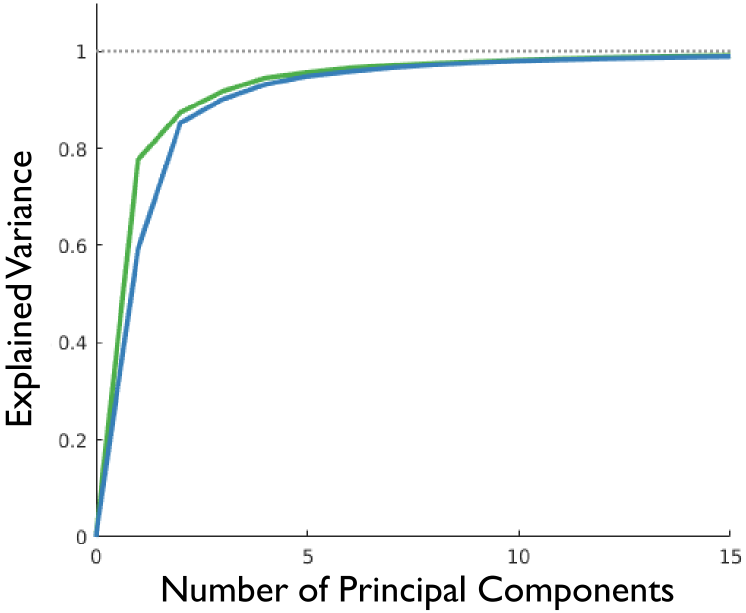


Exploratory Data Analysis: Statistical Shape Modeling



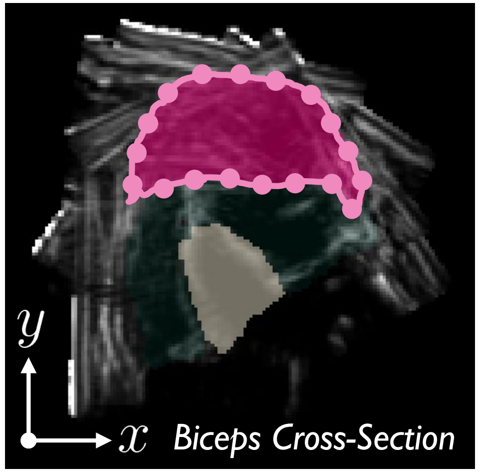
SHAPE DECOMPOSITION :

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



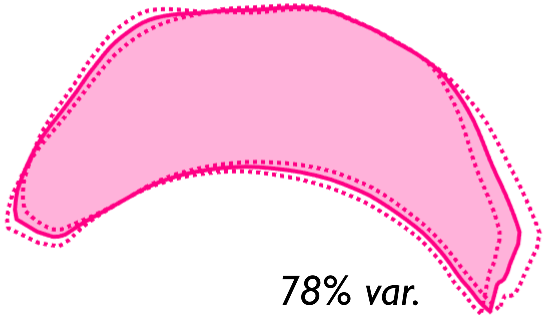
Shape

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

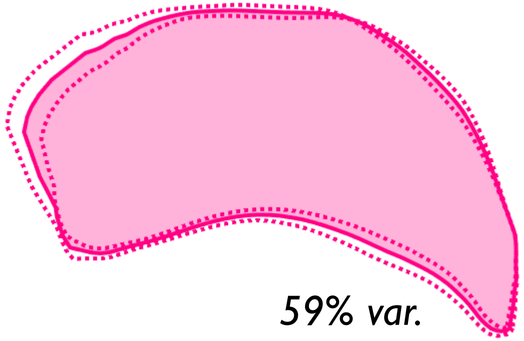


First Shape Modes

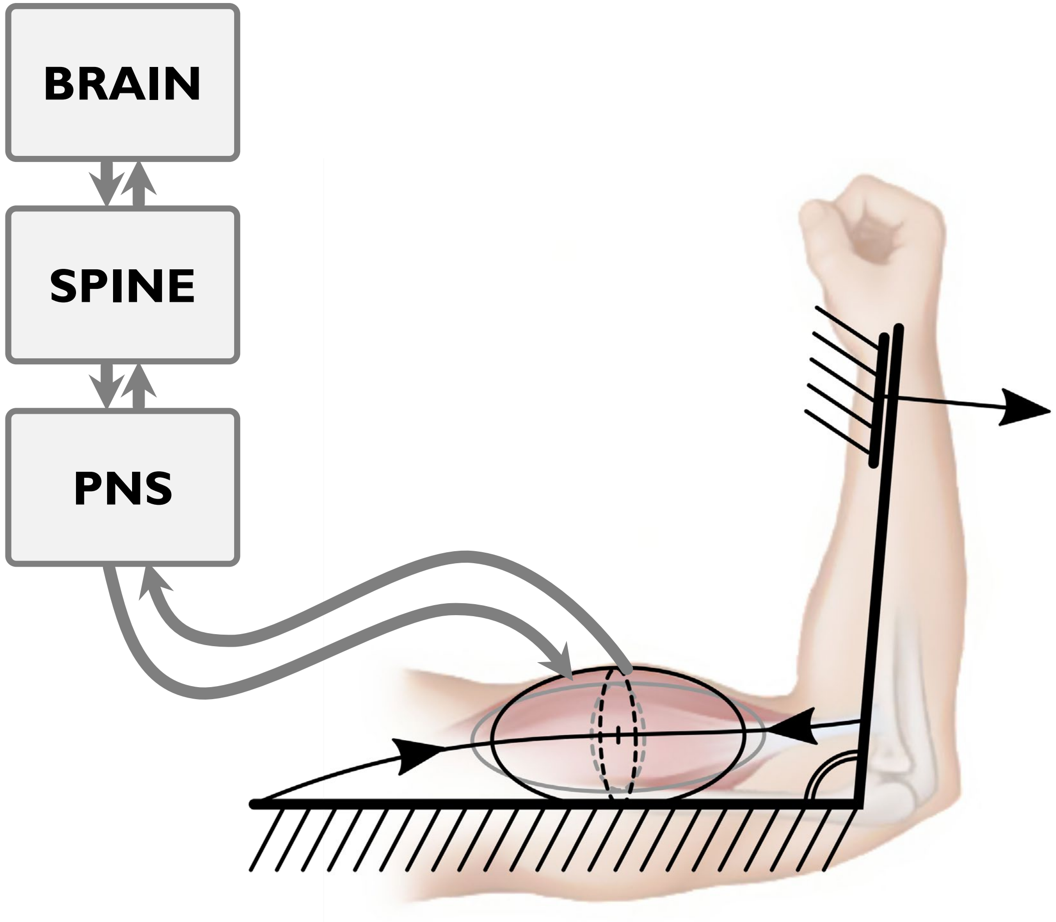
No Force, Vary Angle



30˚ Angle, Vary Force

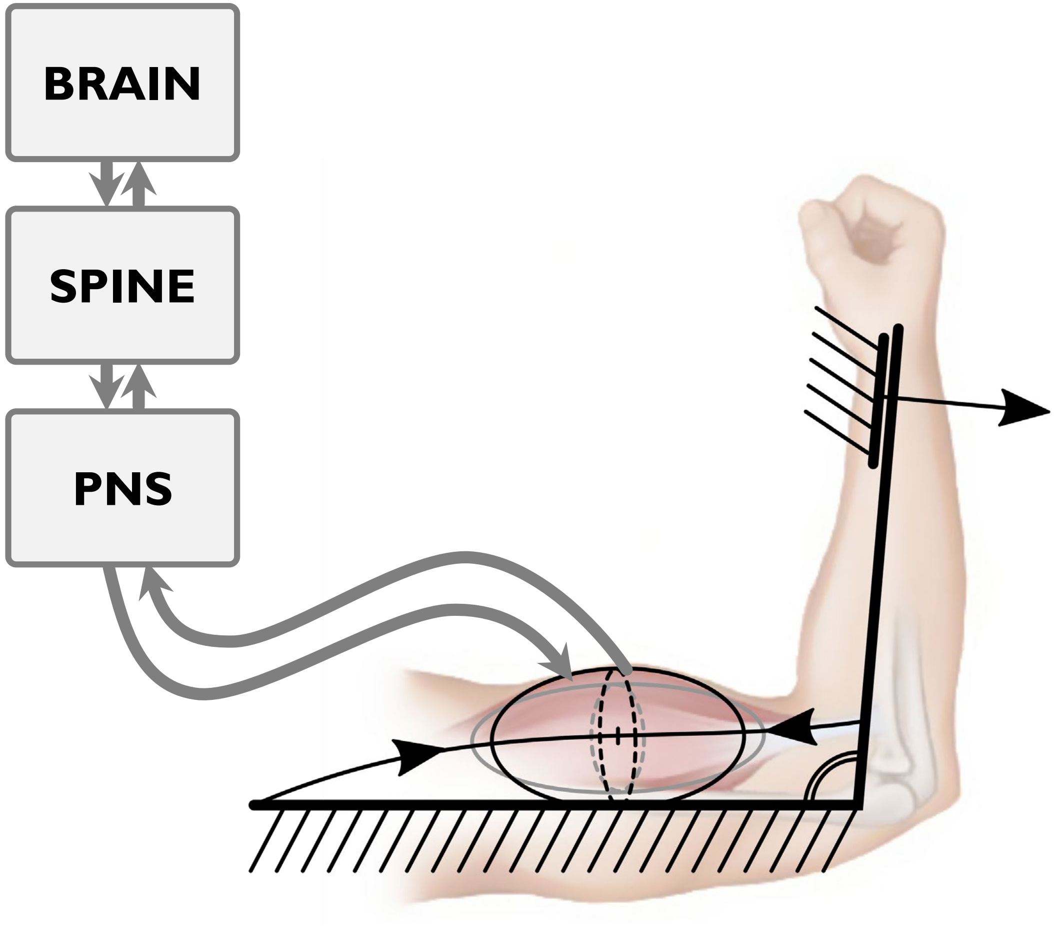


Expanded Biological Mechanism



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

Expanded Biological Mechanism



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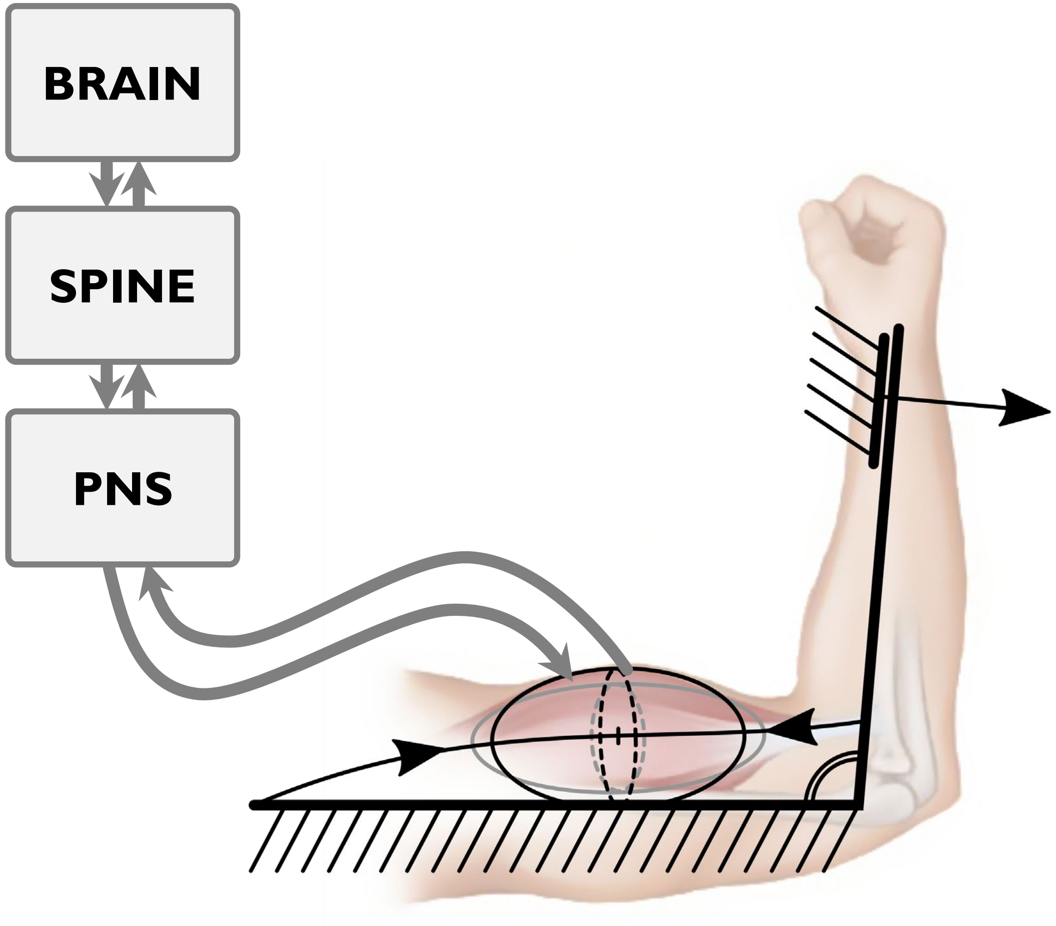
  - contact forces
- **Geometric complexity**
  - nonlinear, config-specific "line of action"
  - pennation angle
  - tendon/aponeurosis thickness

Expanded Biological Mechanism



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  - hysteresis
  - concentric vs. eccentric contraction
  - fatigue

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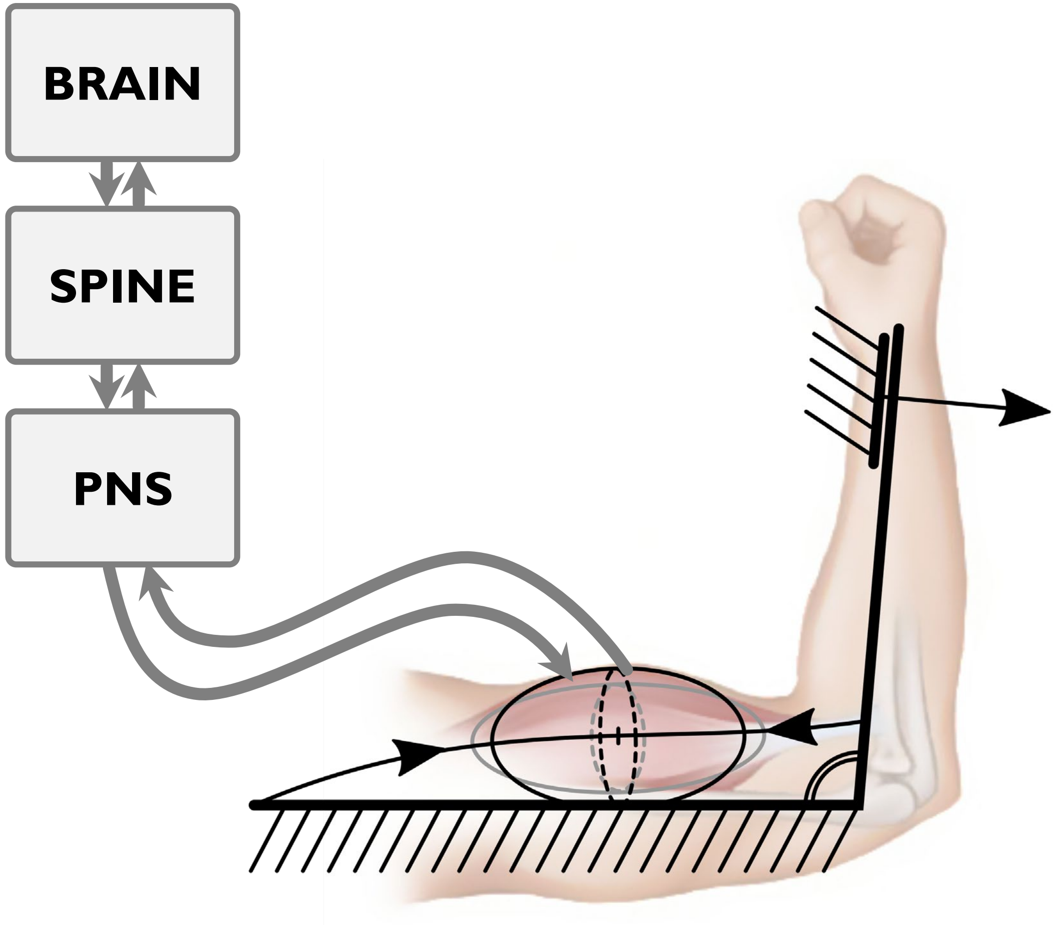

