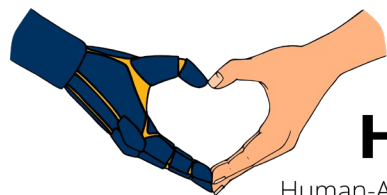


A systematic modeling framework for deformation-based muscle force inference

Laura Hallock

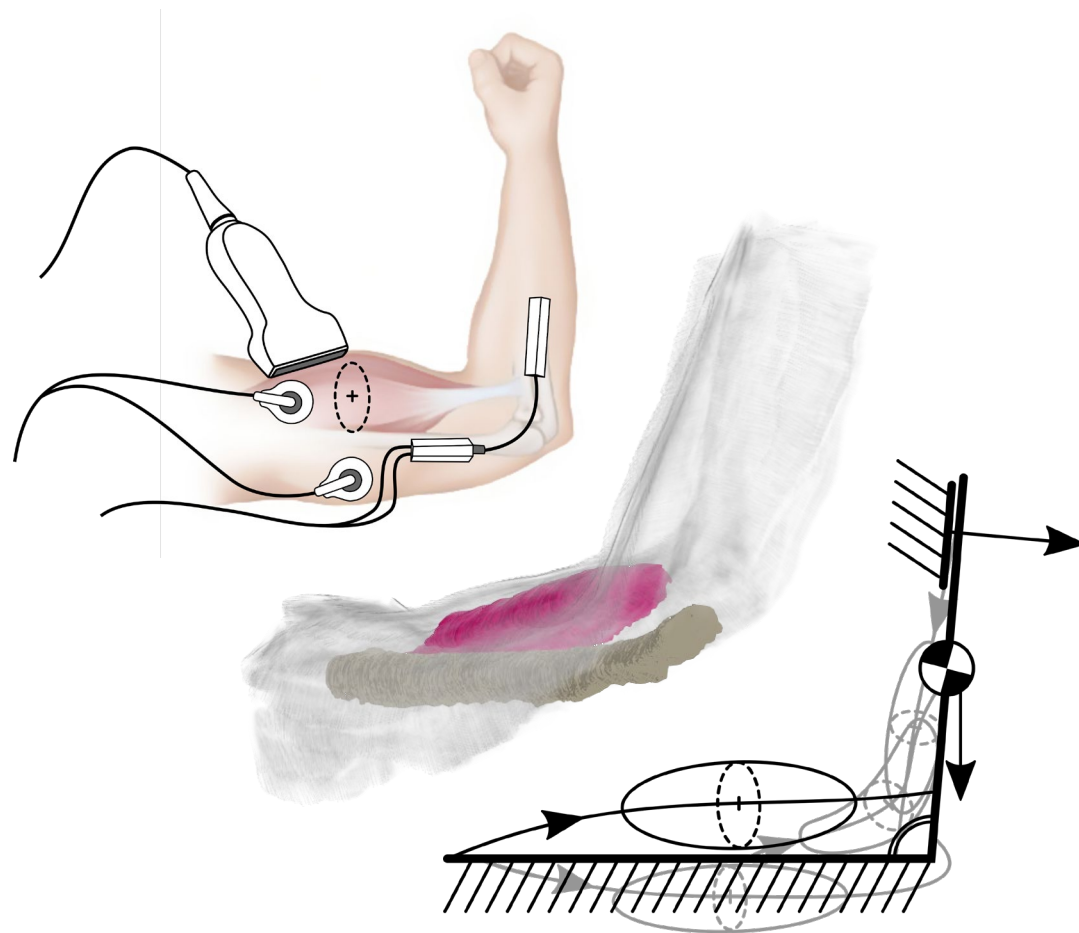
Harvard Visit

2019.09.25



HART Lab

Human-Assistive Robotic Technologies



Berkeley
UNIVERSITY OF CALIFORNIA

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.**”*

—Walter Herzog, 2017

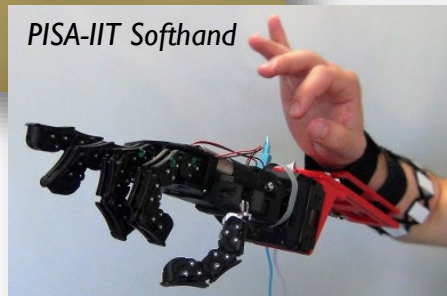
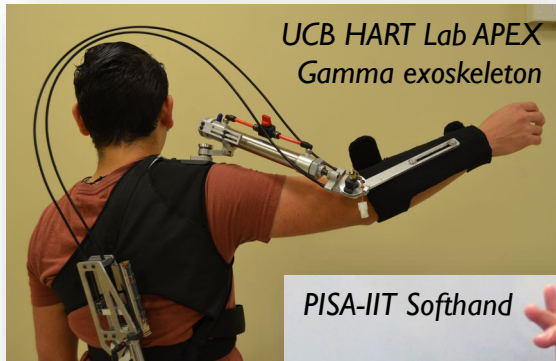


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Safe and Expressive Device Control

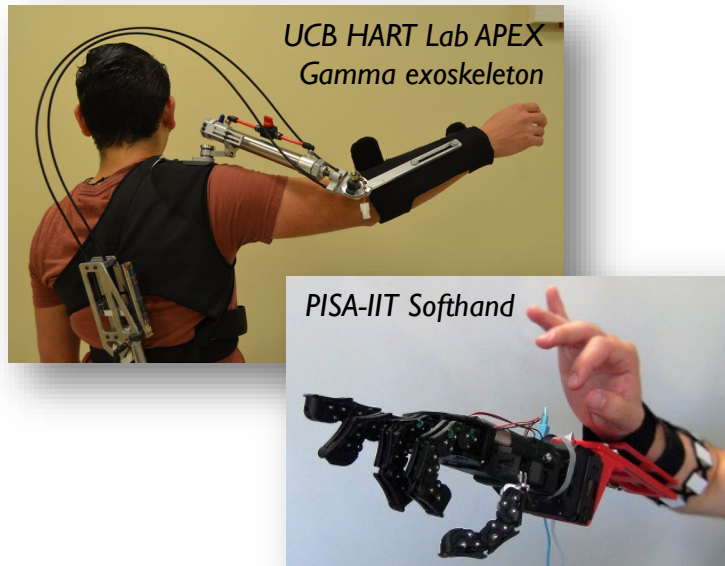


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Safe and Expressive Device Control



Understanding of Highly Dexterous Movements

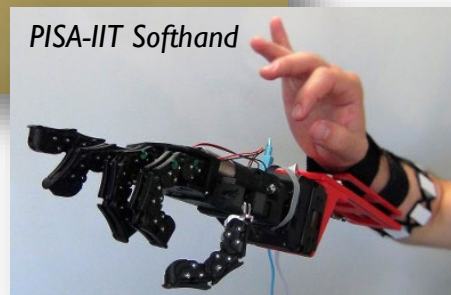
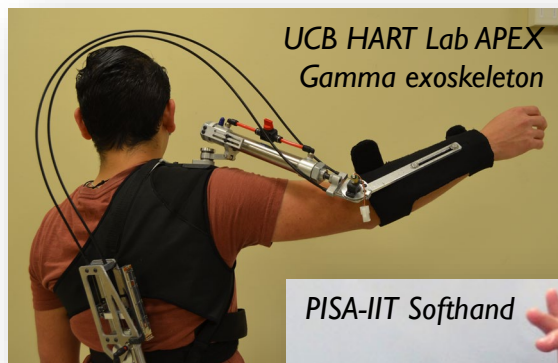


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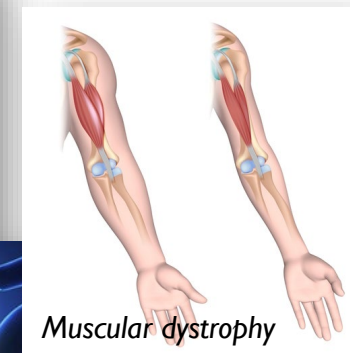
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Understanding of Highly Dexterous Movements



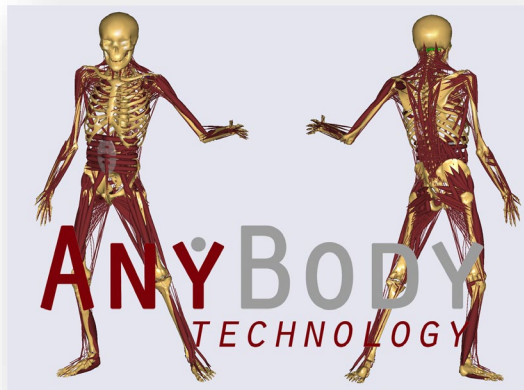
Diagnosis and Rehabilitation of Pathology



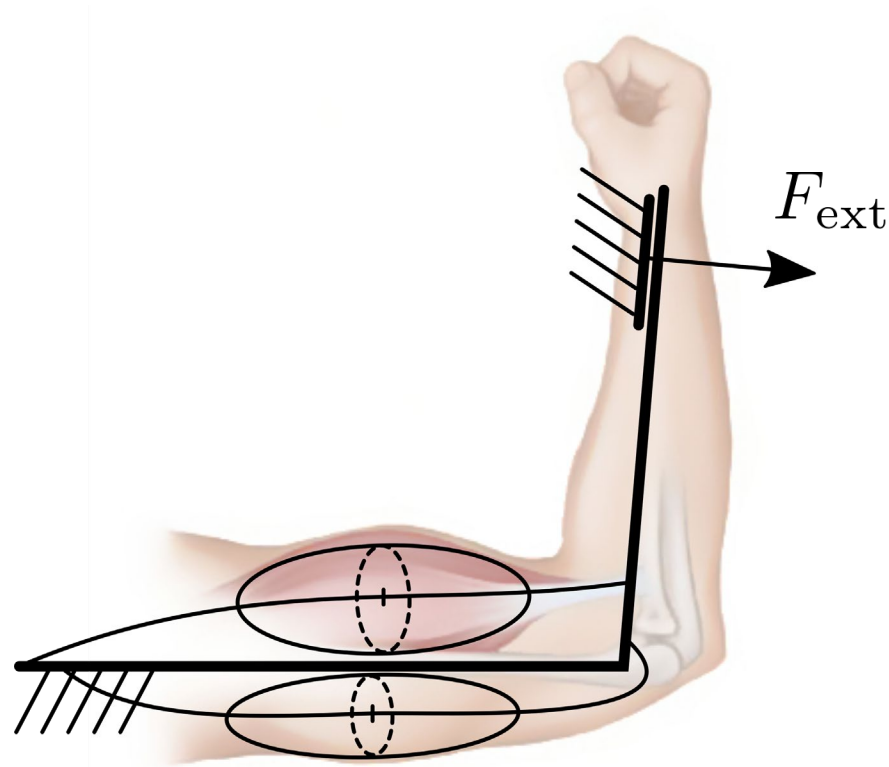
Muscle Force Inference: State-of-the-Art Shortcomings



[Delp et al. 2007]



[Damsgaard et al. 2006]



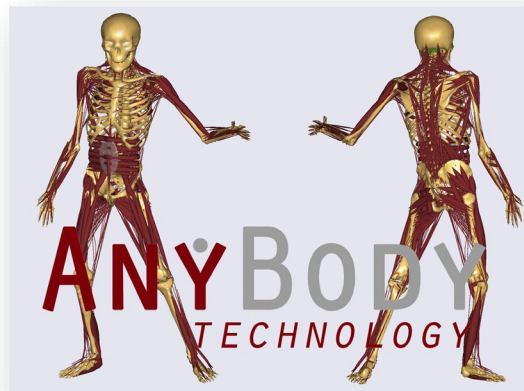
Humans are **highly over-actuated**, and existing modeling frameworks make **significant assumptions about muscle force distribution**.



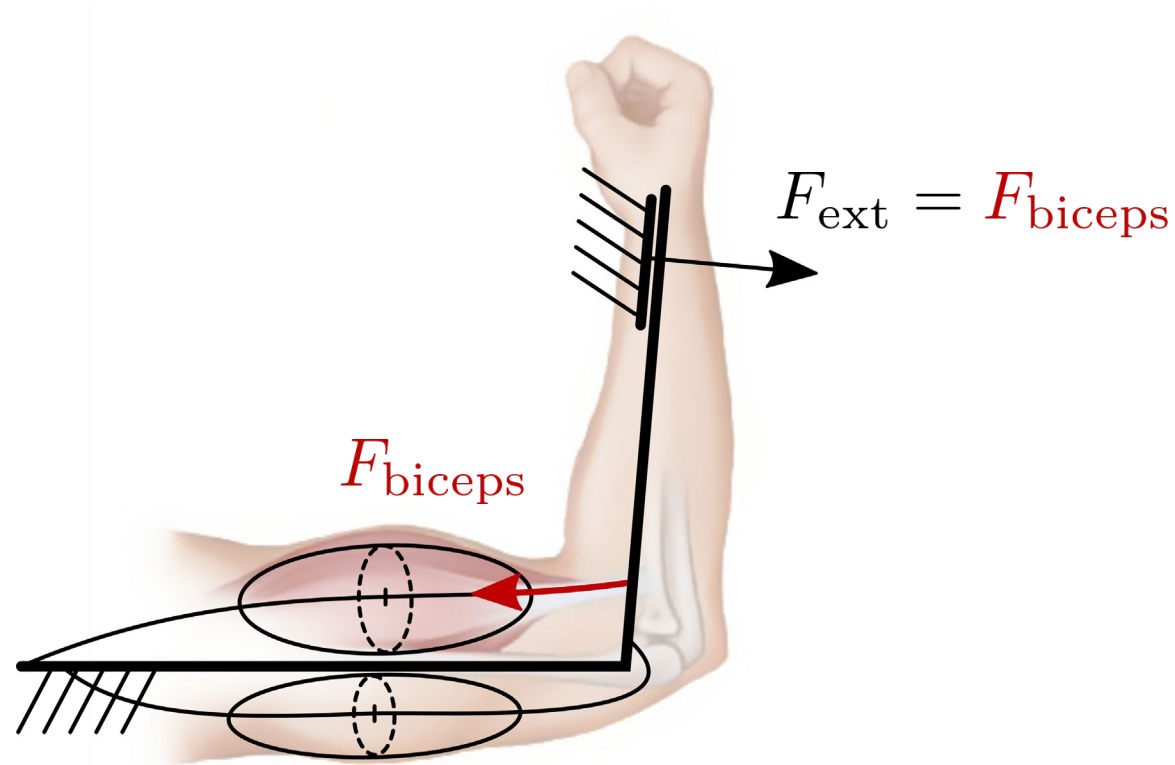
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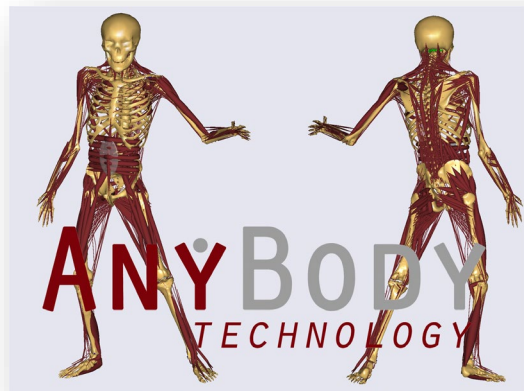
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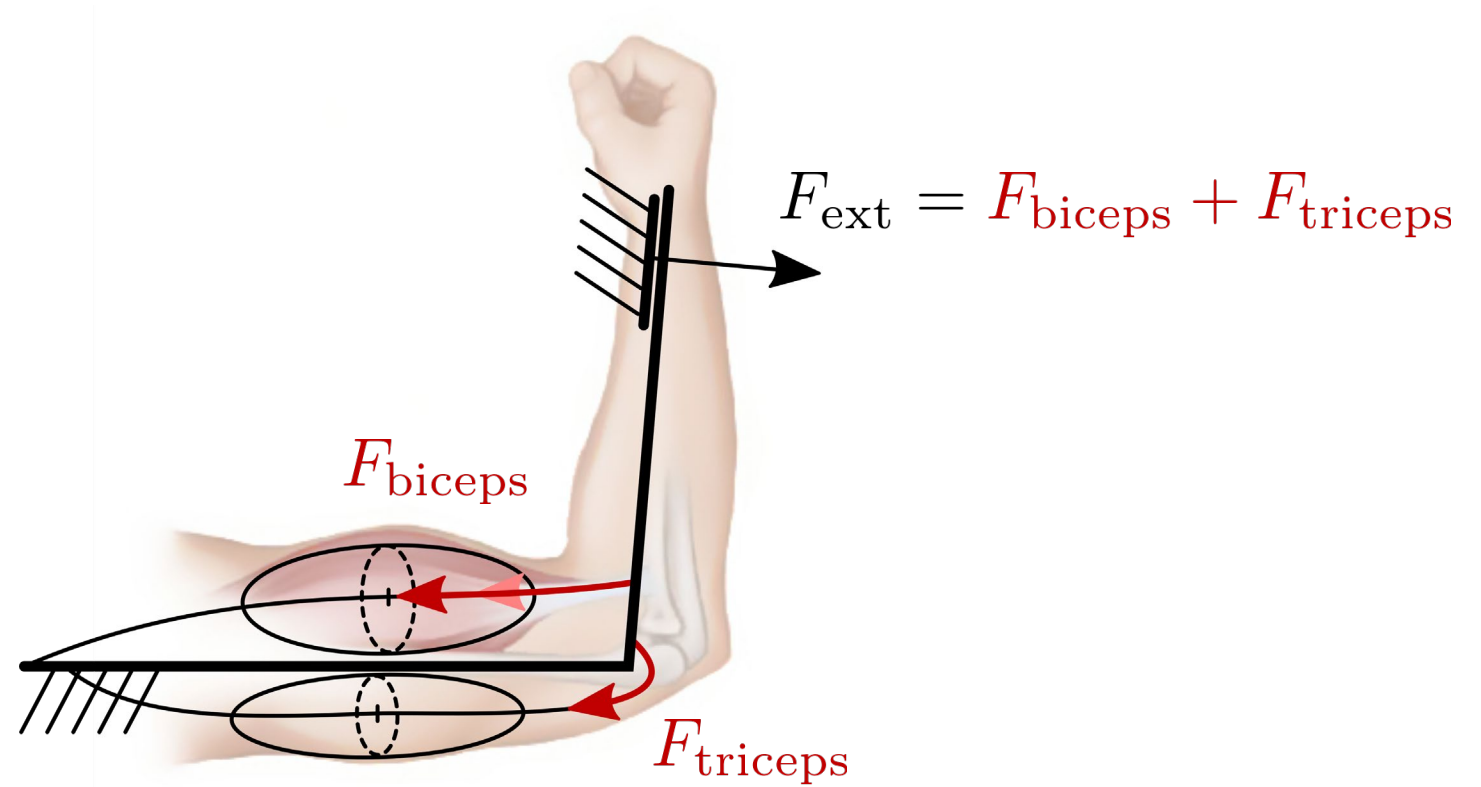
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Muscle Force Inference: State-of-the-Art Shortcomings

Muscle Output

Force

$$F_m = f(a)$$

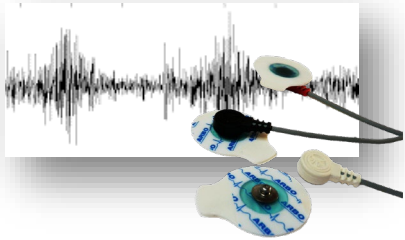
Neurological
Activation

a

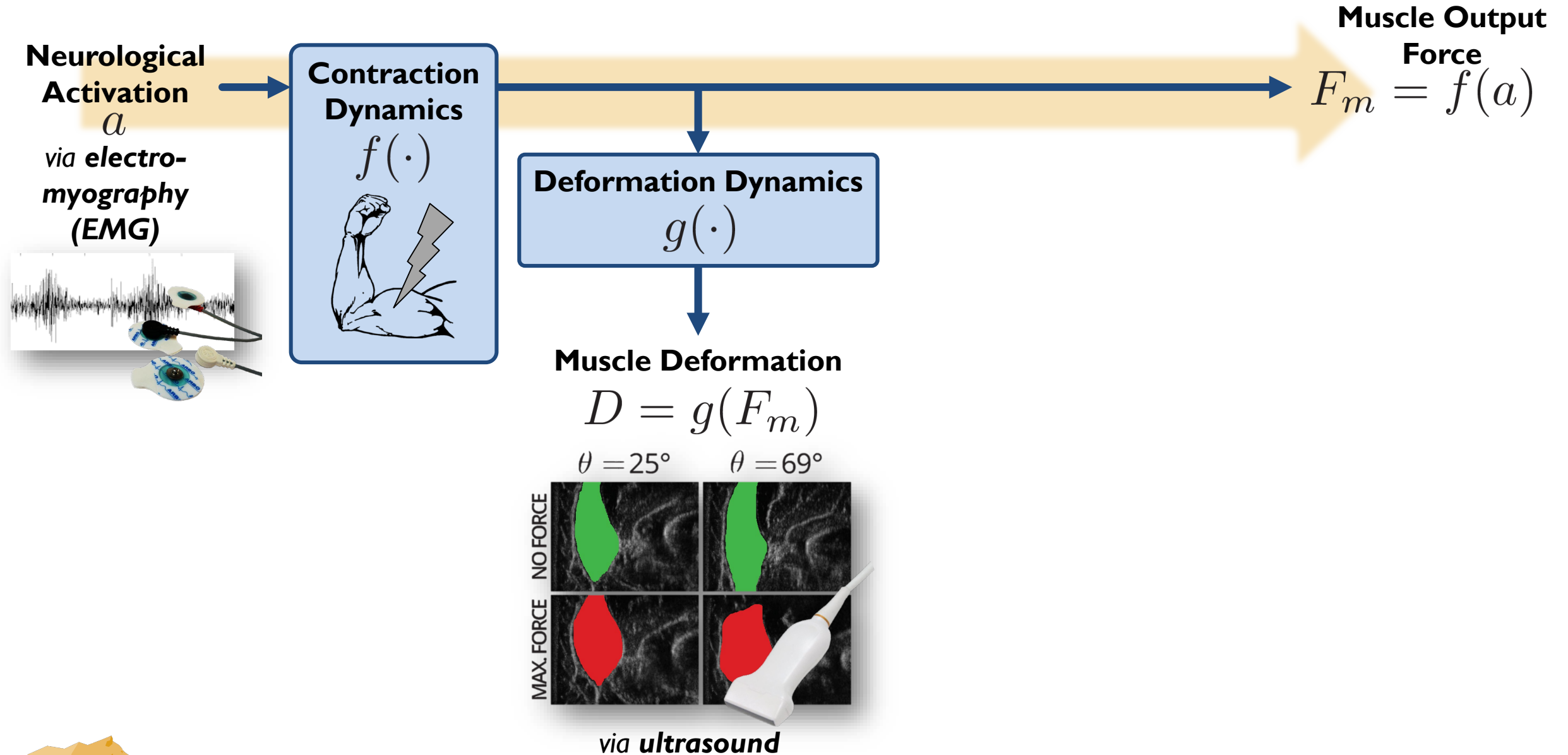
via **electro-
myography
(EMG)**

Contraction
Dynamics

$f(\cdot)$



Muscle Force Inference

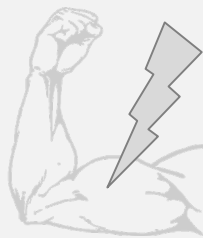


Muscle Force Inference: Our Approach

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

Contraction
Dynamics
 $f(\cdot)$

$f(\cdot)$



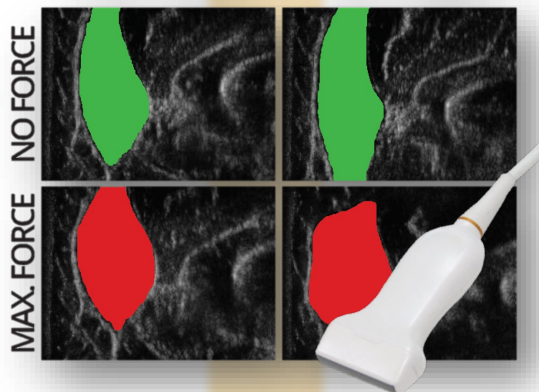
Deformation
Dynamics
 $g(\cdot)$

$g(\cdot)$

Muscle Deformation

$$D = g(F_m)$$

$\theta = 25^\circ$ $\theta = 69^\circ$



via **ultrasound**

Muscle Output
Force

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

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.