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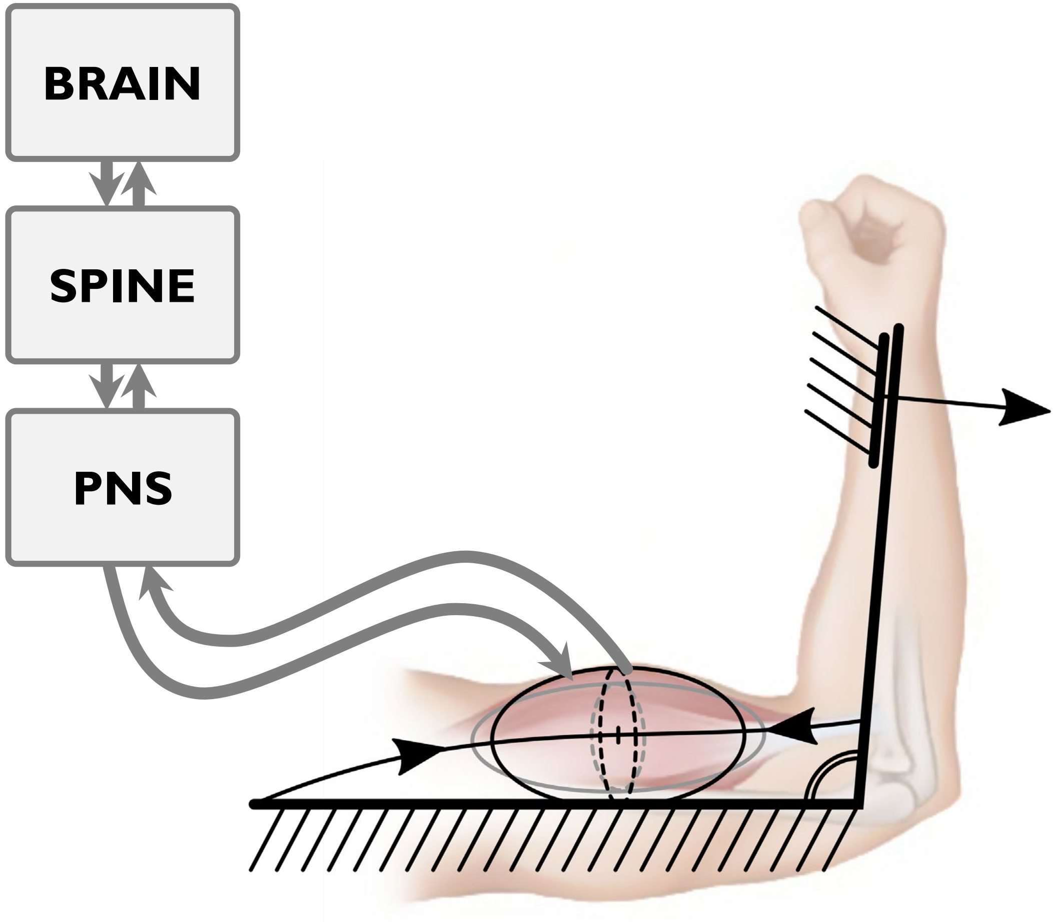
  - tetanic vs. subtetanic contraction
  - feedback vs. feedforward control

Expanded Biological Mechanism



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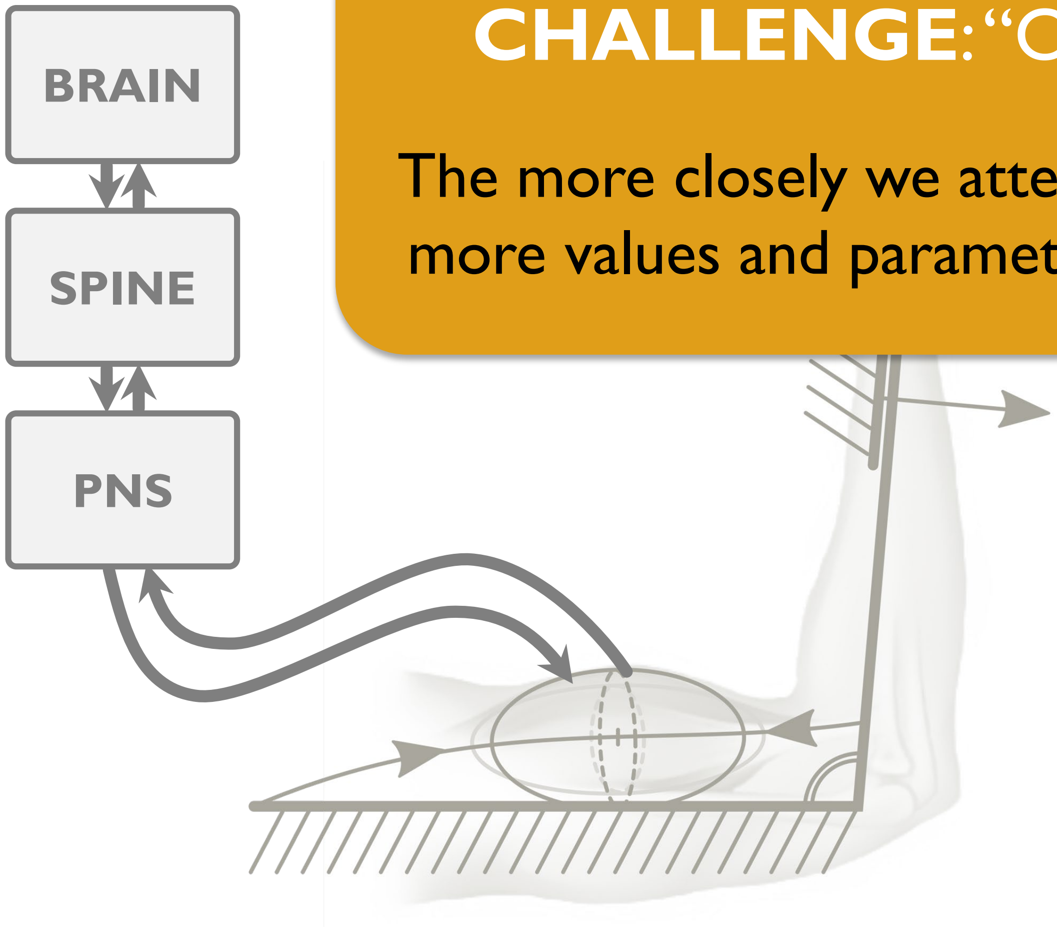
Expanded Biological Mechanism

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.



on”

- pennation angle
- tendon/aponeurosis thickness

- **Mechanical complexity**
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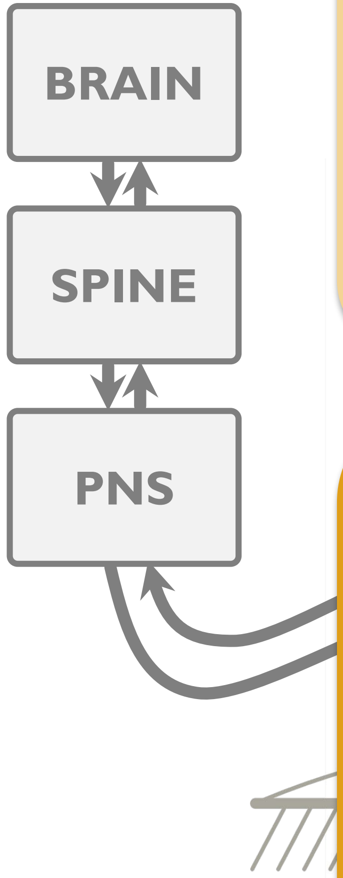
Expanded Biological Mechanism



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.

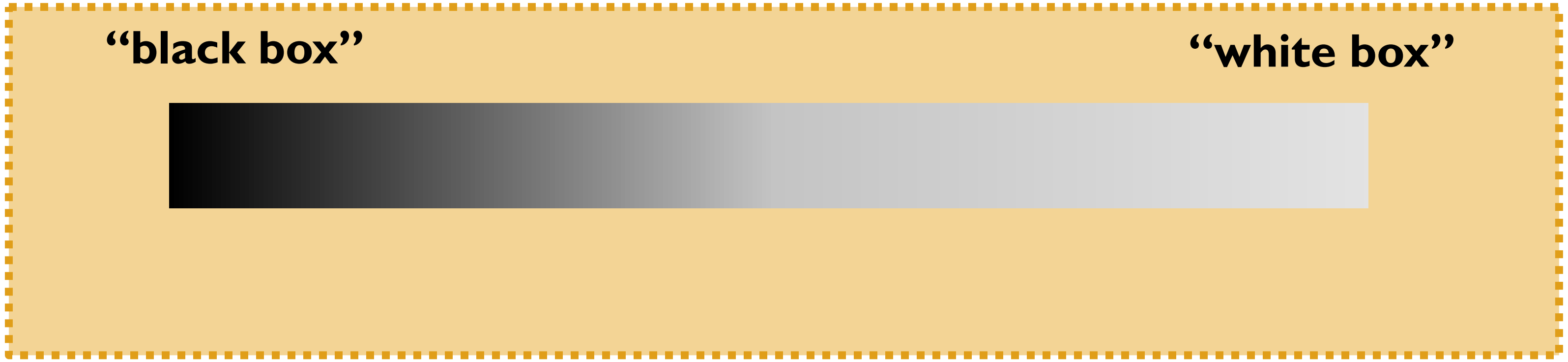
GOAL

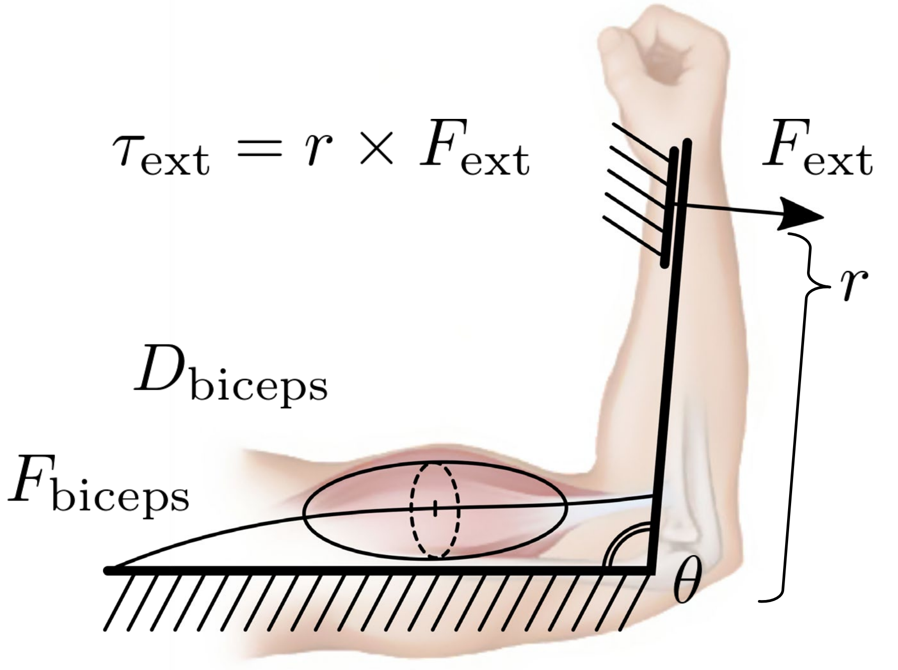
build up a **principled suite of models** that make varying trade-offs between **collected data** and **literature values** in a **quantifiable manner**

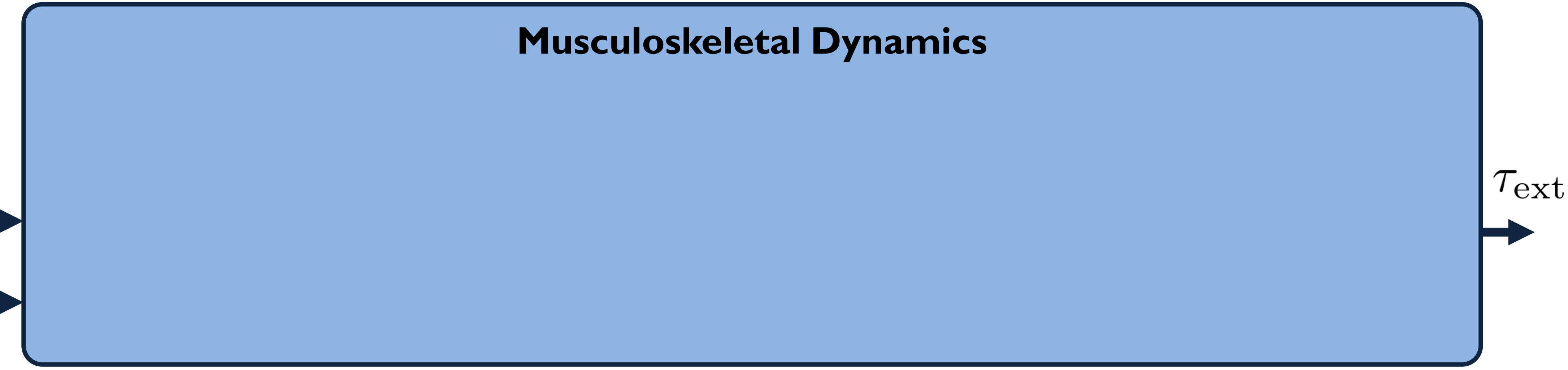
(sidenote: this work can also help validate those literature values!)