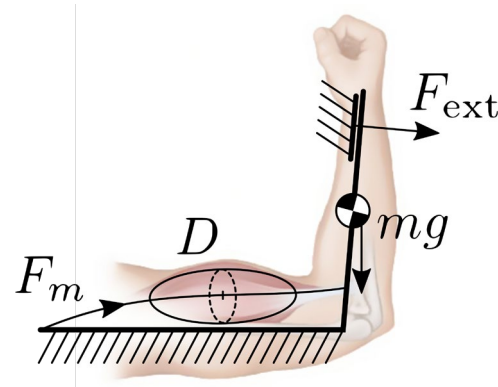


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Model Development & Validation

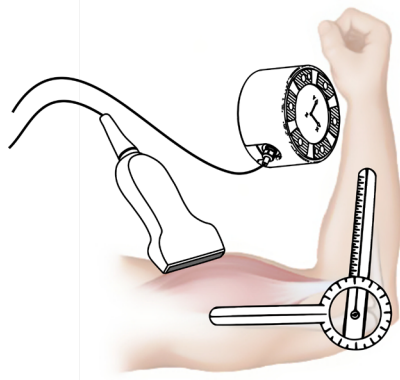


Roadmap

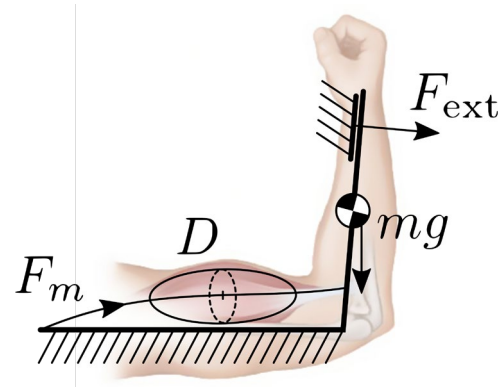
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I Exploratory Data Set Generation



II Model Development & Validation

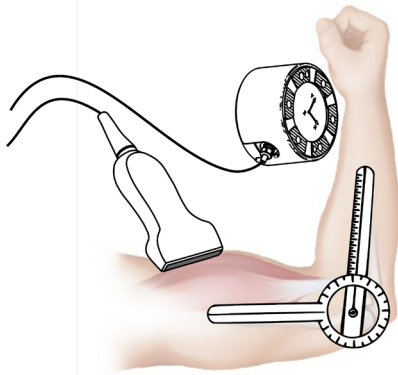


Roadmap

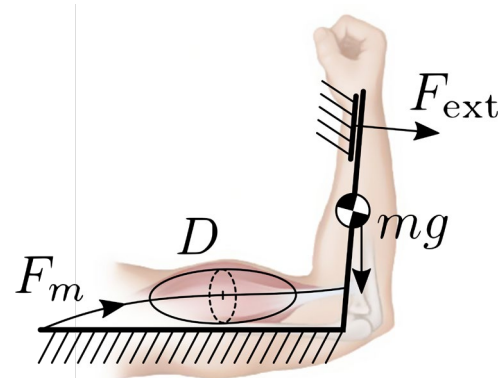
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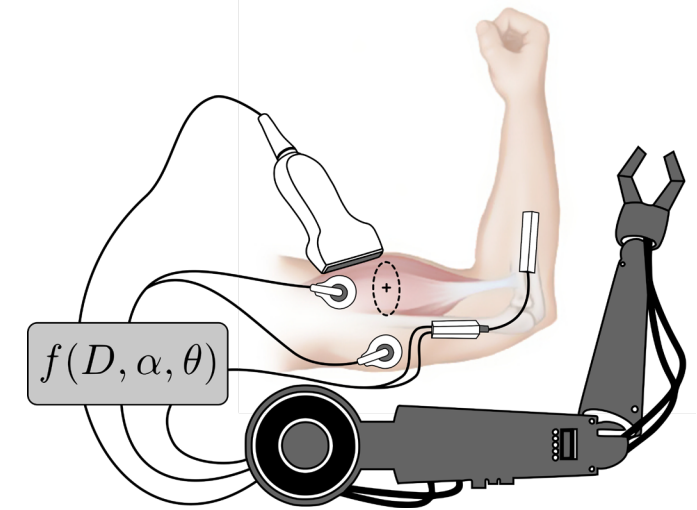
I Exploratory Data Set Generation



II Model Development & Validation



III Proof-of-Concept Applications



Alternate Modalities & Conclusions

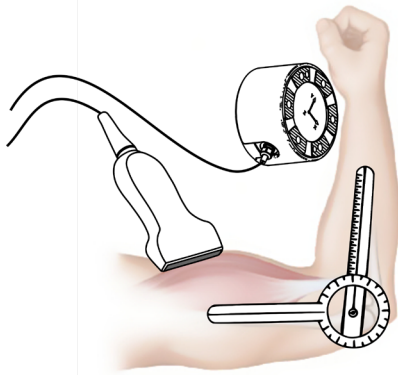


Roadmap

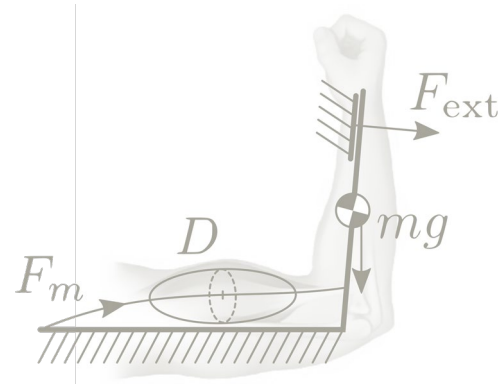
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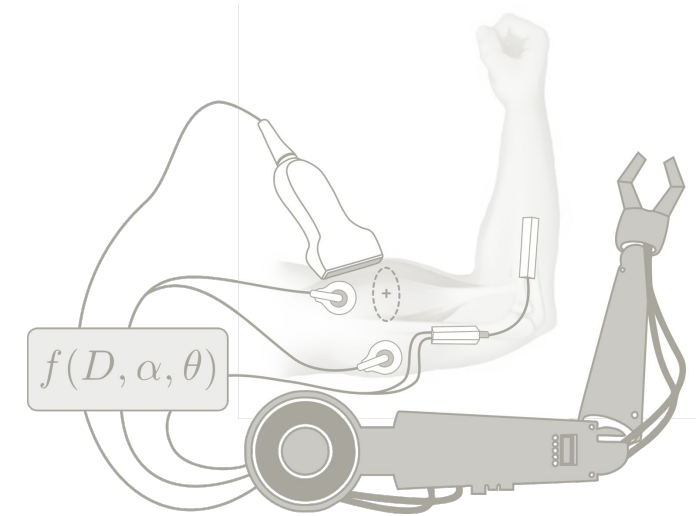
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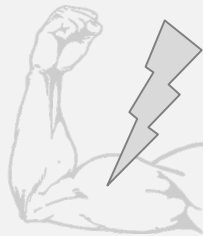


Muscle Force Inference: Our Approach

Neurological
Activation
 a
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Contraction
Dynamics

$f(\cdot)$



Deformation
Dynamics

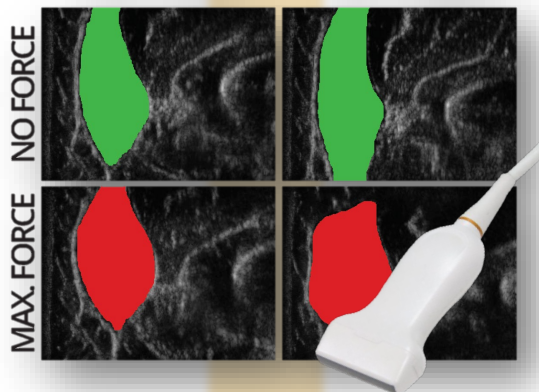
$g(\cdot)$

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via **ultrasound**

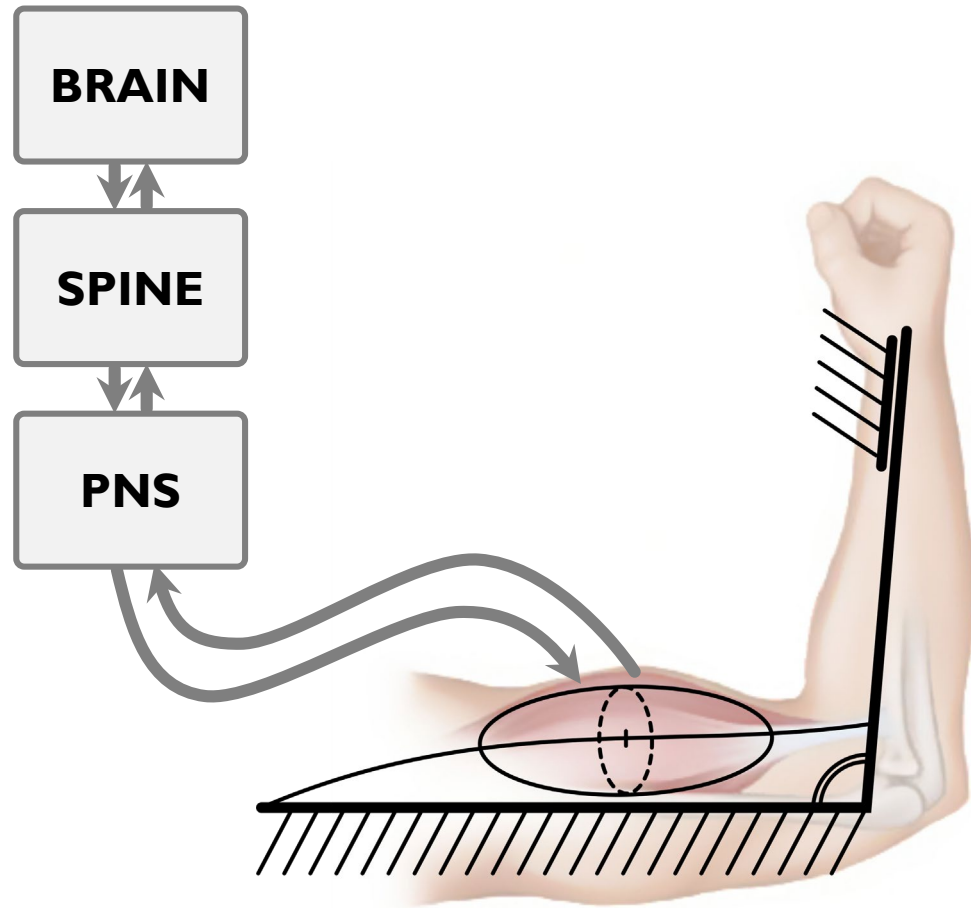
Muscle Output
Force

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

What should this model look like?



(Simplified) Biological Mechanism

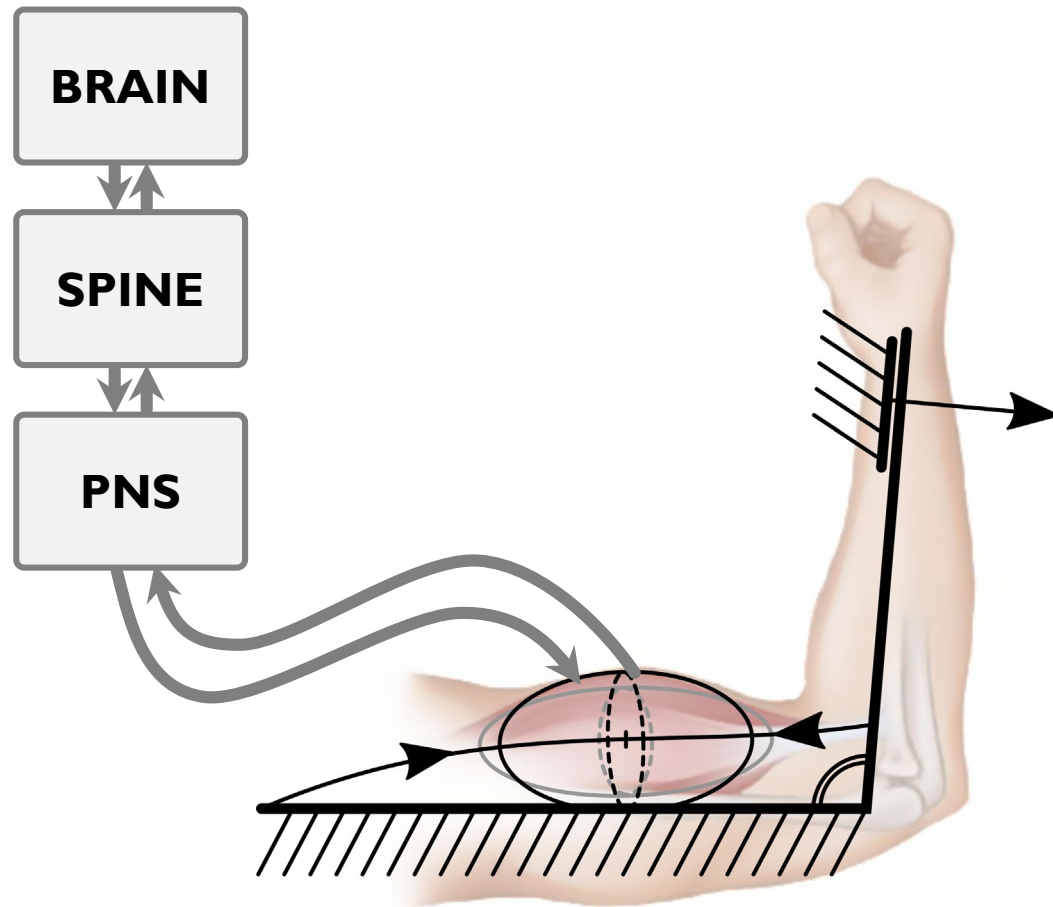


When muscles are activated by the nervous system, they contract, extending springlike **tendons**, which impart force to the skeleton.

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



(Simplified) Biological Mechanism



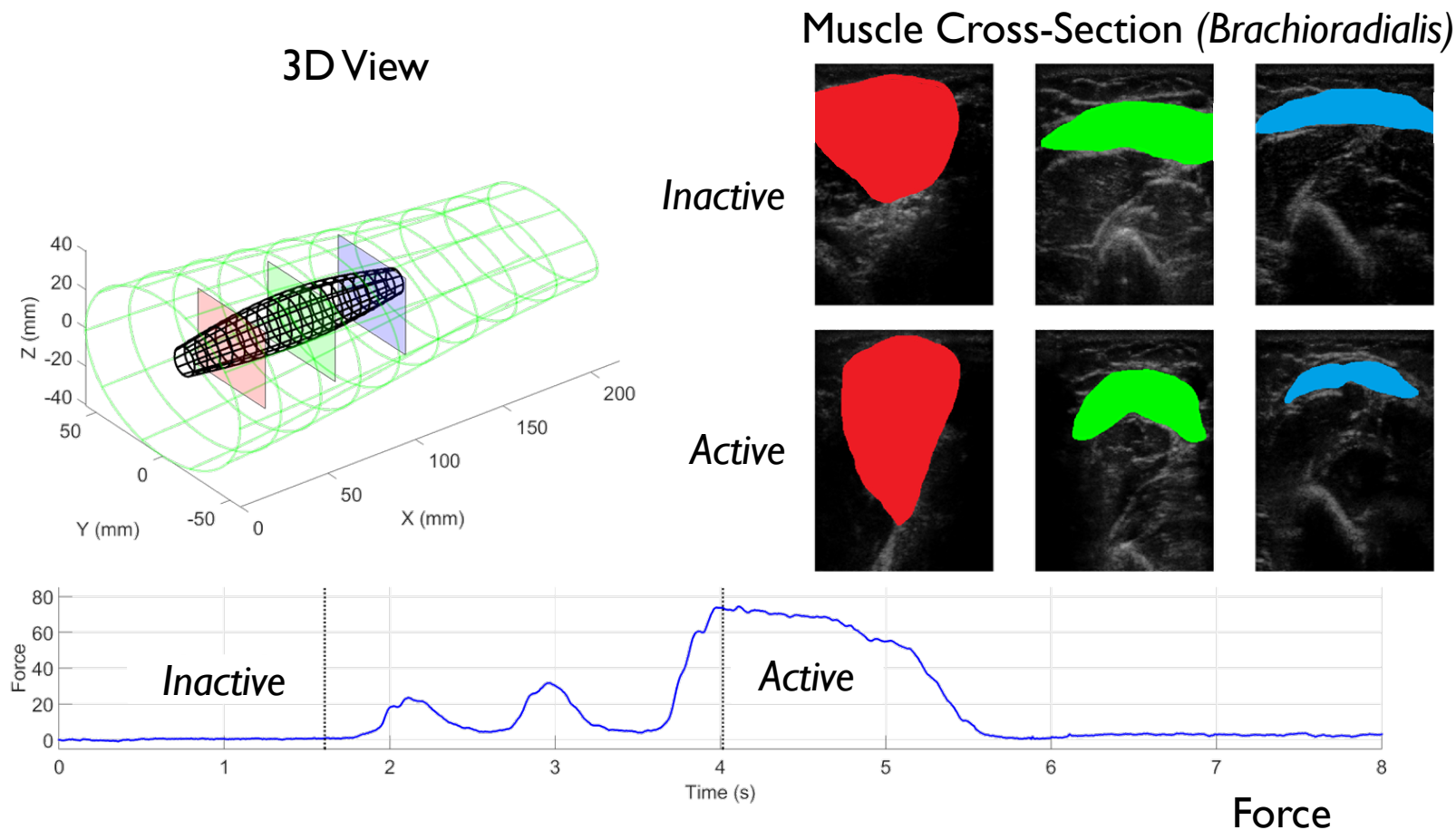
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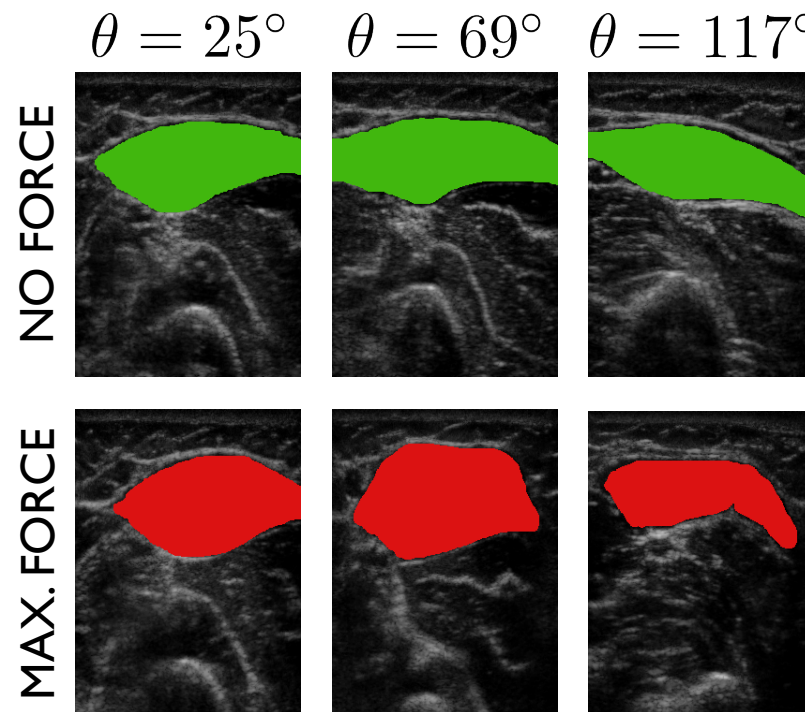
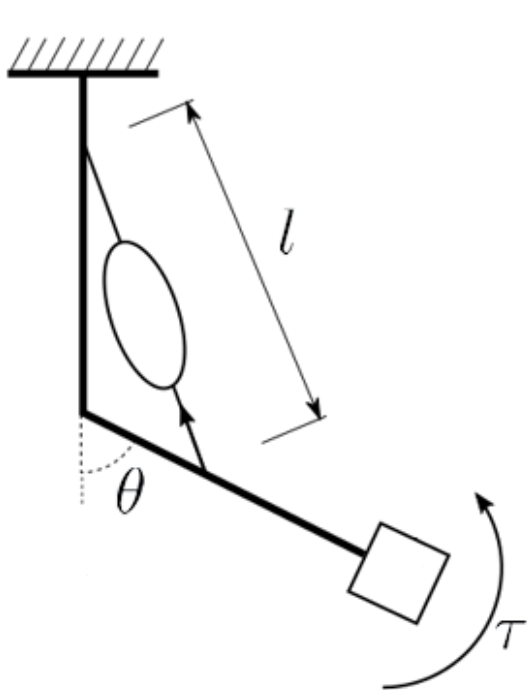
Deformation Modeling Challenges

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



Deformation Modeling Challenges

1. Observed deformation **varies substantially** with **sensor location**.
2. Deformation occurs under changes in both **kinematic configuration** and **force output**.



Deformation Modeling Challenges

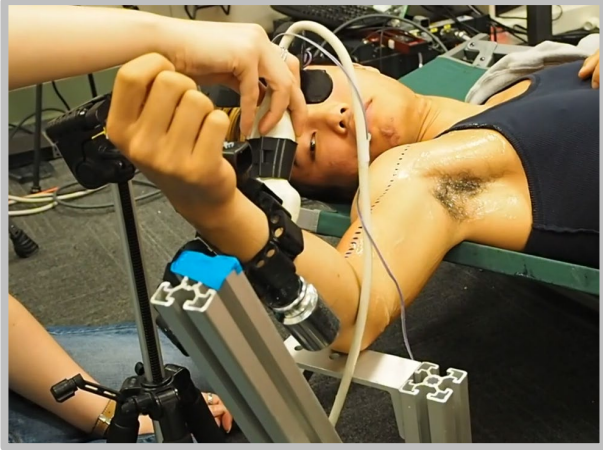
1. Observed deformation **varies substantially** with **sensor location**.
2. Deformation occurs under changes in both **kinematic configuration** and **force output**.

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

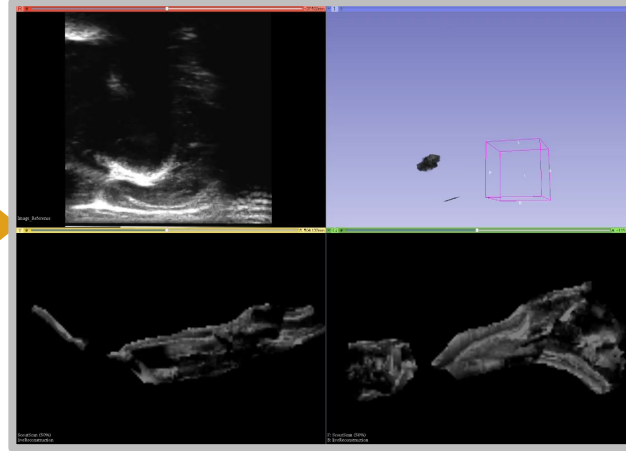


Data Collection Setup: Ultrasound + Motion Capture

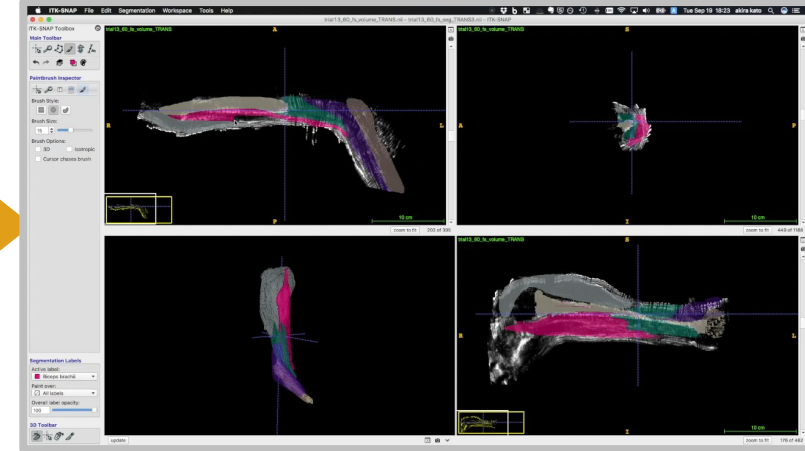
Raw Data Collection
via Ultrasound & Motion Capture



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]

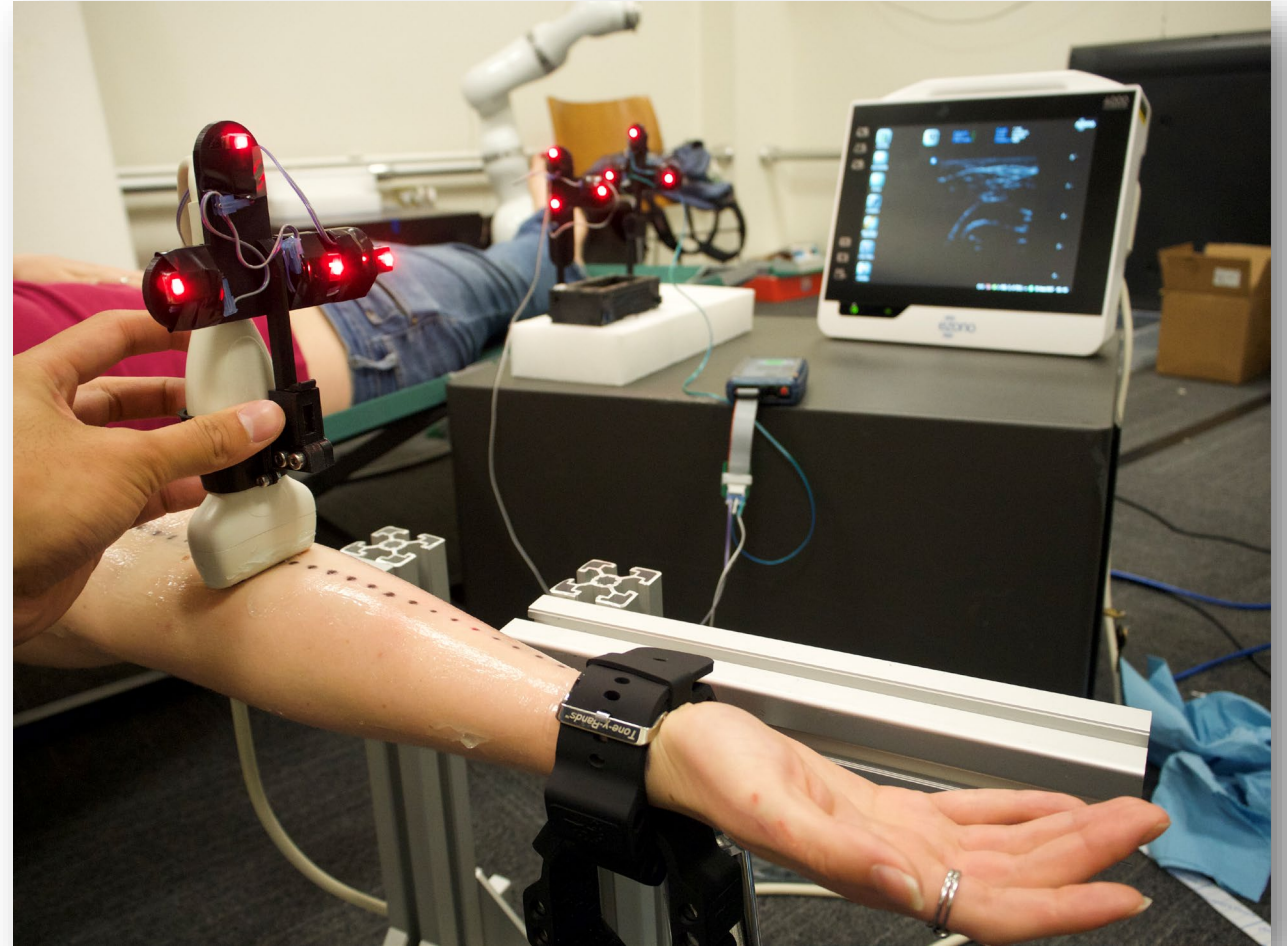


Preliminary Data Set

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)