– feedback vs. feedforward control

(Proposed) **Suite of Models**







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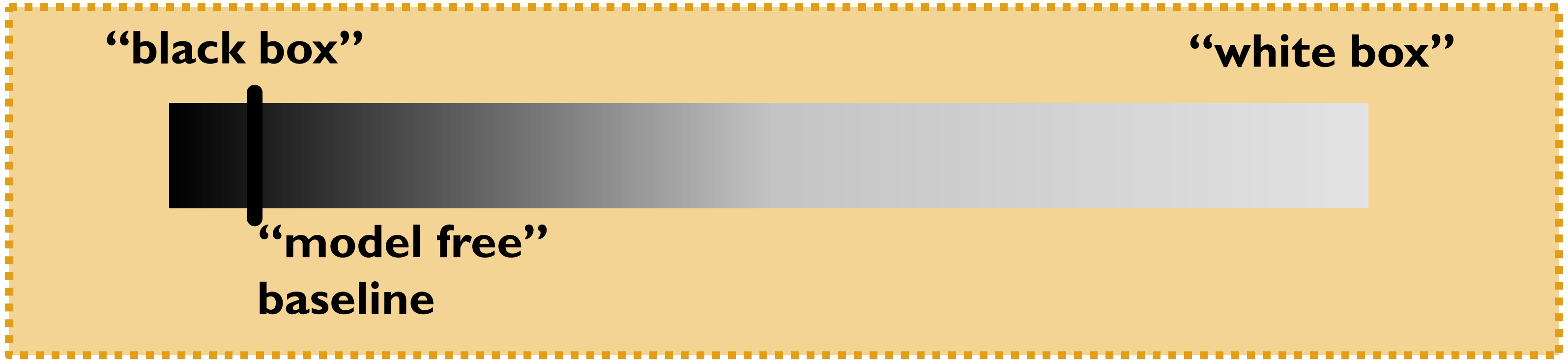
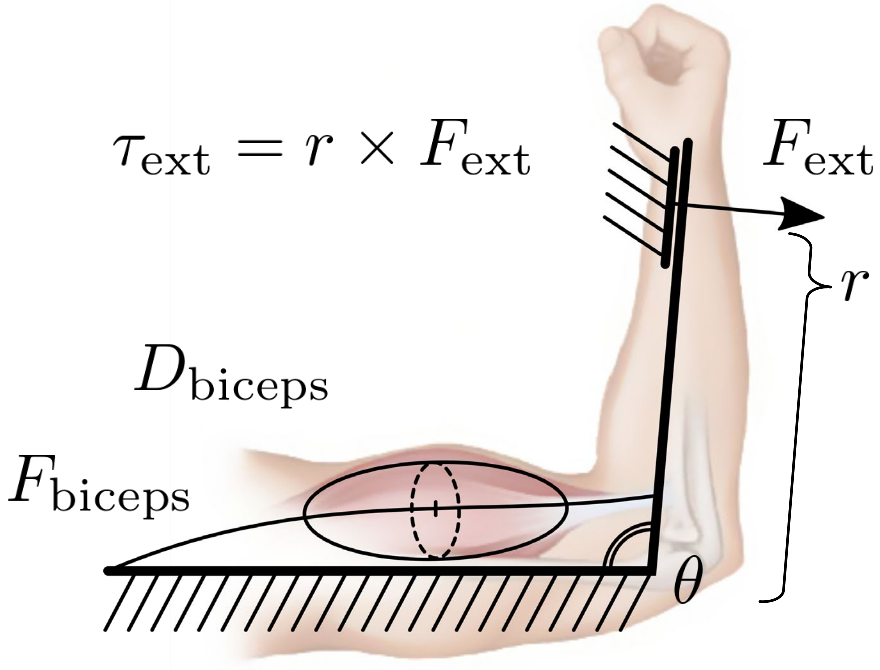
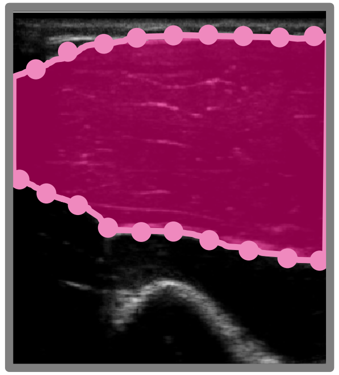
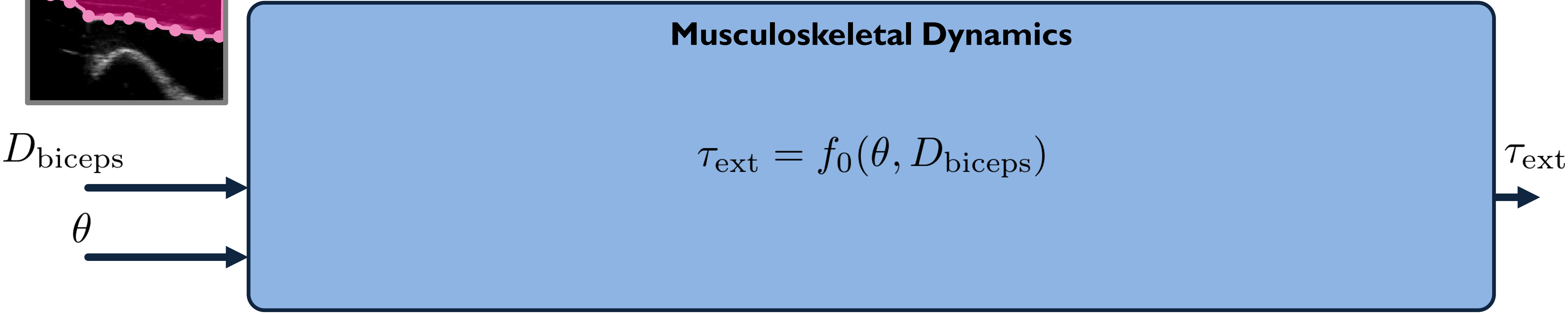








Musculoskeletal Dynamics

$$\tau_{\text{ext}} = f_0(\theta, D_{\text{biceps}})$$

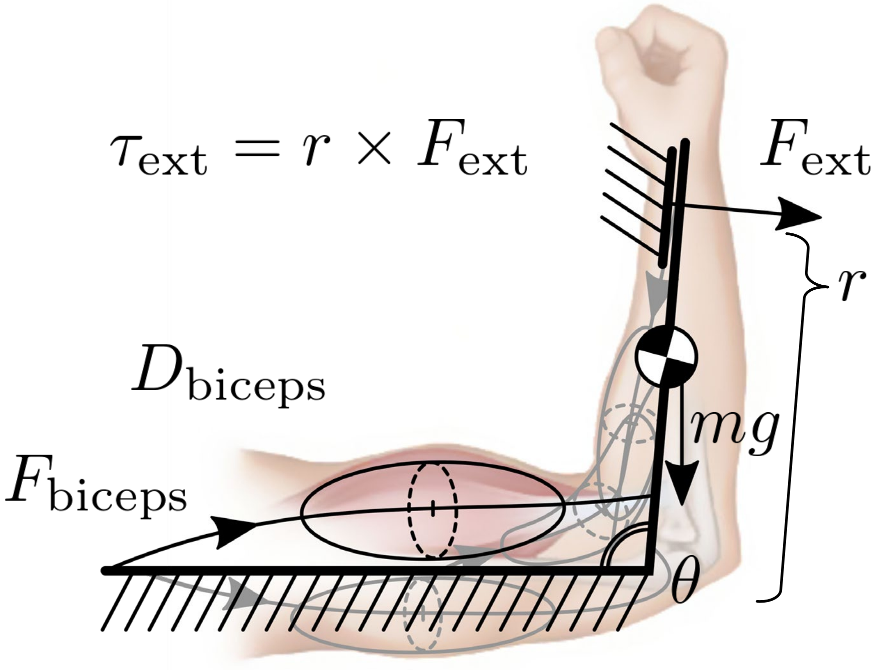
(Proposed) **Suite of Models**

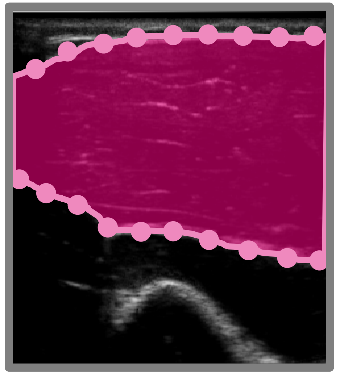
“black box”

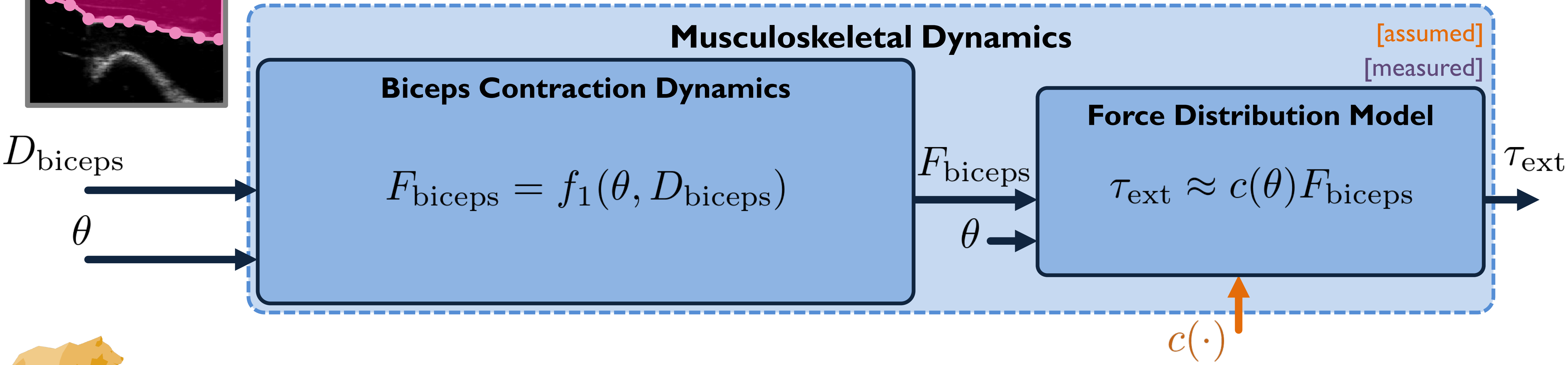
“white box”

“model free” baseline

+ multi-muscle dynamics







Musculoskeletal Dynamics

[assumed]

[measured]

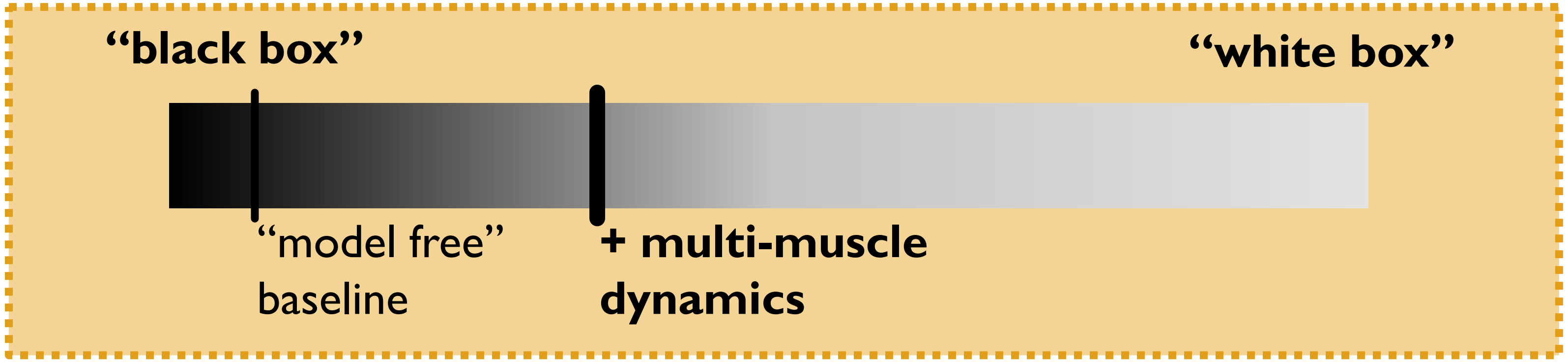
Biceps Contraction Dynamics

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

Force Distribution Model

$$\tau_{\text{ext}} \approx c(\theta) F_{\text{biceps}}$$

(Proposed) **Suite of Models**



“black box”

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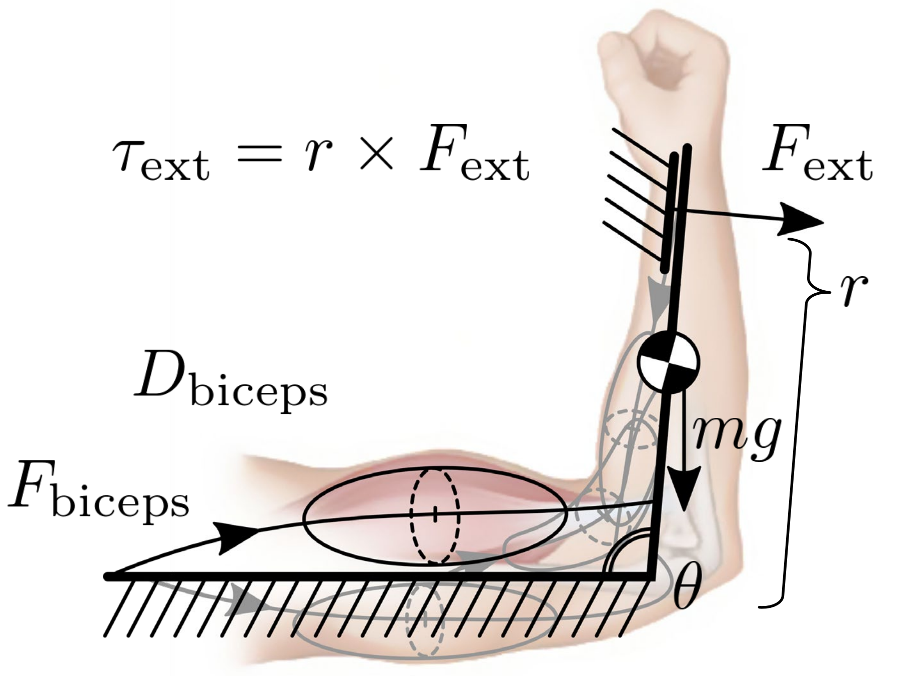
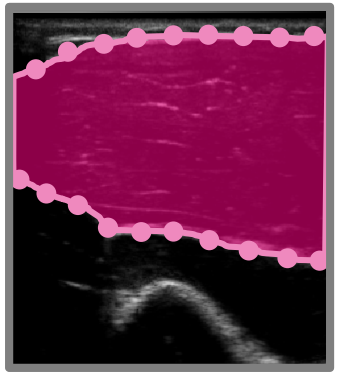
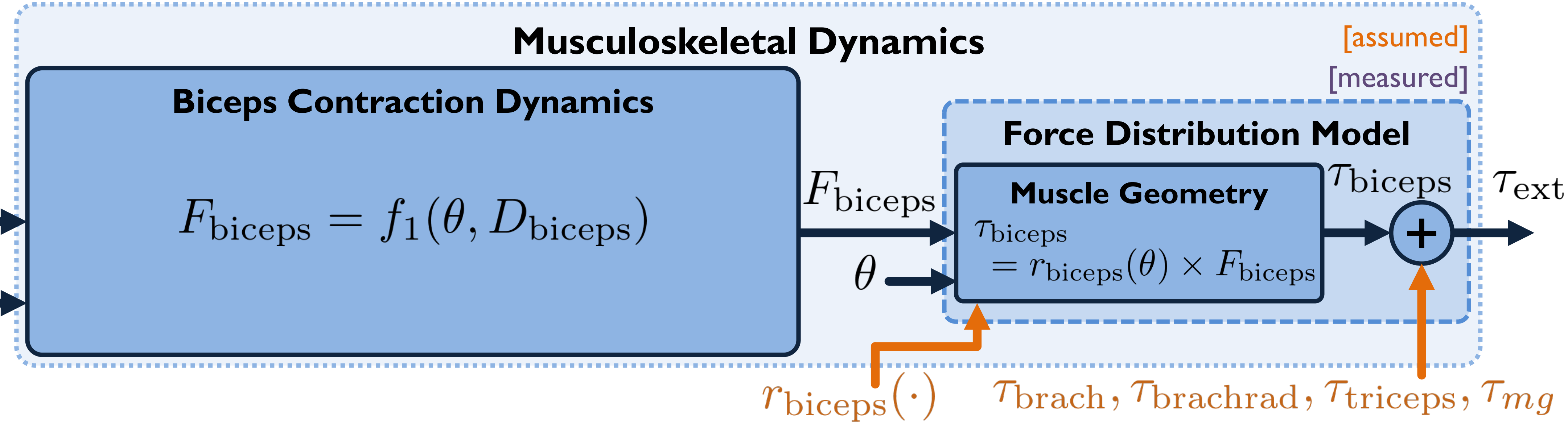