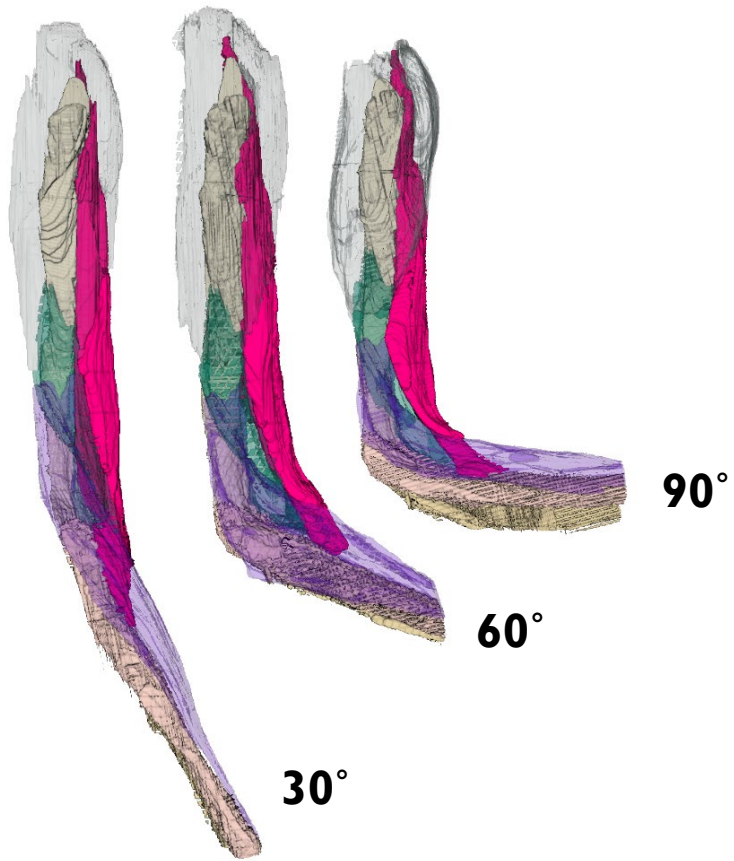
Ultrasound volumetric data collection, HART Lab 2017

[Hallock, Kato, Bajcsy, ICRA 2018]



Preliminary Results: Qualitative

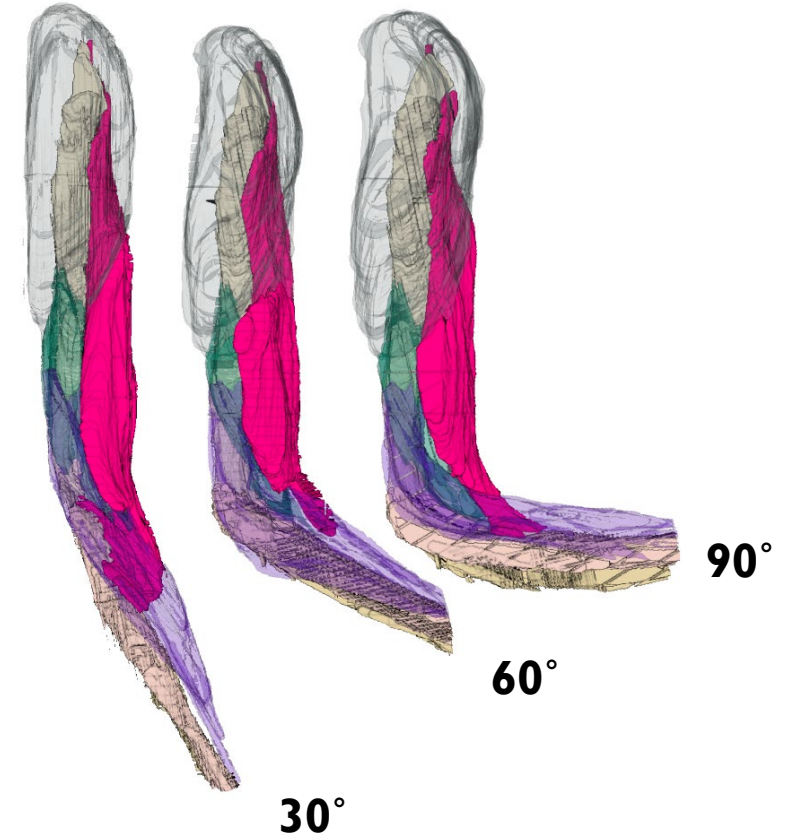
FS
("Fully Supported")



LF
("Low Force")



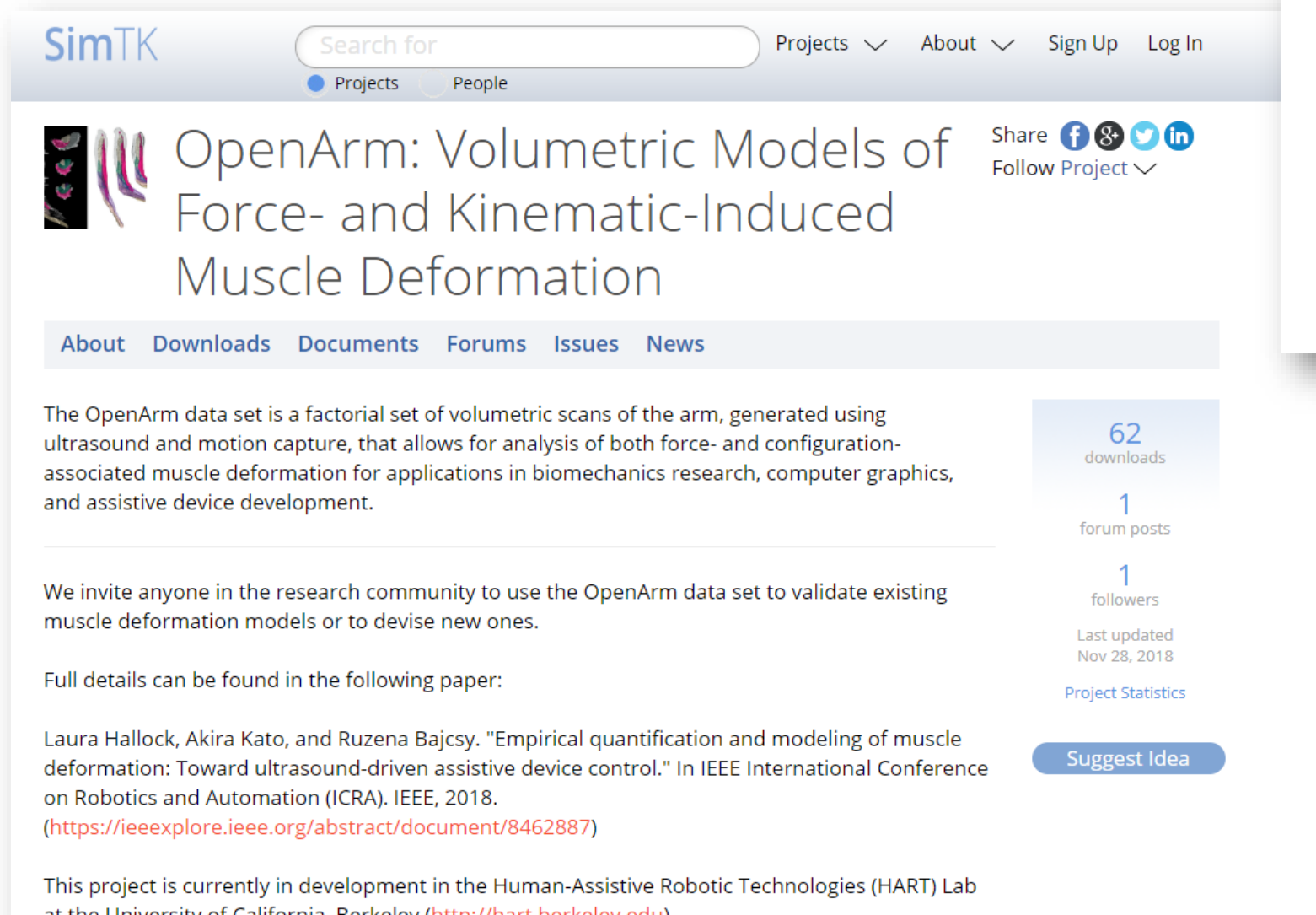
HF
("High Force")



[Hallock, Kato, Bajcsy, ICRA 2018]



Data Set Release: OpenArm 1.0



The screenshot shows the SimTK website for the OpenArm project. The header includes the SimTK logo, a search bar, and navigation links for Projects, About, Sign Up, and Log In. The main title is "OpenArm: Volumetric Models of Force- and Kinematic-Induced Muscle Deformation". Below the title are tabs for About, Downloads, Documents, Forums, Issues, and News. The main content area describes the data set as a factorial set of volumetric scans of the arm, generated using ultrasound and motion capture. It also includes an invitation to the research community to use the data set and a link to the paper by Laura Hallock, Akira Kato, and Ruzena Bajcsy. On the right side, there is a sidebar with statistics: 62 downloads, 1 forum post, and 1 follower. A "Suggest Idea" button is also present.