D_{biceps}

θ

Musculoskeletal Dynamics

[assumed]

[measured]

Biceps Contraction Dynamics

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

F_{biceps}

θ

Force Distribution Model

Muscle Geometry

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

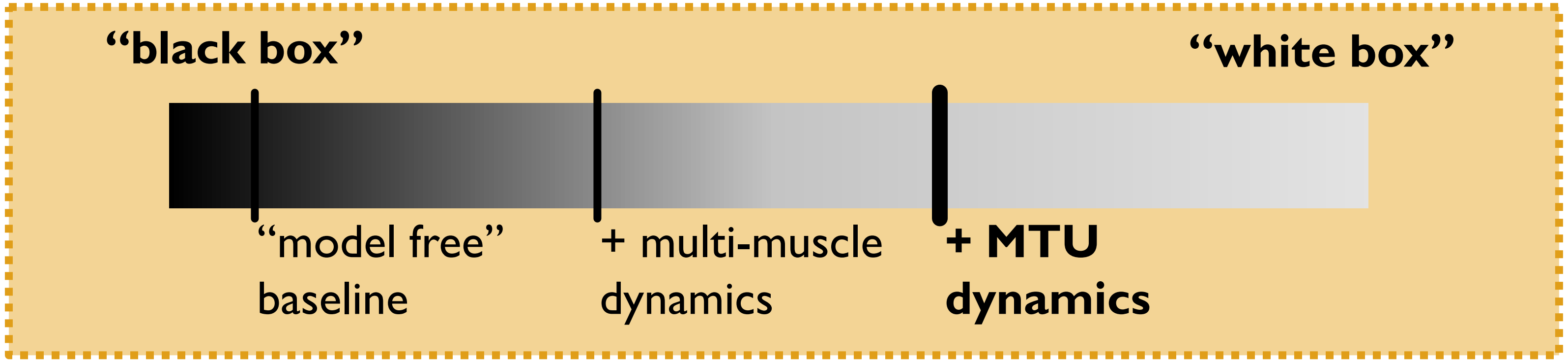
τ_{biceps}

τ_{ext}

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

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

(Proposed) **Suite of Models**



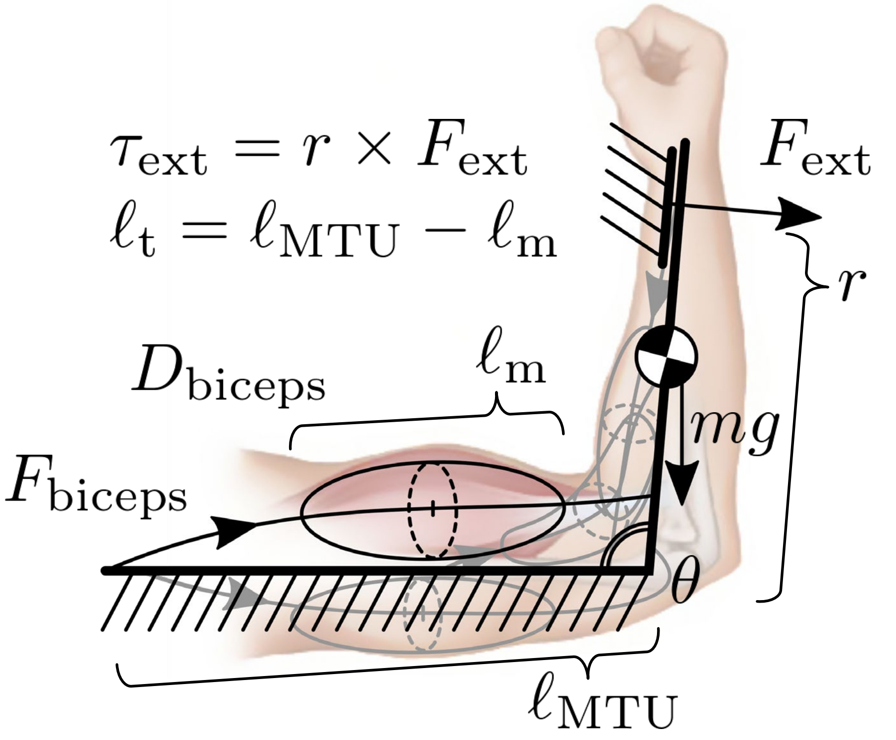
"black box"

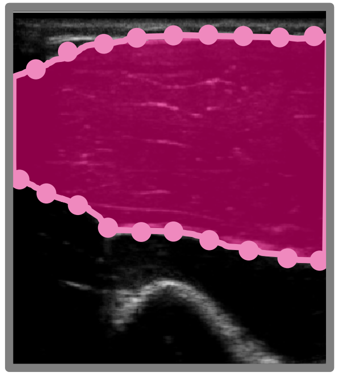
"white box"

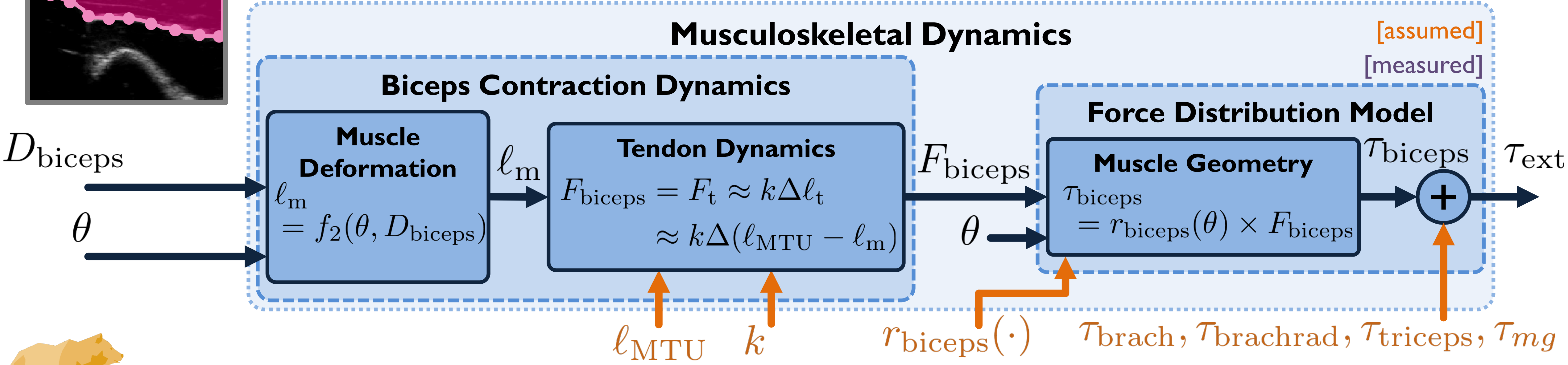
"model free" baseline

+ multi-muscle dynamics

+ MTU dynamics







Musculoskeletal Dynamics

[assumed]

[measured]

Biceps Contraction Dynamics

Muscle Deformation

$\ell_{\text{m}} = f_2(\theta, D_{\text{biceps}})$

Tendon Dynamics

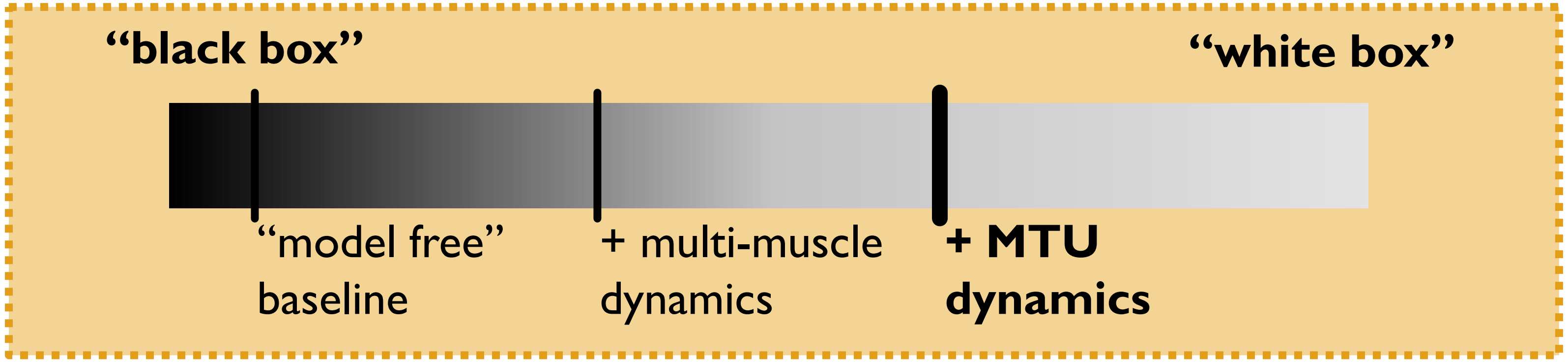
$F_{\text{biceps}} = F_{\text{t}} \approx k\Delta\ell_{\text{t}} \approx k\Delta(\ell_{\text{MTU}} - \ell_{\text{m}})$

Force Distribution Model

Muscle Geometry

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

(Proposed) **Suite of Models**



“black box”

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“model free” baseline

+ multi-muscle dynamics

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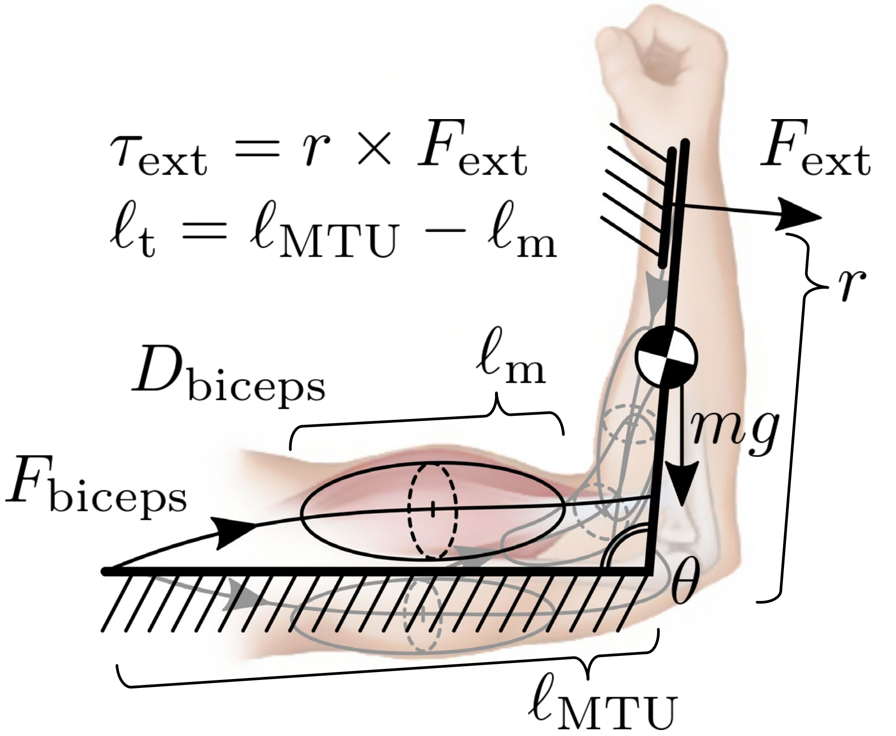
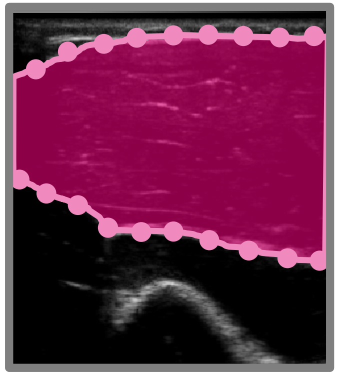
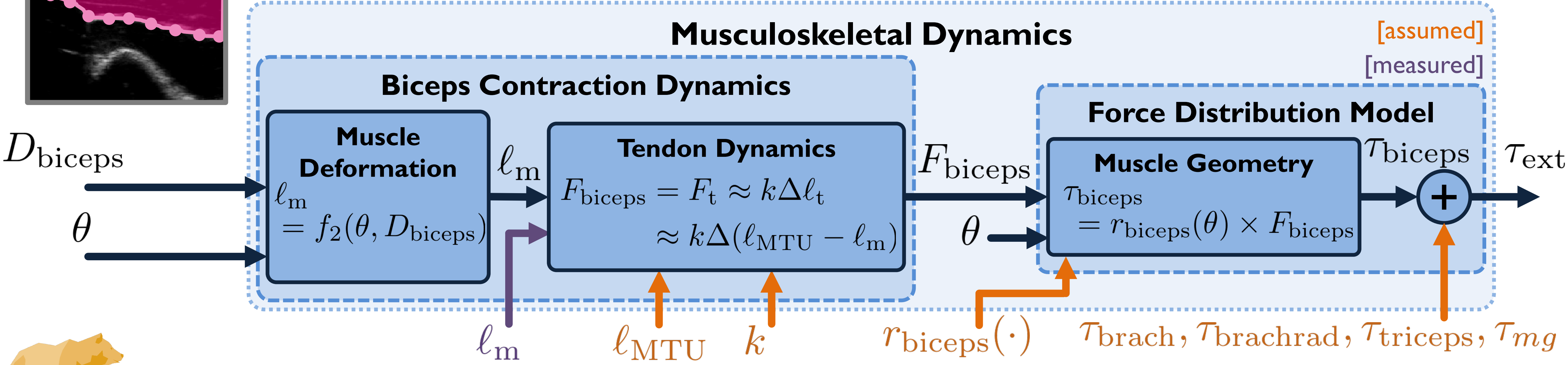


$$\tau_{\text{ext}} = r \times F_{\text{ext}}$$
$$\ell_{\text{t}} = \ell_{\text{MTU}} - \ell_{\text{m}}$$





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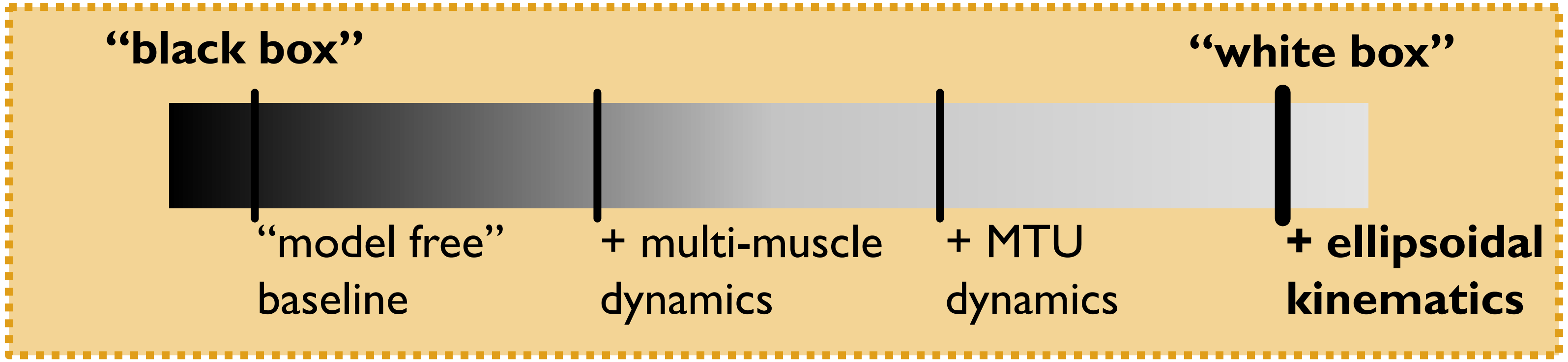
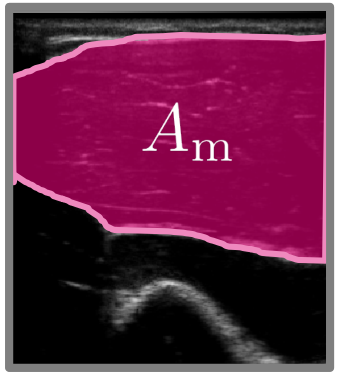
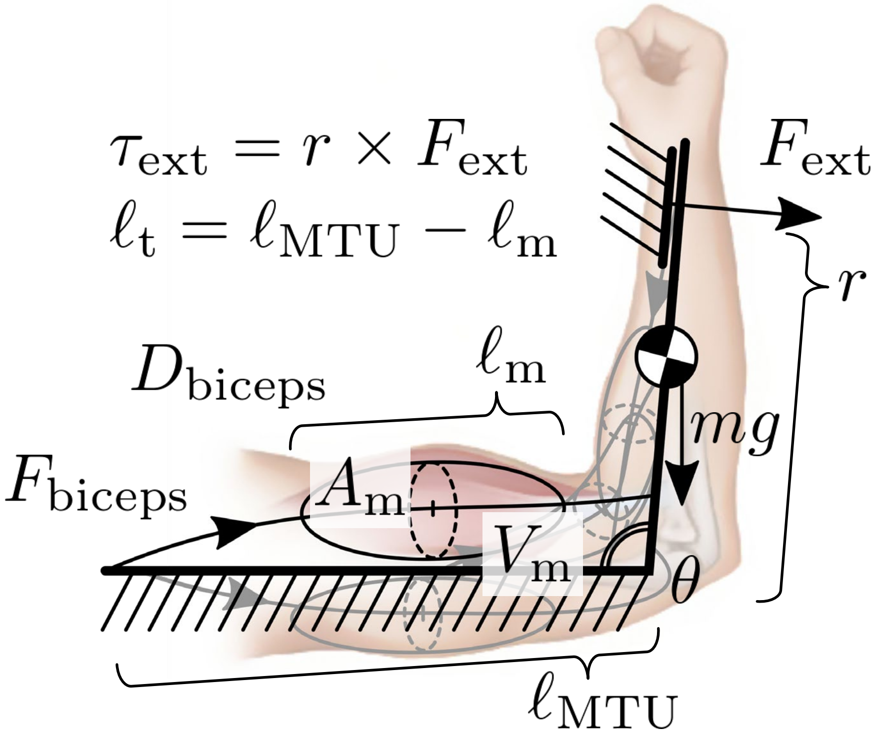
(Proposed) **Suite of Models**

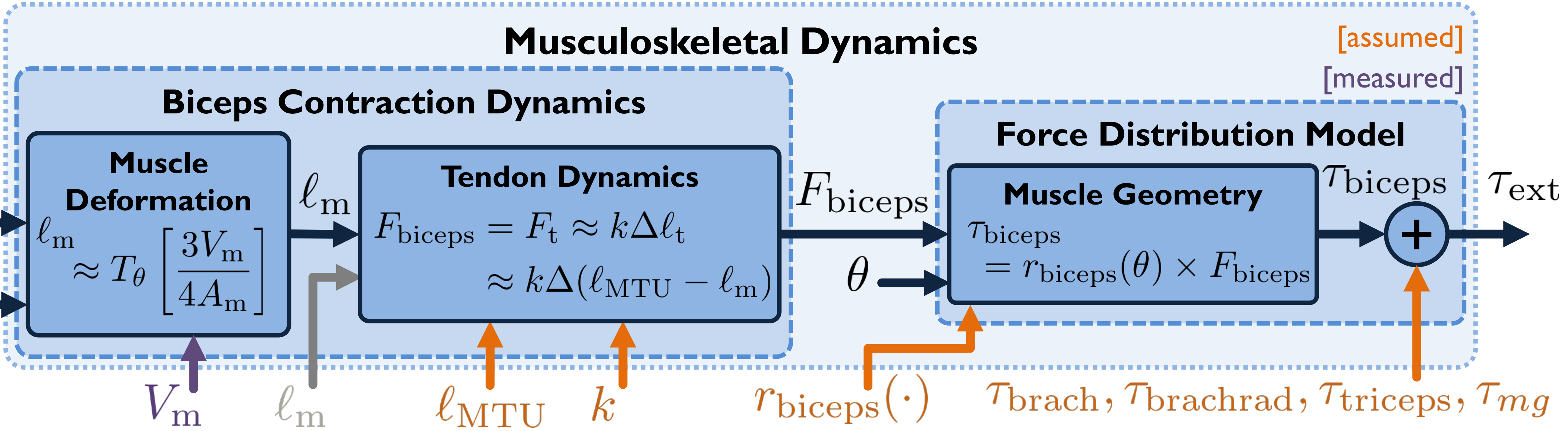






$\tau_\mathrm{ext} = r \times F_\mathrm{ext}$

$\ell_\mathrm{t} = \ell_\mathrm{MTU} - \ell_\mathrm{m}$

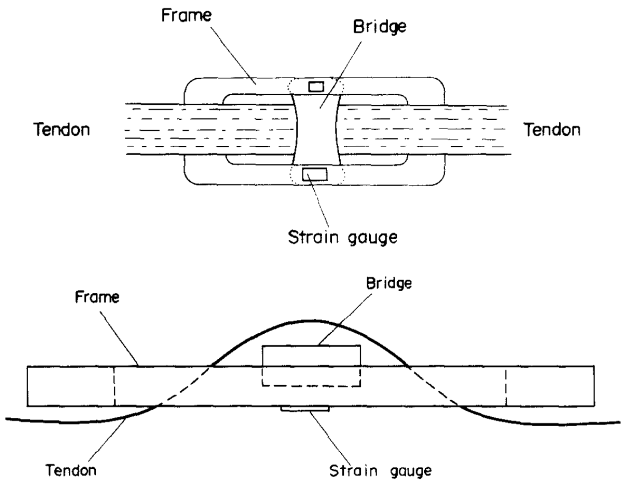


$D_\mathrm{biceps} \triangleq A_\mathrm{m}$

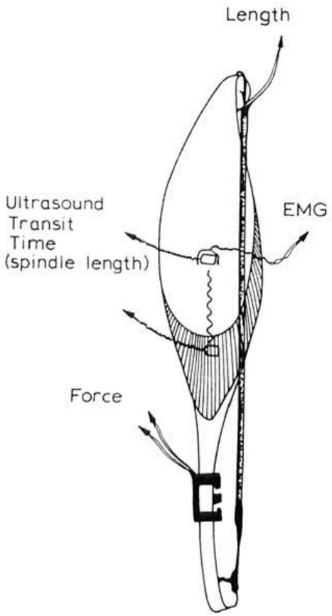
θ

Model Validation

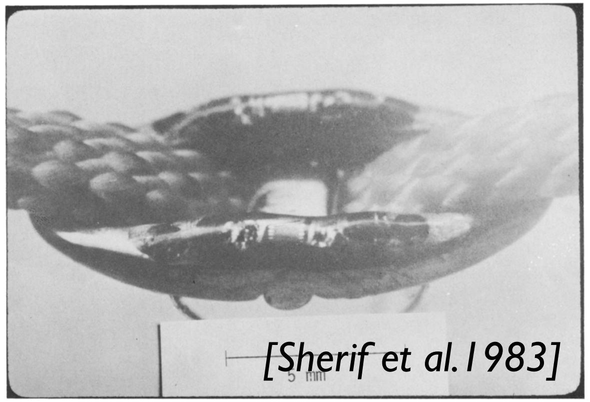
Direct, Invasive Force Measurement



[Barnes & Pinder 1974]



[Hoffer et al. 1989]

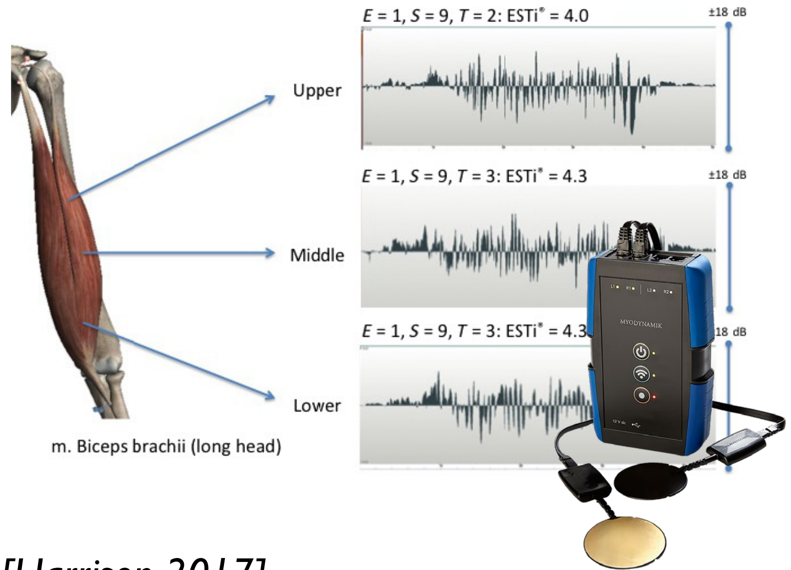


[Sherif et al. 1983]

[Salmons 1969]
[Yager 1972]

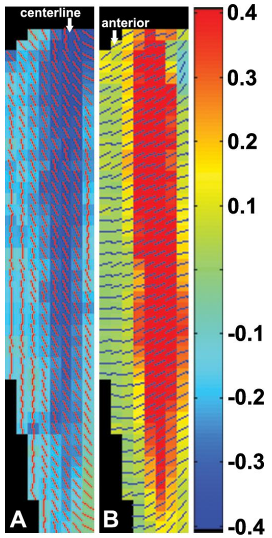
Consistency Across Sensors

AMG



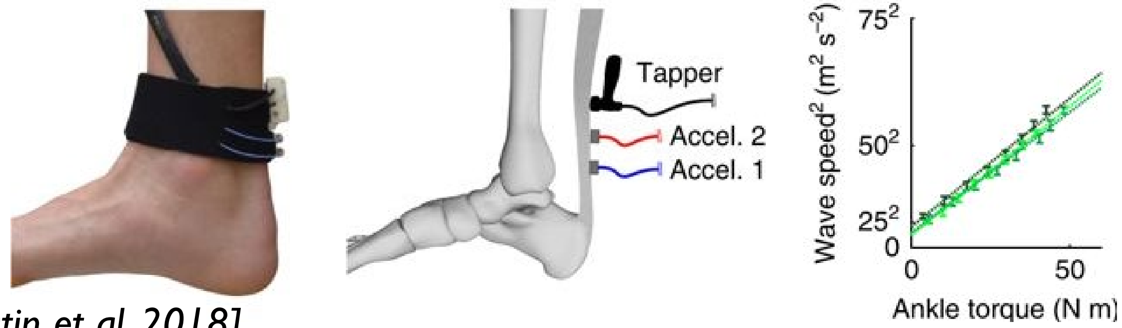
[Harrison 2017]

cine DENSE MRI



[Zhong et al. 2008]

“tapping tendons”



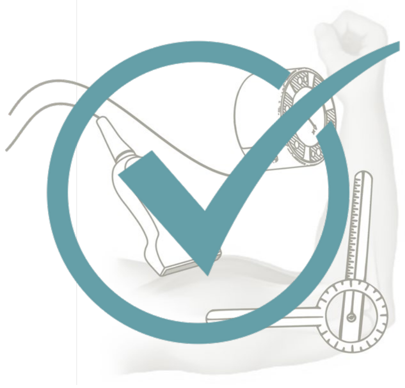
[Martin et al. 2018]

Roadmap

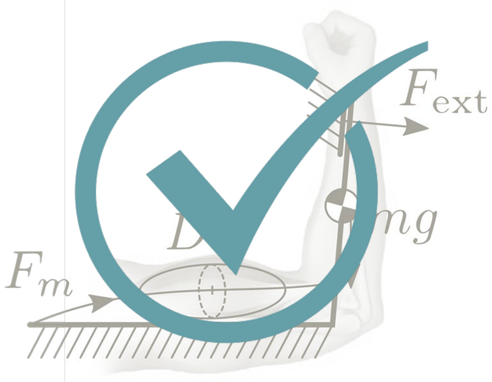
CORE OBJECTIVE

We seek to measure **individual muscle forces** in vivo via **ultrasound** based on **shape changes** under loading.