SimTK

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Projects About Sign Up Log In

Projects People

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

Share Follow Project

About Downloads Documents Forums Issues News

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

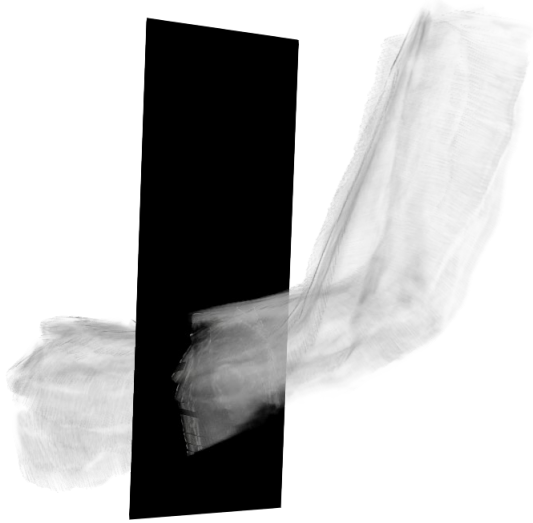


[Hallock, Kato, Bajcsy, ICRA 2018]

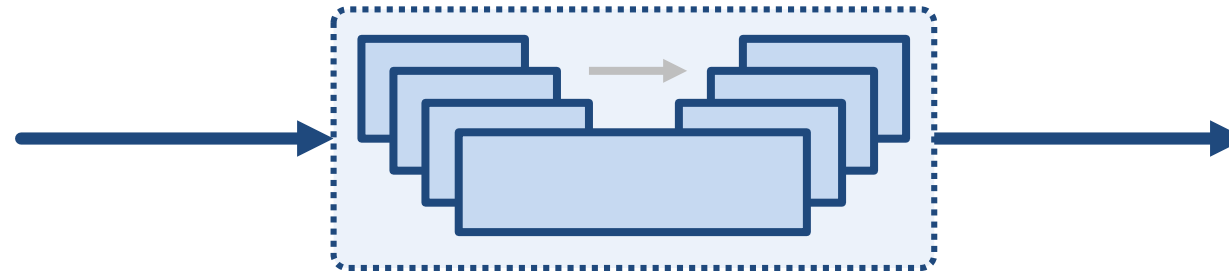


Automated Tissue Segmentation: U-Net

intensity map (2D slice)

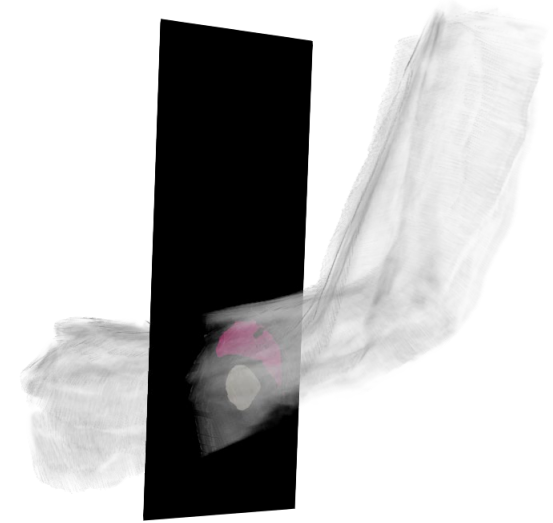


(2D) U-Net



[Ronneberger et al. 2015]

output segmentation (2D slice)

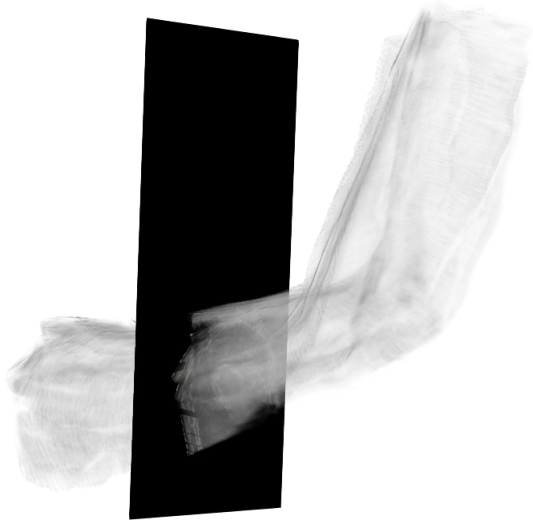


[Nozik*, **Hallock***, Ho, Mandava, Mitchell, Li, Bajcsy, EMBC 2019]

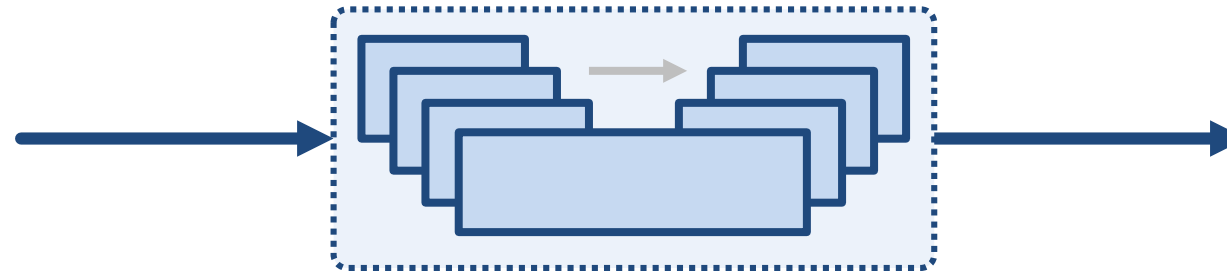


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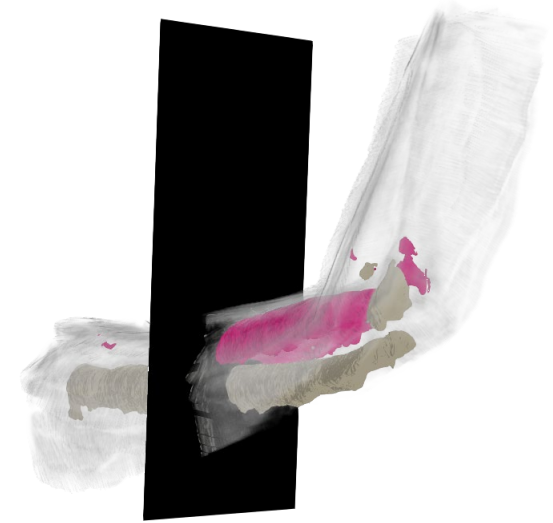


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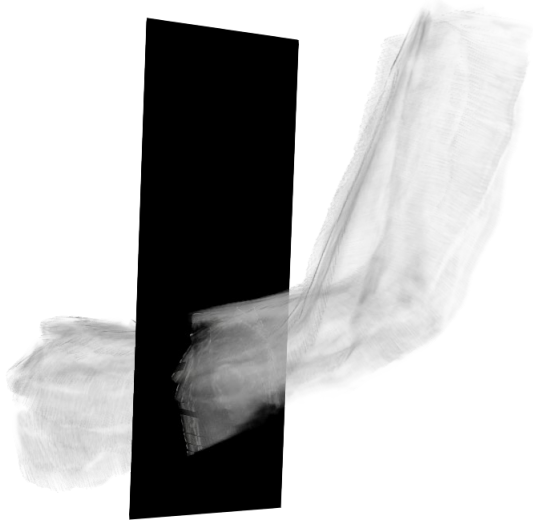


[Nozik*, **Hallock***, Ho, Mandava, Mitchell, Li, Bajcsy, EMBC 2019]

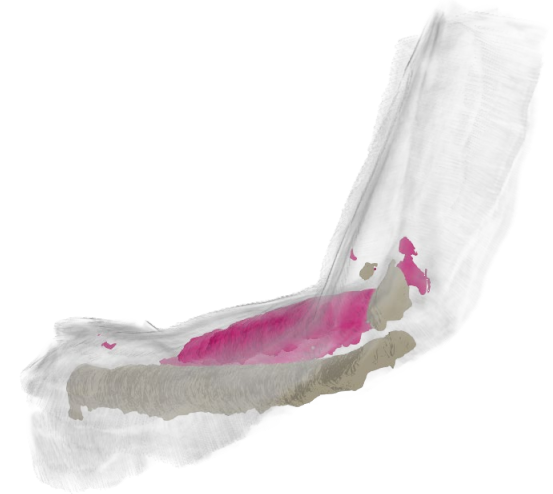


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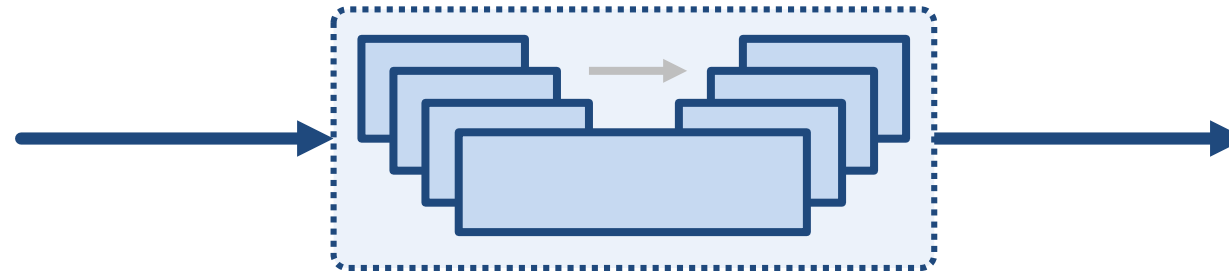
intensity map (2D slice)



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(2D) U-Net



[Ronneberger et al. 2015]

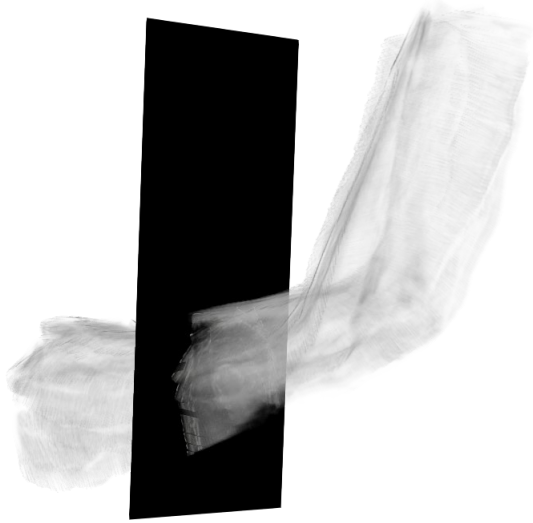
CNN-based segmentation performs better than classical registration on the **center of the muscle**, where we focus our modeling analyses.

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



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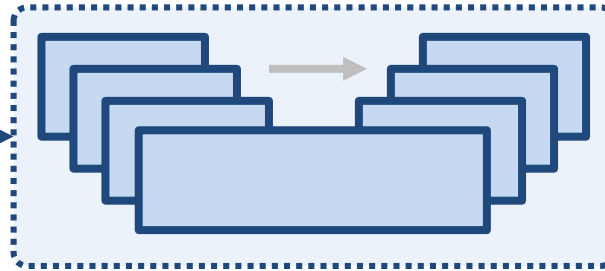
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Automated Tissue Segmentation: Preliminary Results

Ground Truth

Registration

U-NET

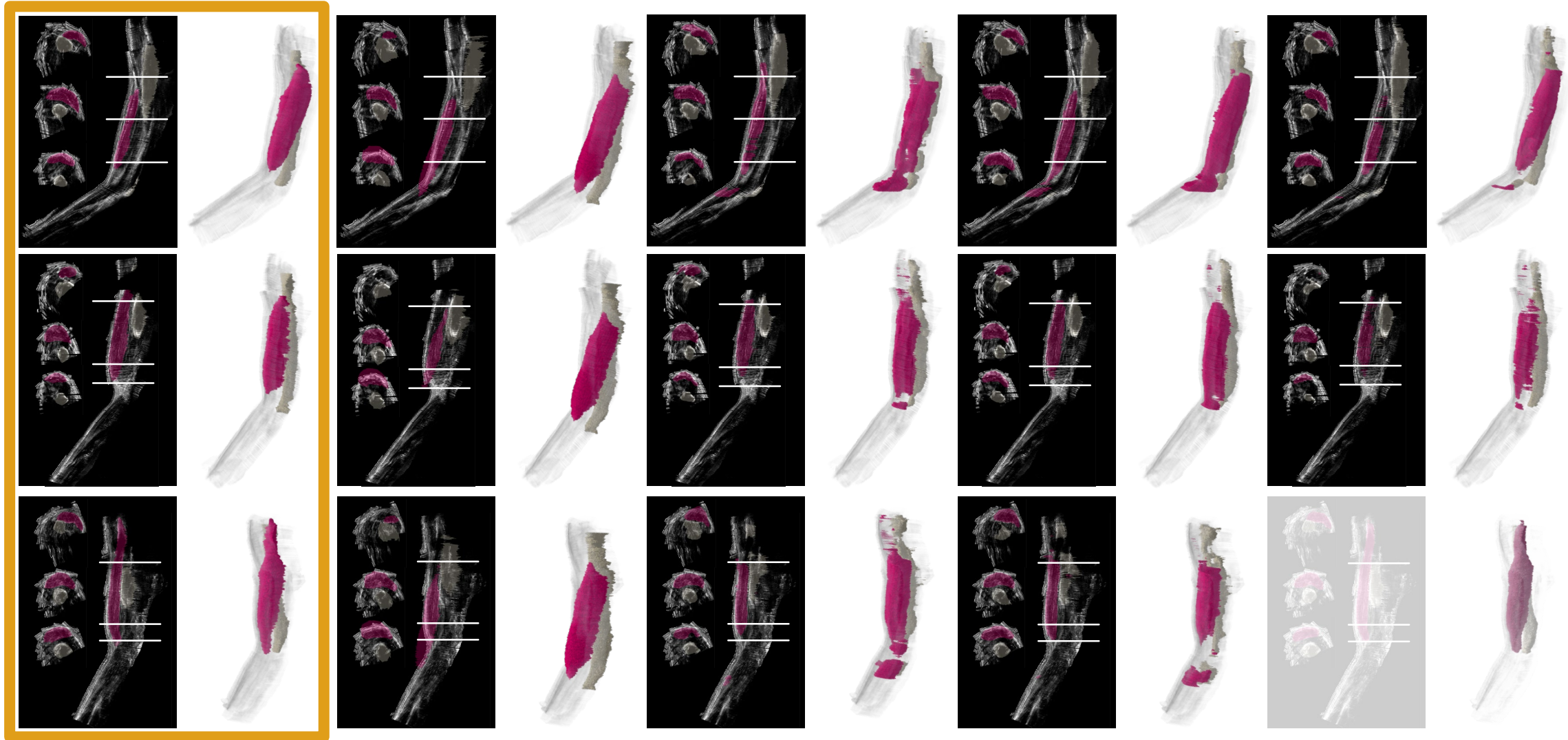
U-NET+EA

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]