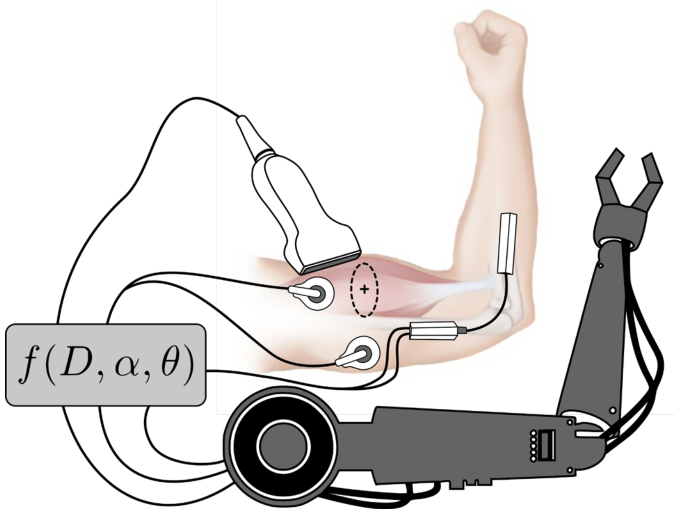
I Exploratory Data Set Generation



II Model Development & Validation

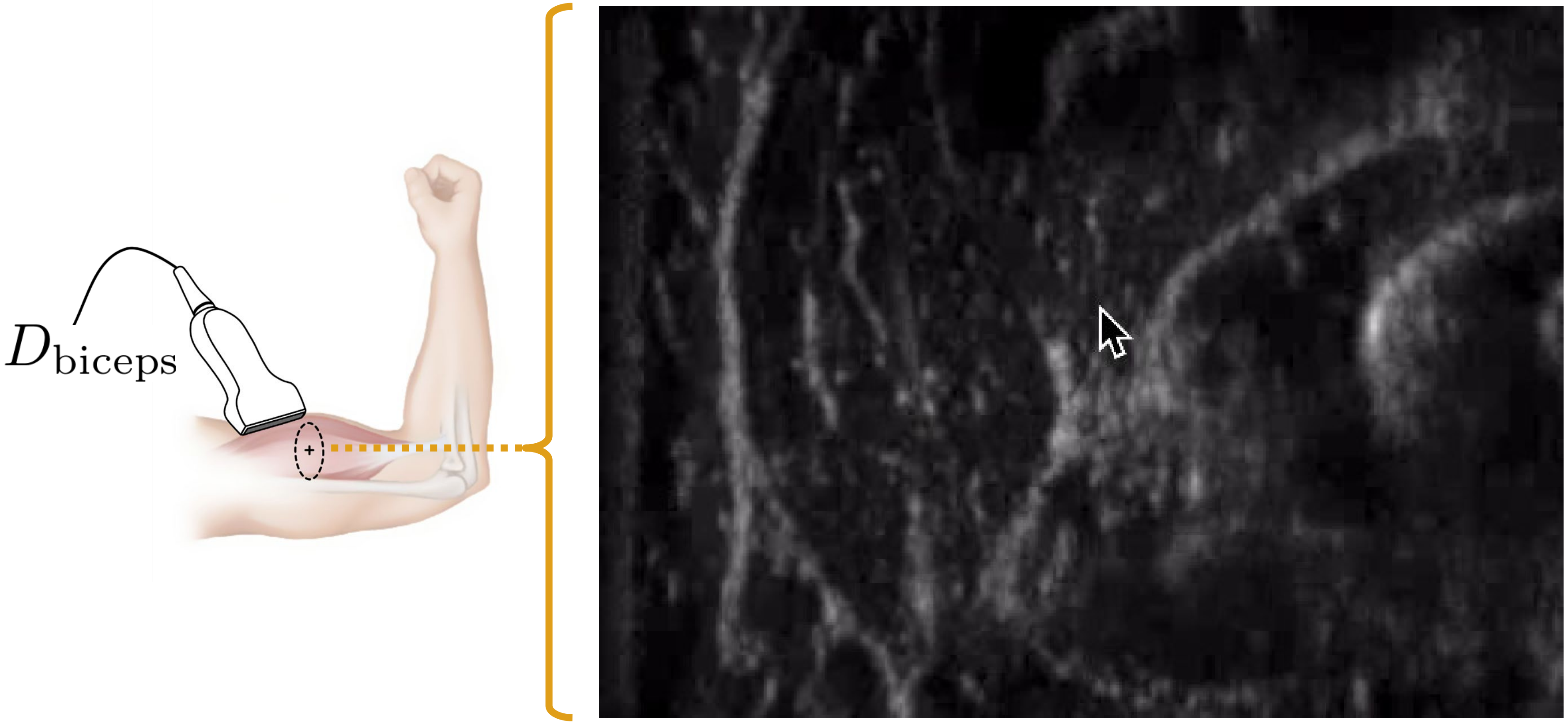


III Proof-of-Concept Applications



Alternate Modalities & Conclusions

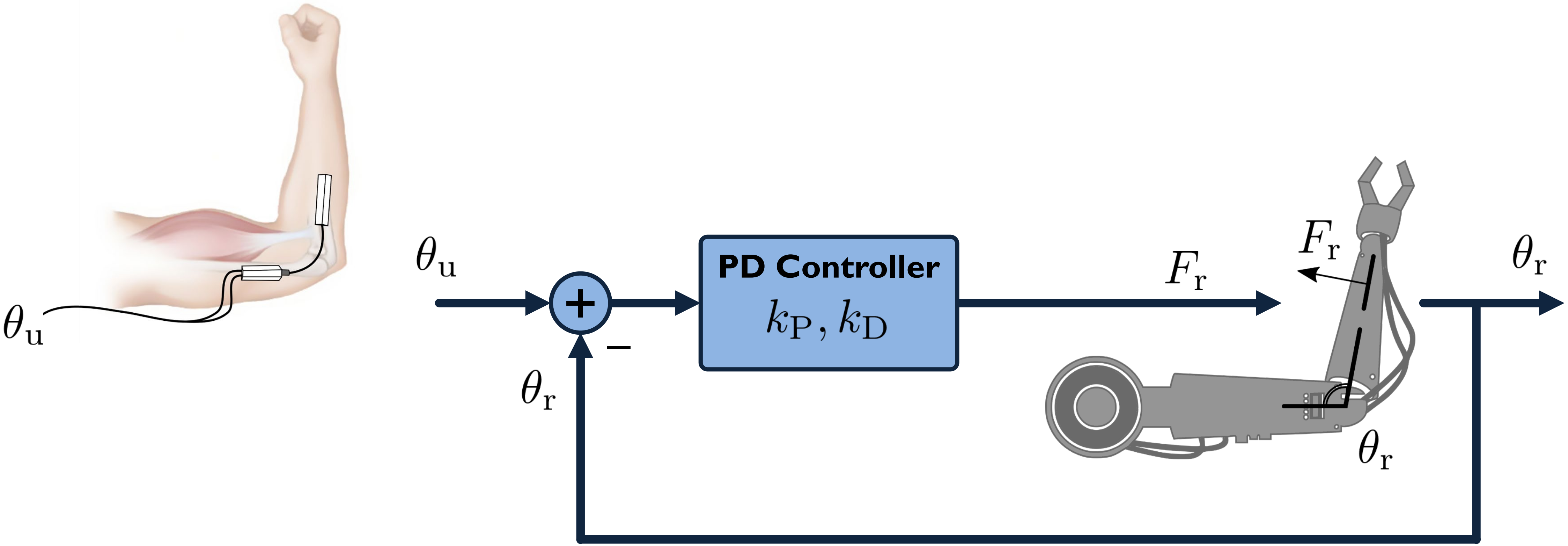
Preliminary Deformation Signal Tracking



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

[Schwartz, Velu]

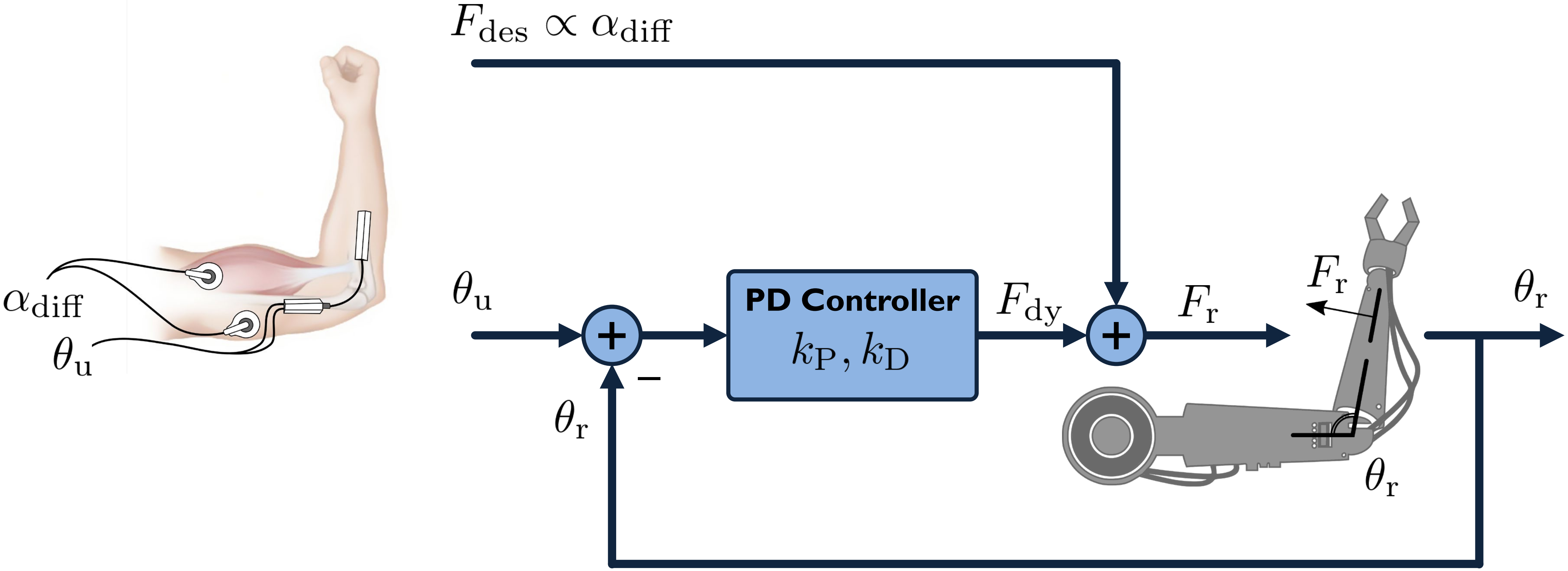
Real-Time Device Control: Robot Teleoperation



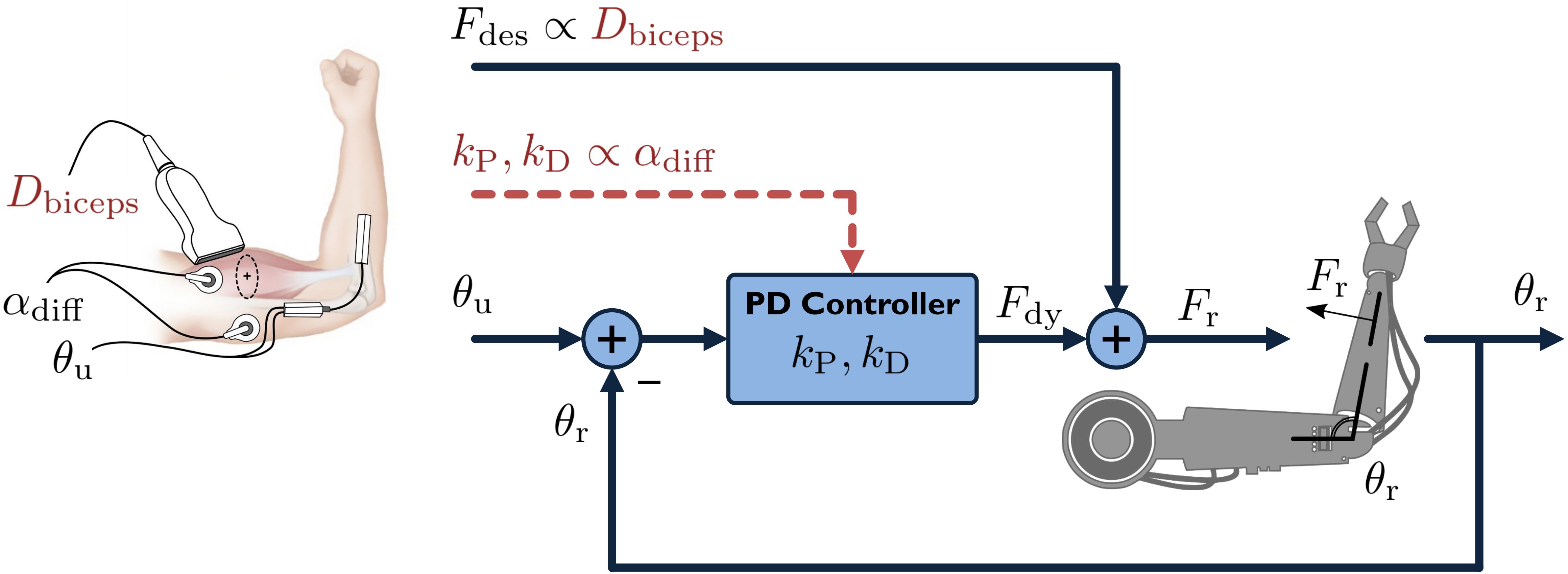
PD Controller

$k_{\mathrm{P}}, k_{\mathrm{D}}$

Real-Time Device Control: Baseline sEMG Control

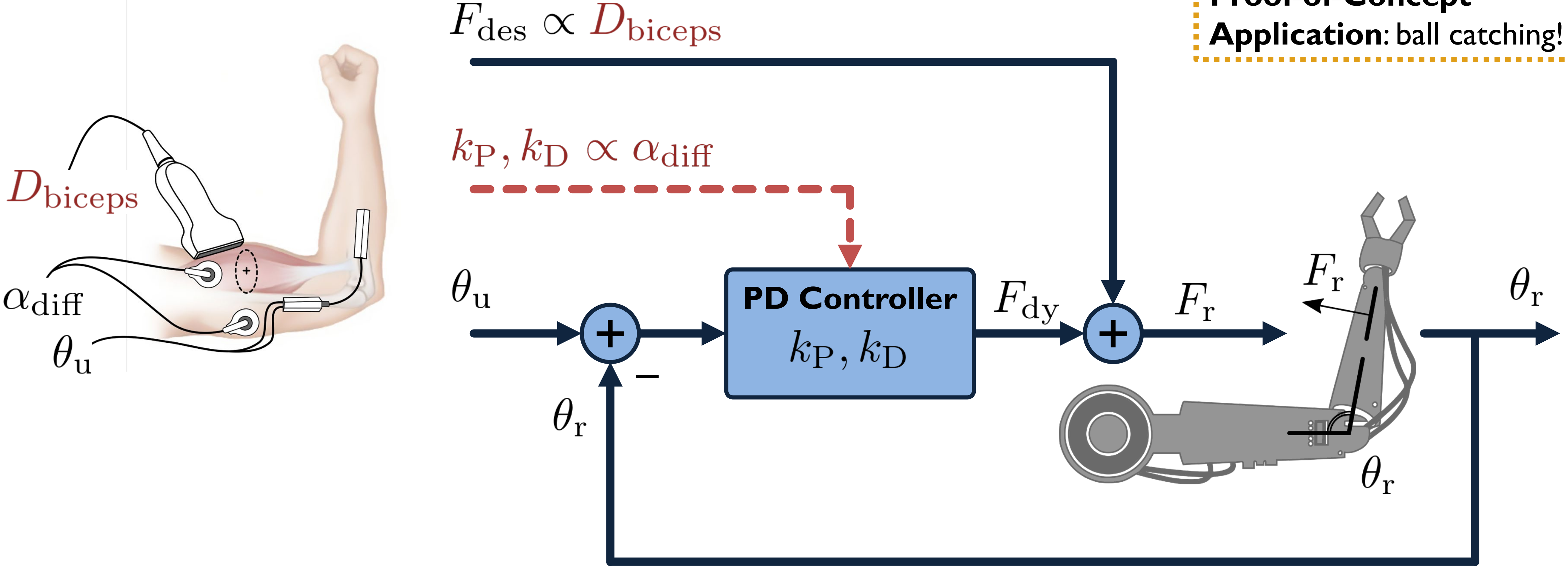


Real-Time Device Control: Proposed Control

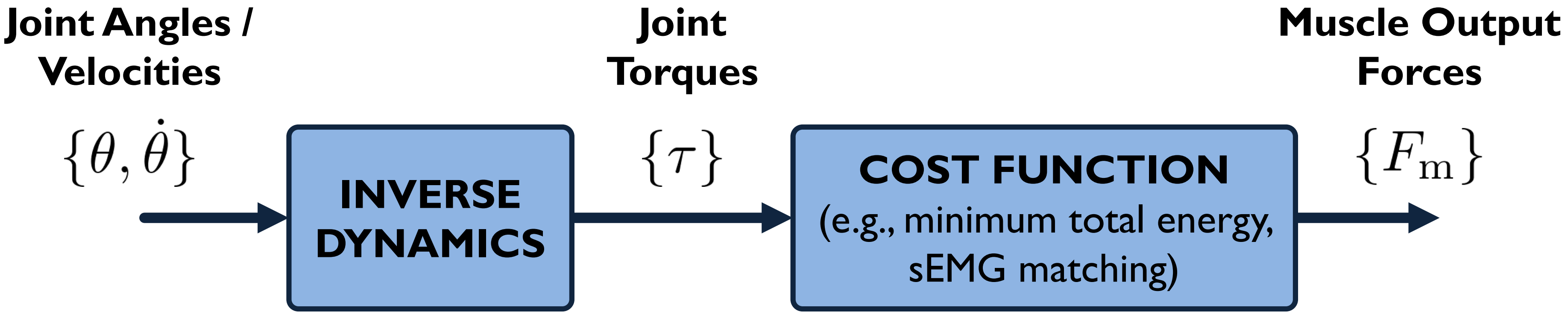


Real-Time Device Control: Proposed Control

Proof-of-Concept Application: ball catching!



In Vivo Muscle Force Inference: State-of-the-Art



Joint Angles / Velocities

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

INVERSE DYNAMICS

Joint Torques

$\{\tau\}$

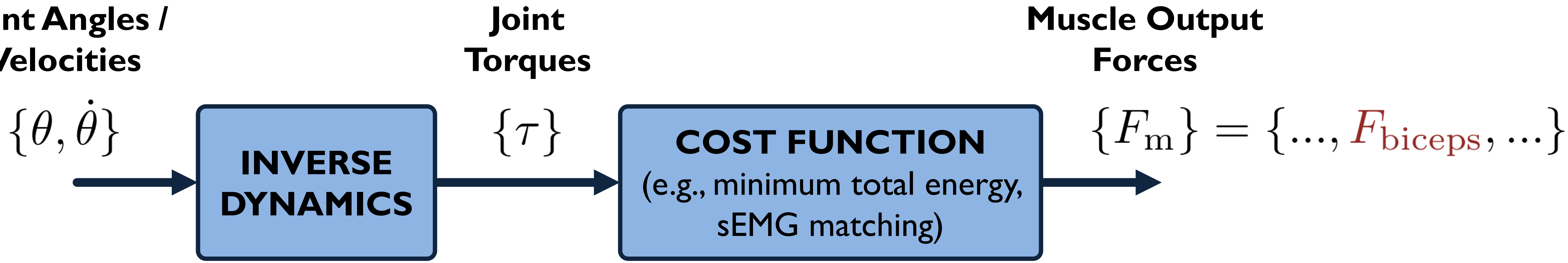
COST FUNCTION
(e.g., minimum total energy, sEMG matching)

Muscle Output Forces

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

[e.g., OpenSIM, AnyBody]

Deformation-Enhanced In Vivo Muscle Force Inference



Joint Angles / Velocities

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INVERSE DYNAMICS

Joint Torques

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COST FUNCTION
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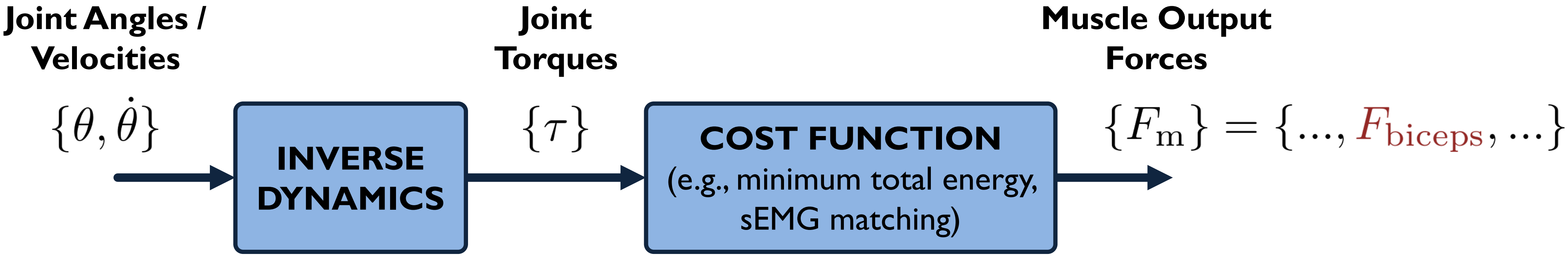
Muscle Output Forces

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

[e.g., OpenSIM, AnyBody]

Deformation-Enhanced In Vivo Muscle Force Inference



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

INVERSE DYNAMICS

Joint Torques

$\{\tau\}$

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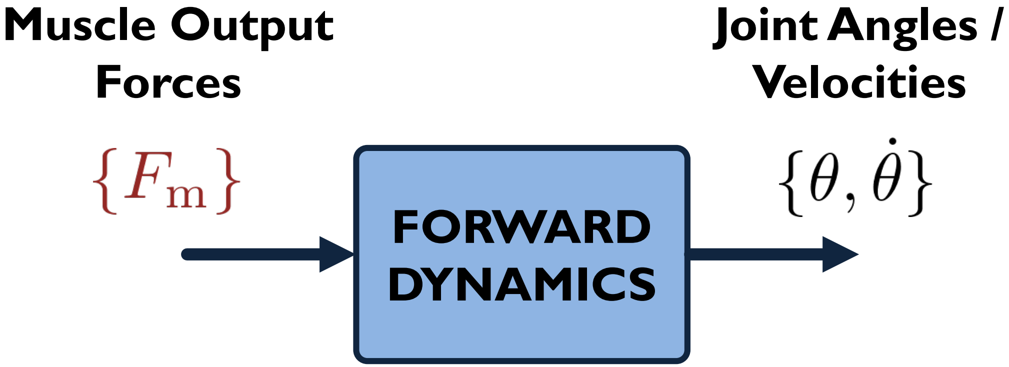
[e.g., OpenSIM, AnyBody]



Muscle Output Forces

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

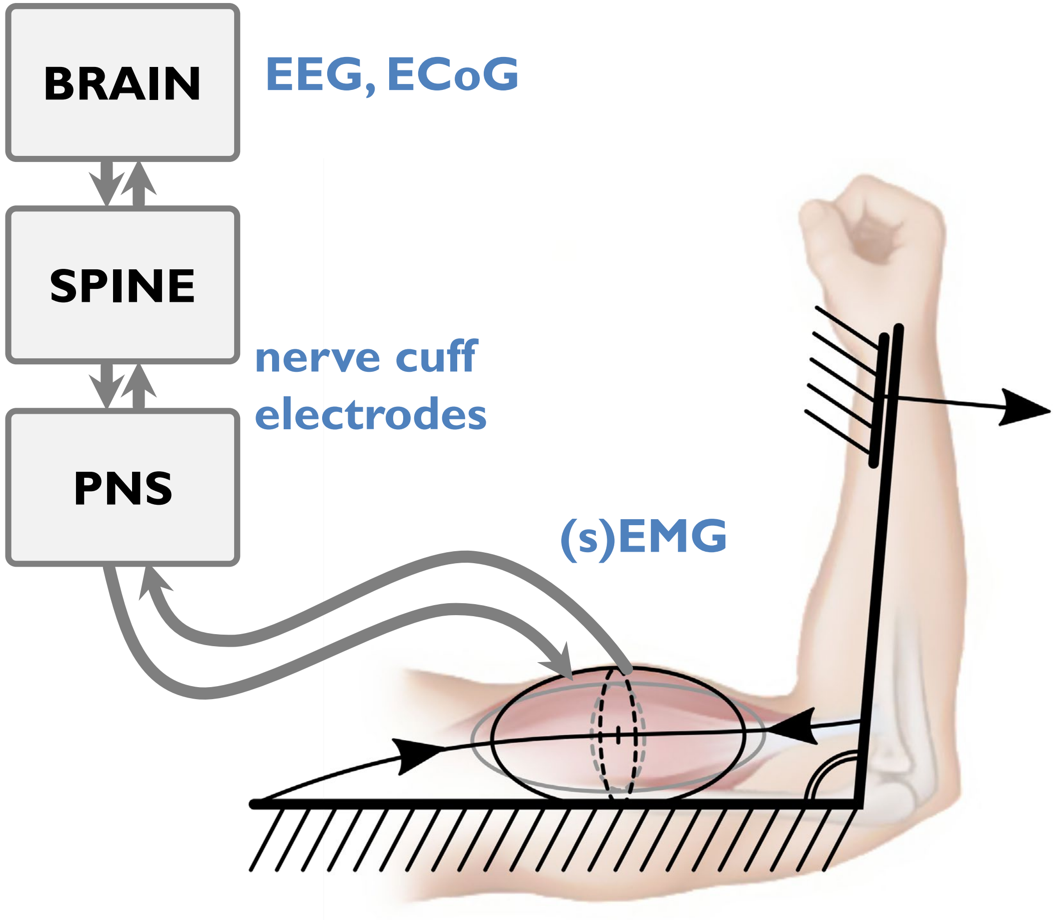
FORWARD DYNAMICS

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.

Future Directions: Closing the Loop



BRAIN

SPINE

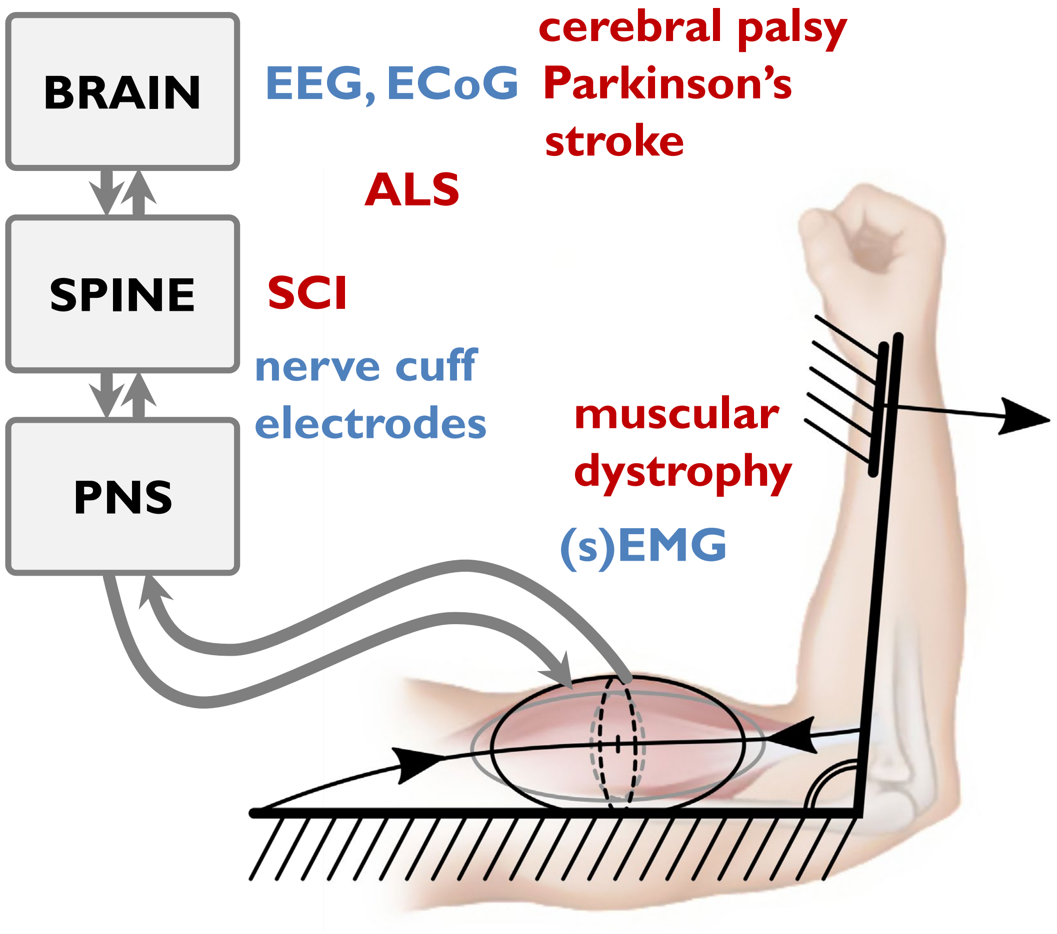
PNS

EEG, ECoG

nerve cuff
electrodes

(s)EMG

Future Directions: Closing the Loop



BRAIN

SPINE

PNS

EEG, ECoG

cerebral palsy
Parkinson’s
stroke

ALS

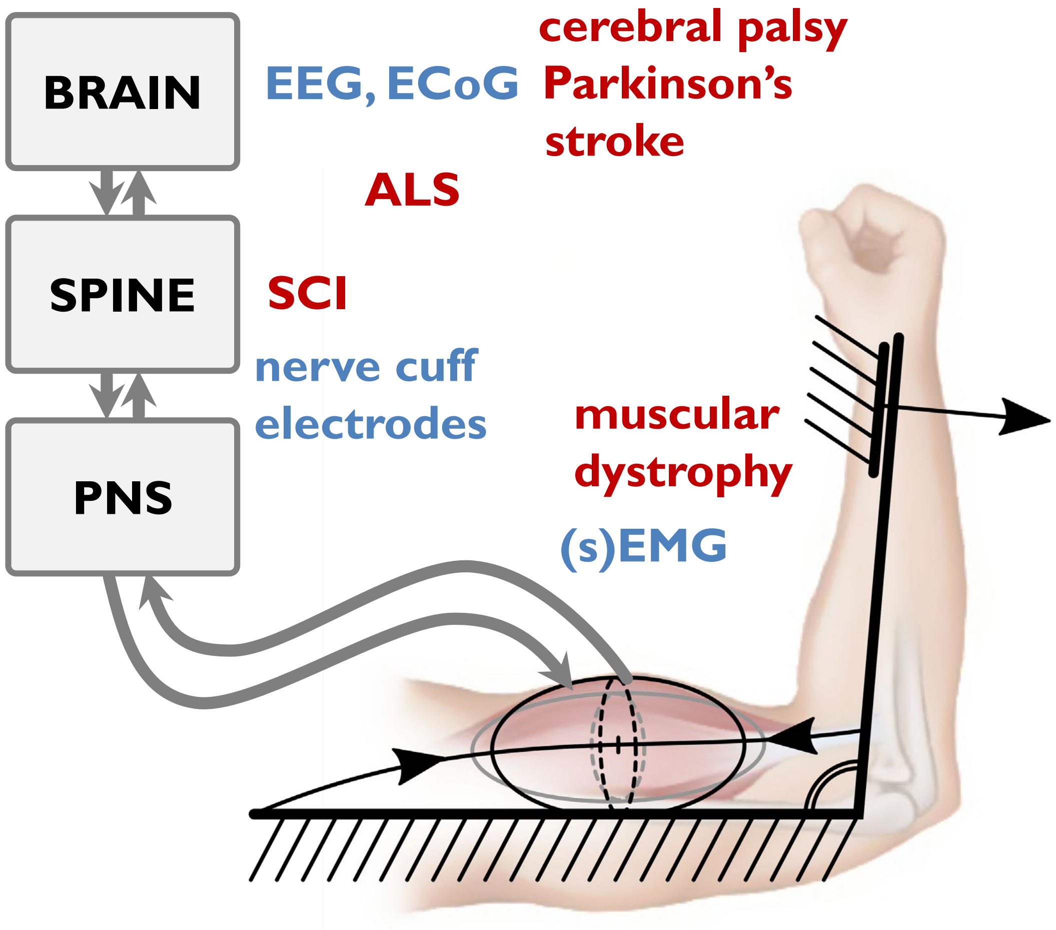
SCI

nerve cuff
electrodes

muscular
dystrophy

(s)EMG

Future Directions: Closing the Loop



BRAIN

SPINE

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Parkinson's
stroke

ALS

SCI

nerve cuff
electrodes

muscular
dystrophy

(s)EMG

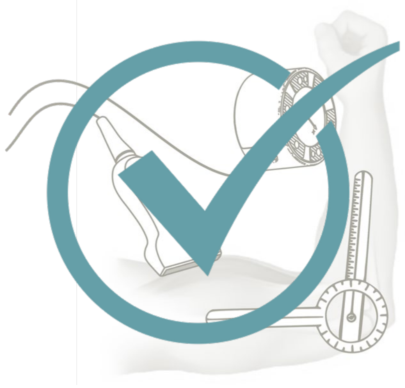
Measuring muscle output force directly would allow for **improved interpretation of existing sensing modalities**, as well as **better understanding, diagnosis, and treatment of neuromuscular pathology**.