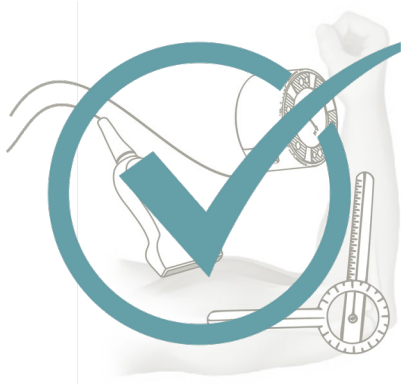


Roadmap

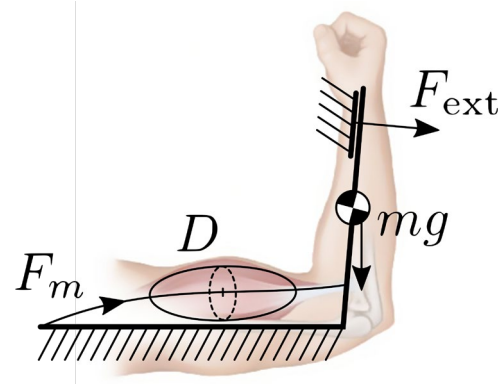
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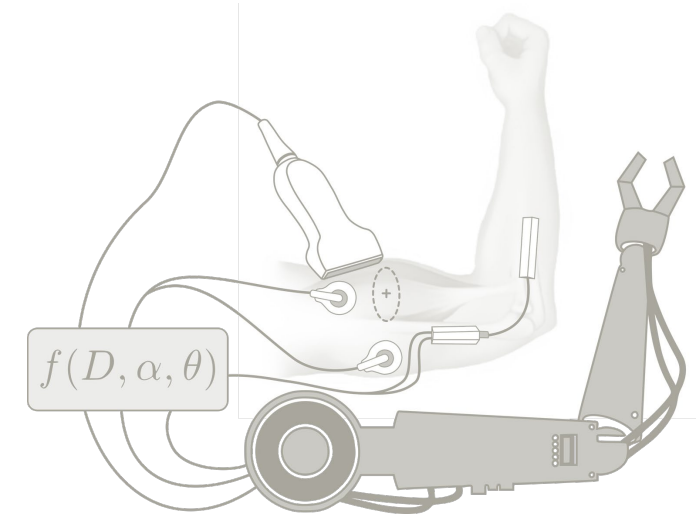
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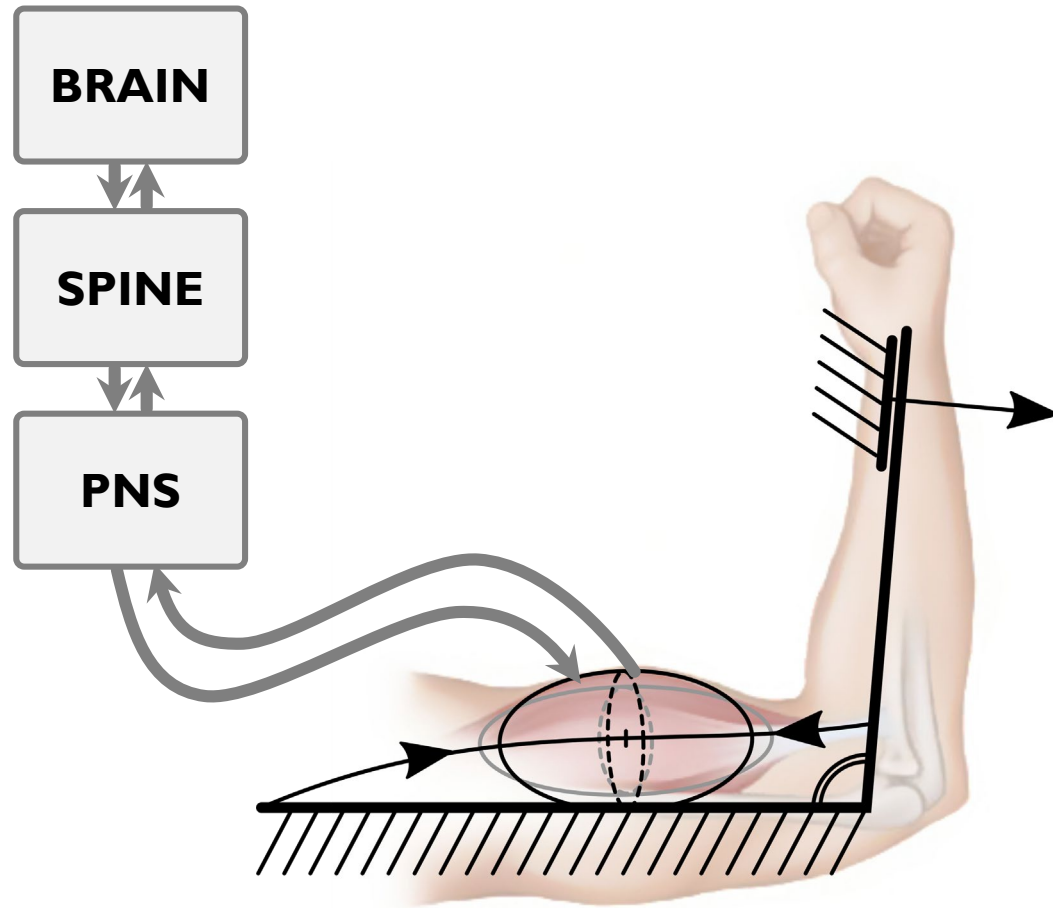
III Proof-of-Concept Applications



Alternate Modalities & Conclusions



(Simplified) Biological Mechanism

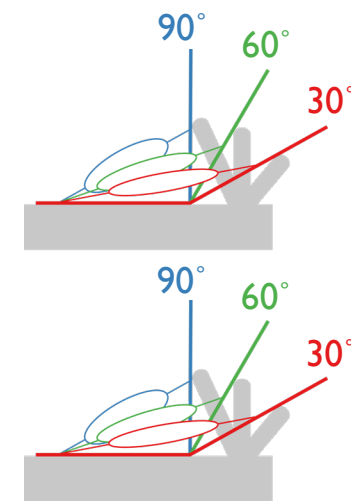
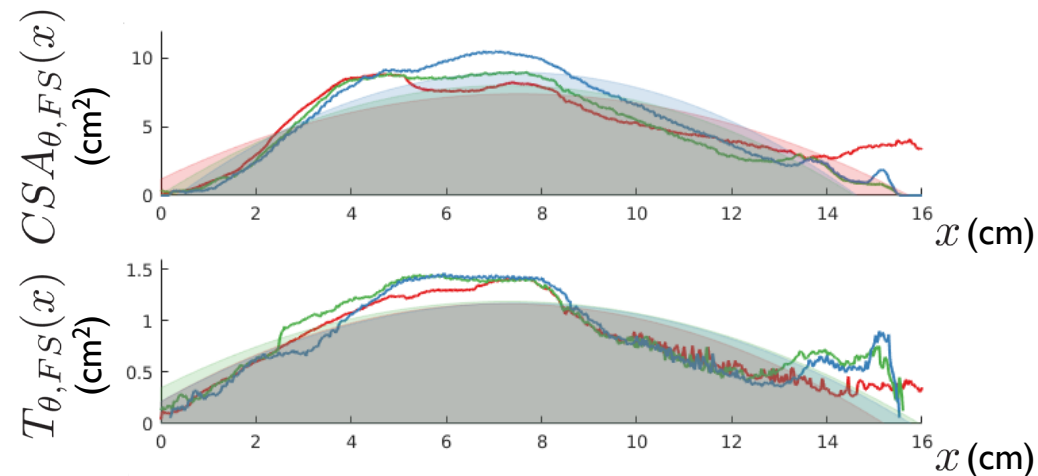
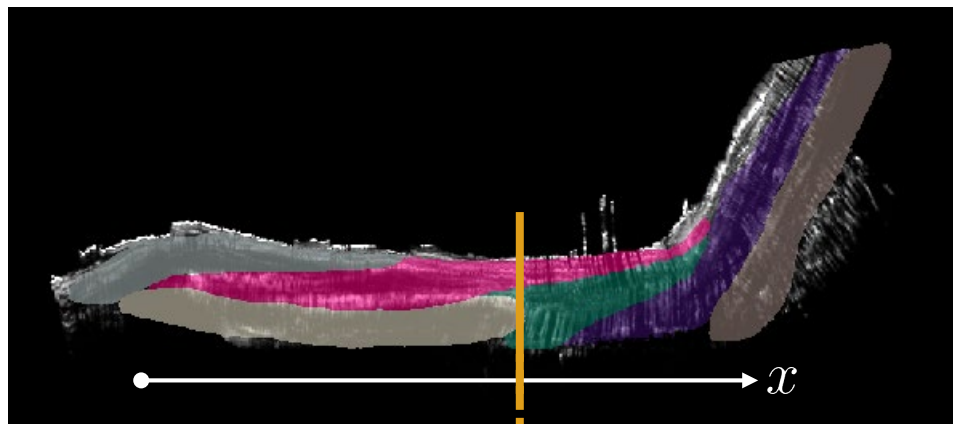


How close is what we observe to the simplified model?



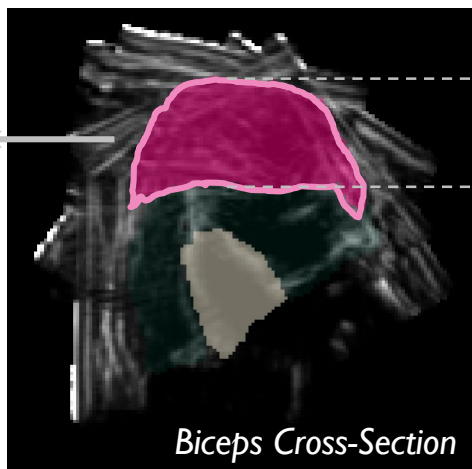
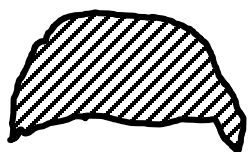
Exploratory Data Analysis: OpenArm 1.0

[Hallock, Kato, Bajcsy, ICRA 2018]



Cross-Sectional Area

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



Thickness

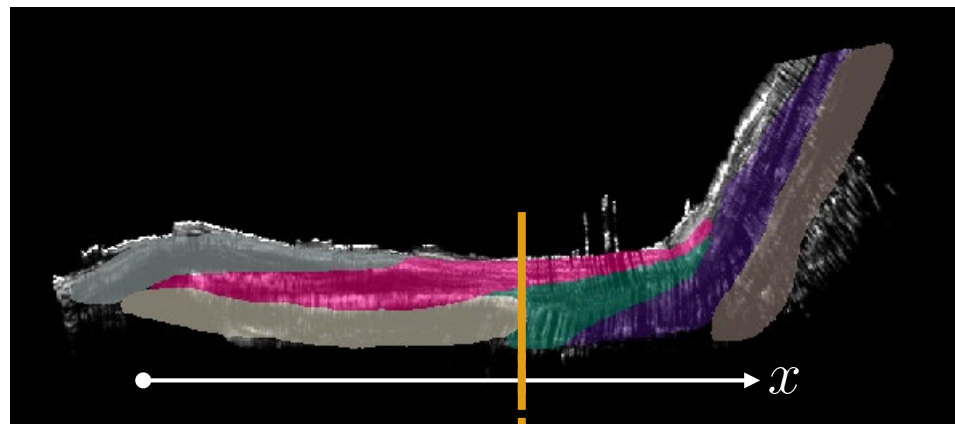
$T_{\theta,LC}(x)$

Biceps Cross-Section



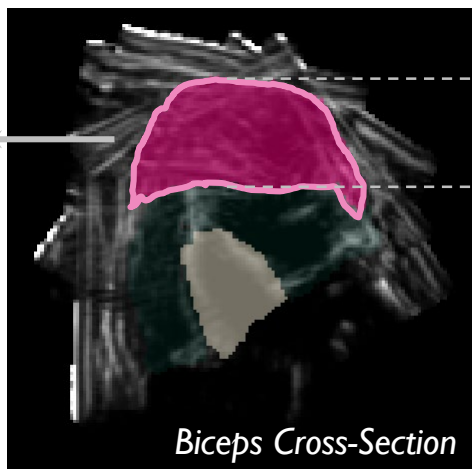
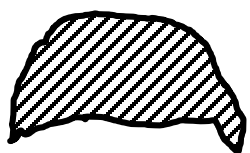
Exploratory Data Analysis: OpenArm 1.0