Roadmap

CORE OBJECTIVE

We seek to measure **individual muscle forces** in vivo via **ultrasound** based on **shape changes** under loading.

I Exploratory Data Set Generation



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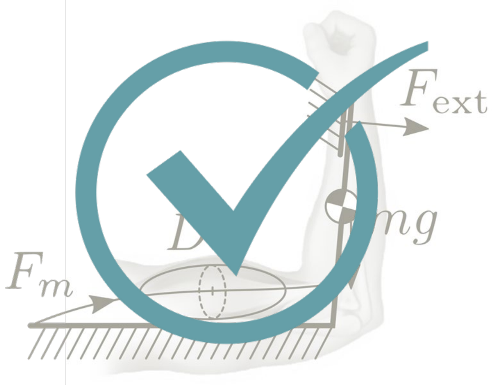
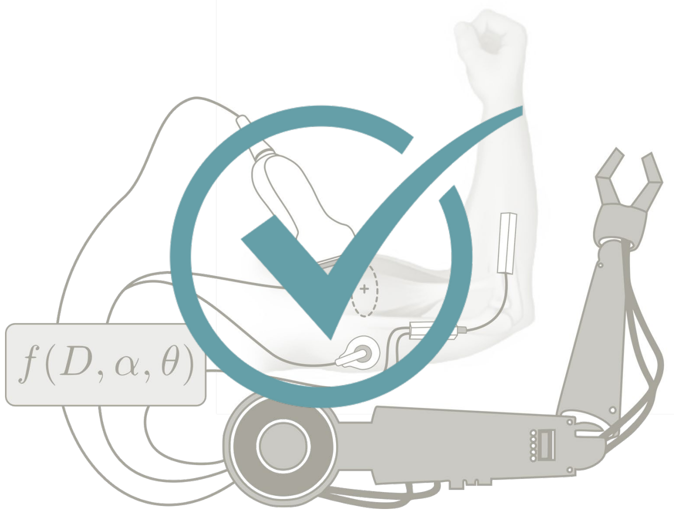
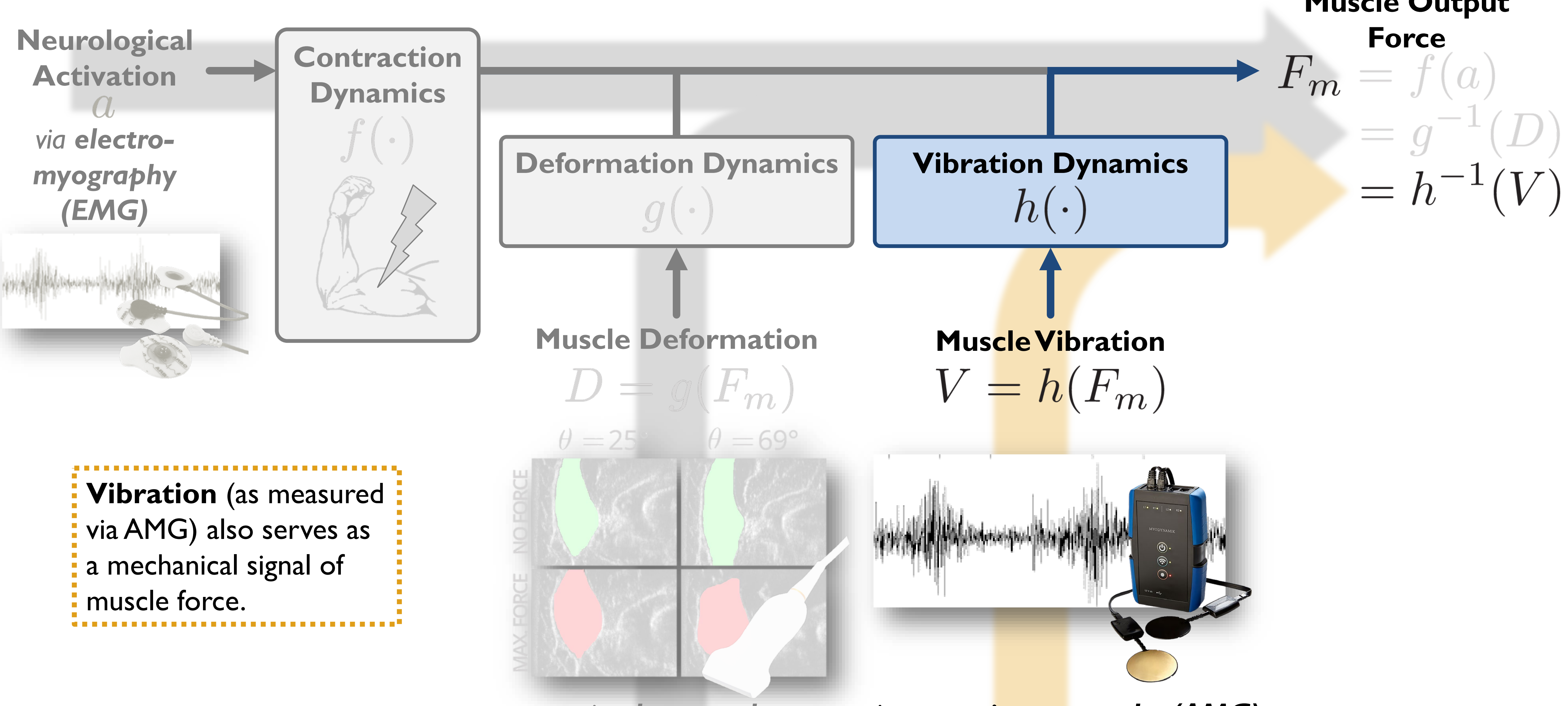


III Proof-of-Concept Applications



Alternate Modalities & Conclusions

Muscle Force Inference: AMG



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

Contraction Dynamics
$f(\cdot)$

Deformation Dynamics
$g(\cdot)$

Vibration Dynamics
$h(\cdot)$

Muscle Output Force

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

Muscle Deformation

$$D = g(F_m)$$

*via **ultrasound***

Muscle Vibration

$$V = h(F_m)$$

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

Vibration (as measured via AMG) also serves as a mechanical signal of muscle force.

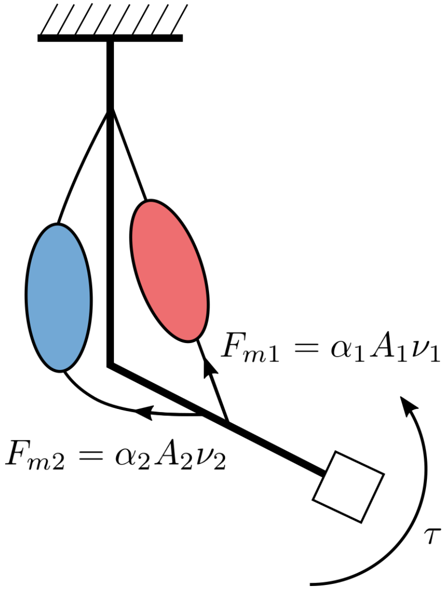
Preliminary AMG-Force Model

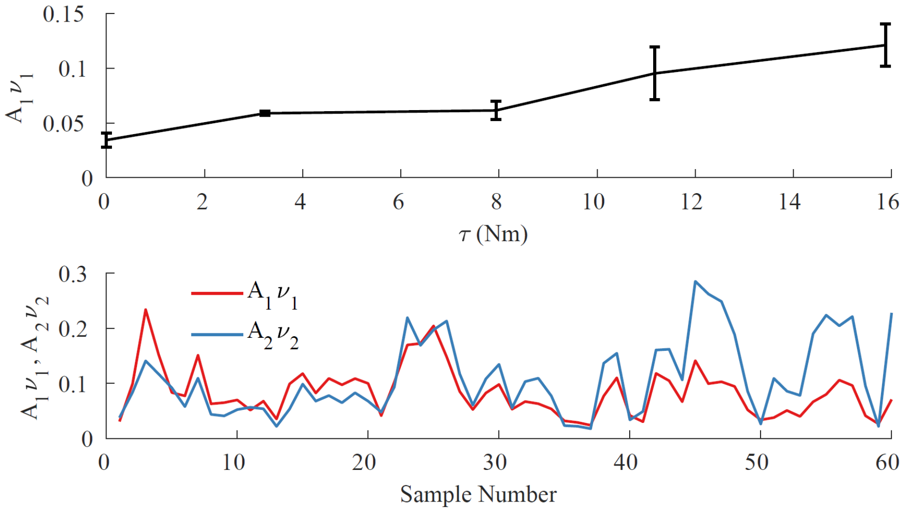
AMG amplitude $A \propto$ [# activated muscle fibers]

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

[Harrison '18]

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**

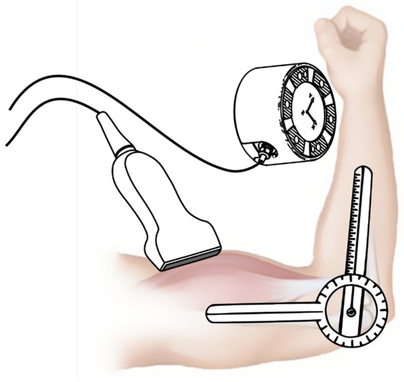
*[**Hallock**, Bajcsy, EMBC 2018]*

Roadmap: Recap

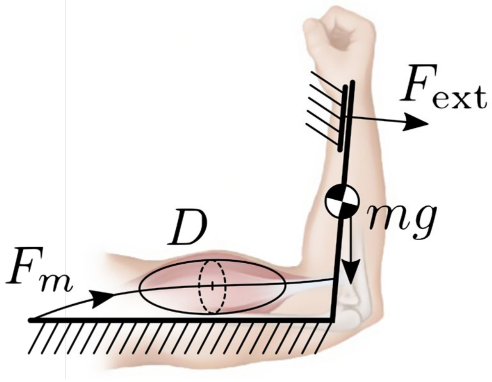
CORE OBJECTIVE

We seek to measure **individual muscle forces** in vivo via **ultrasound** based on **shape changes** under loading.

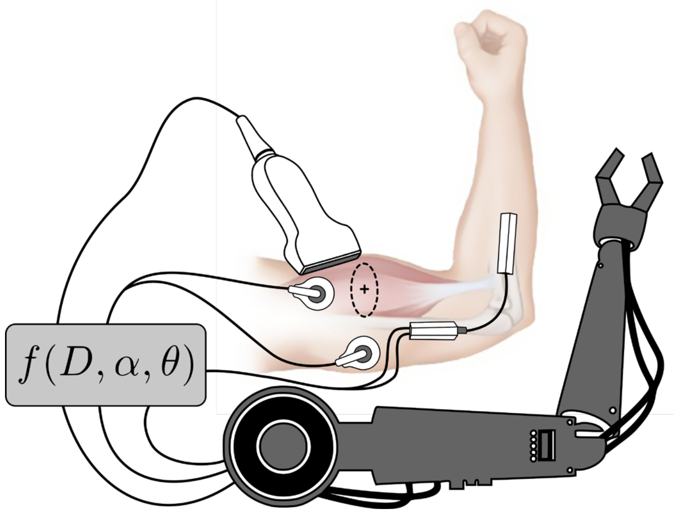
I Exploratory Data Set Generation



II Model Development & Validation



III Proof-of-Concept Applications



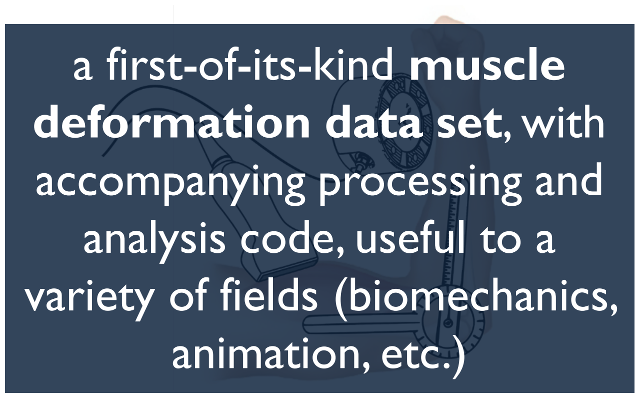
Alternate Modalities & Conclusions

Roadmap: Recap of Planned Contributions

CORE OBJECTIVE

We seek to measure **individual muscle forces** in vivo via **ultrasound** based on **shape changes** under loading.

I Exploratory Data Set Generation

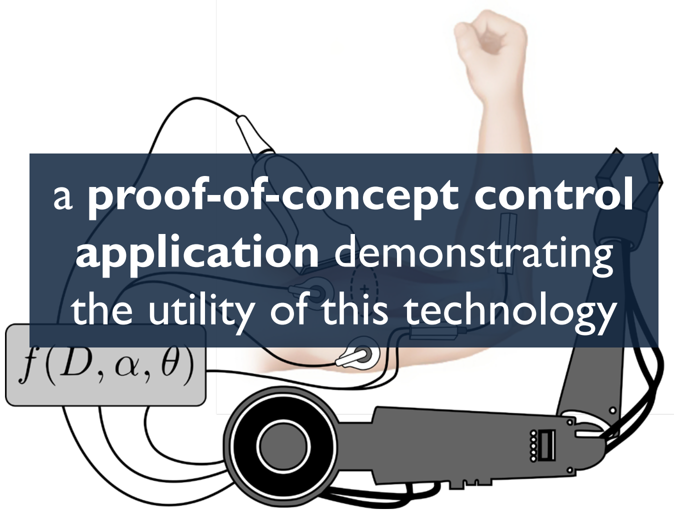


a first-of-its-kind **muscle deformation data set**, with accompanying processing and analysis code, useful to a variety of fields (biomechanics, animation, etc.)

II Model Development & Validation

a **suite of models** resulting in the **first in vivo non-invasive individual muscle force measurement**

III Proof-of-Concept Applications



a **proof-of-concept control application** demonstrating the utility of this technology

Alternate Modalities & Conclusions

Acknowledgments & Sponsors

THANKS TO:
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Shivani Sharma
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Amanda Schwartz
Akash Velu

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`eecs.berkeley.edu/~lhallock`

List of Publications

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

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

J. Zhang, S. Gajjala, P. Agrawal, G. H. Tison, **L. A. Hallock**, L. Beussink-Nelson, M. H. Lassen, E. Fan, M. A. Aras, C. Jordan, K. E. Fleischmann, M. Melisko, A. Qasim, S. J. Shah, R. Bajcsy, and R. C. Deo. "Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy." *Circulation*, vol. 138, no. 16, pp. 1623–1635, 2018.

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

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