[Hallock, Kato, Bajcsy, ICRA 2018]



Cross-Sectional Area

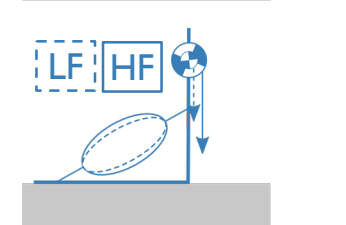
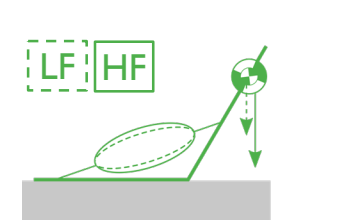
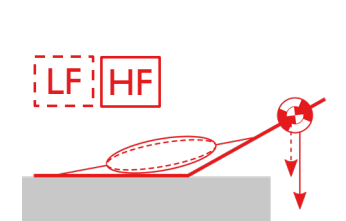
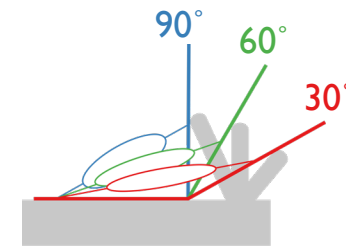
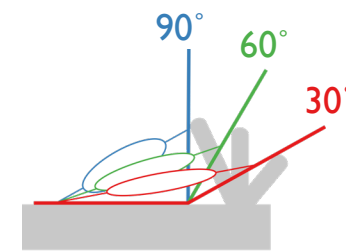
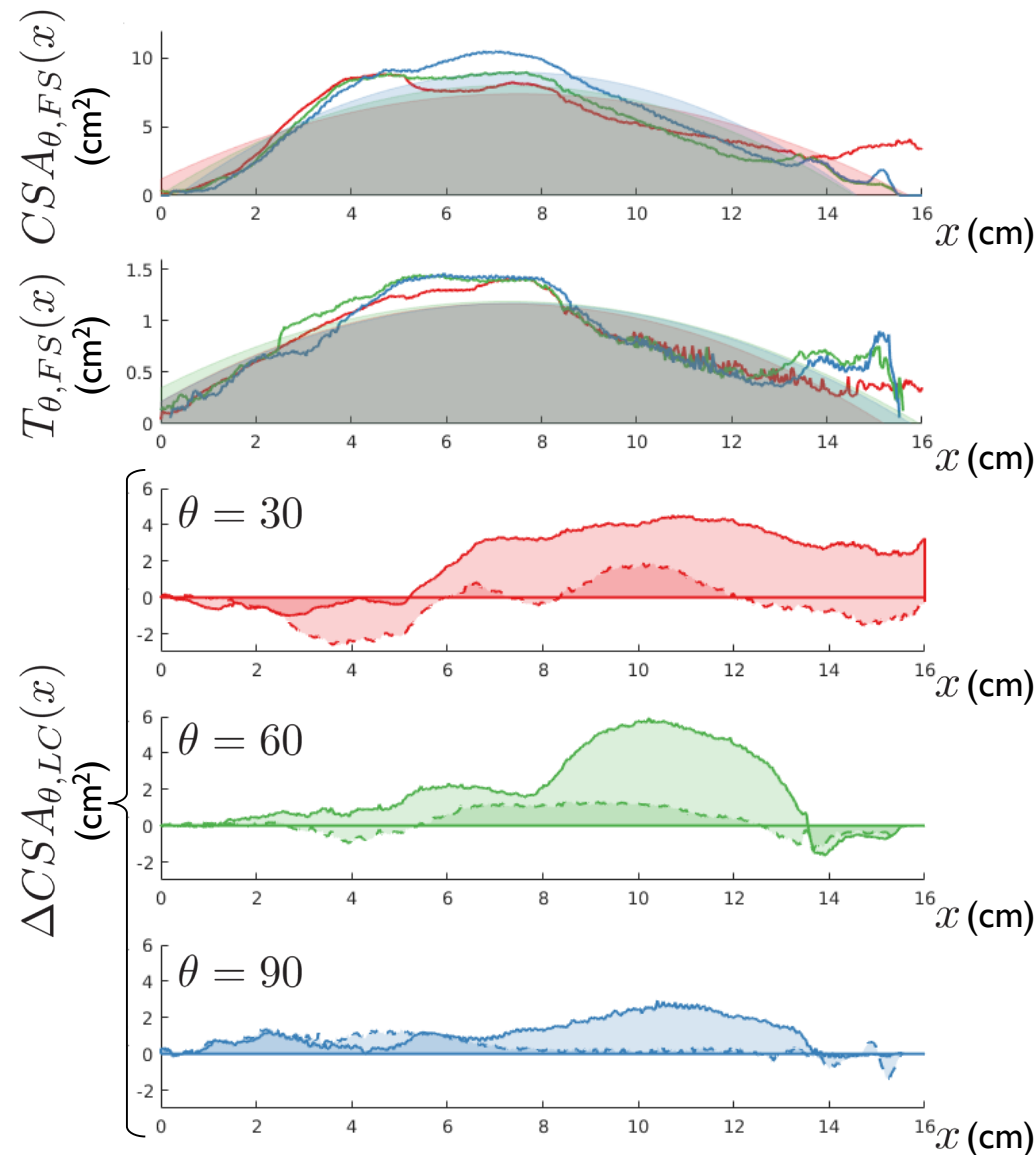
$$CSA_{\theta,LC}(x)$$



Biceps Cross-Section

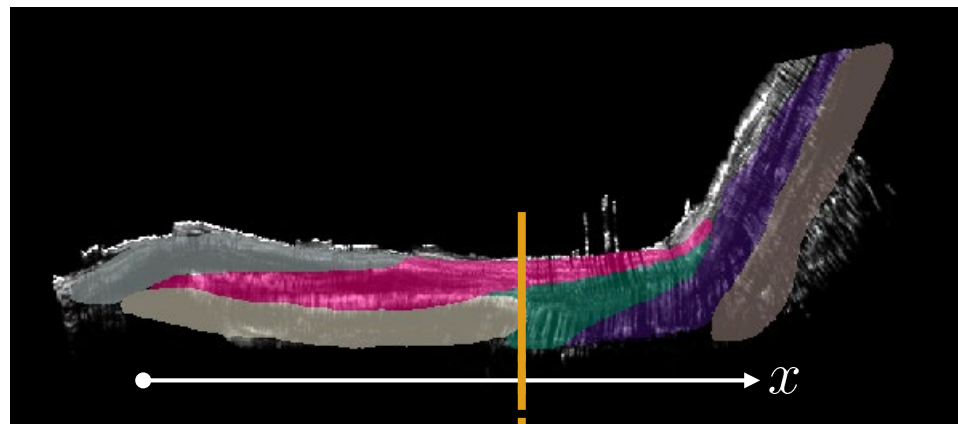
Thickness

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



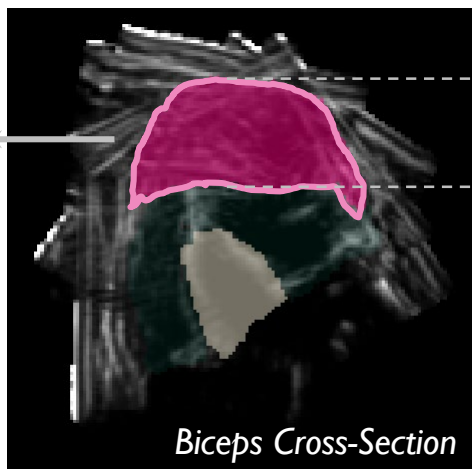
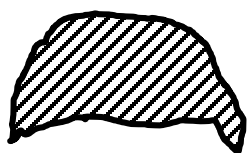
Exploratory Data Analysis: OpenArm 1.0

[Hallock, Kato, Bajcsy, ICRA 2018]



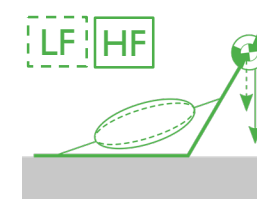
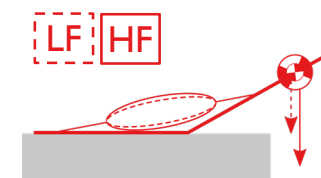
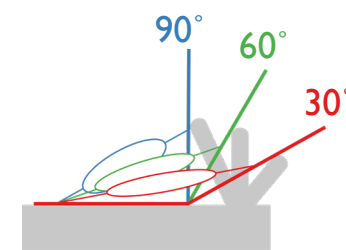
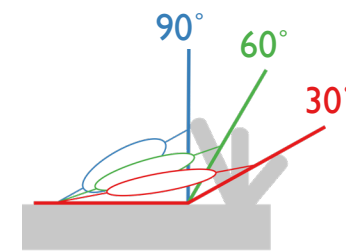
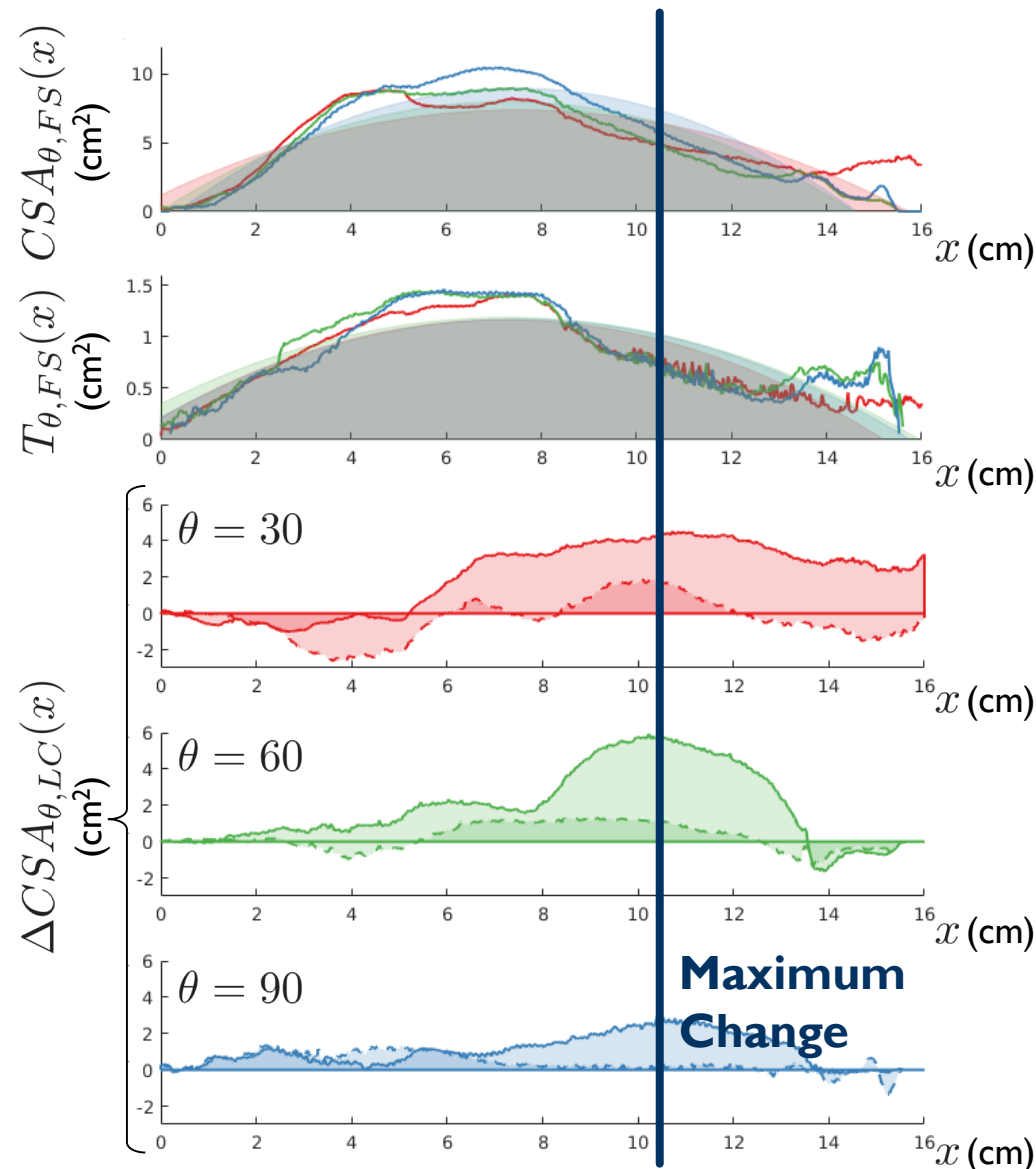
Cross-Sectional Area

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



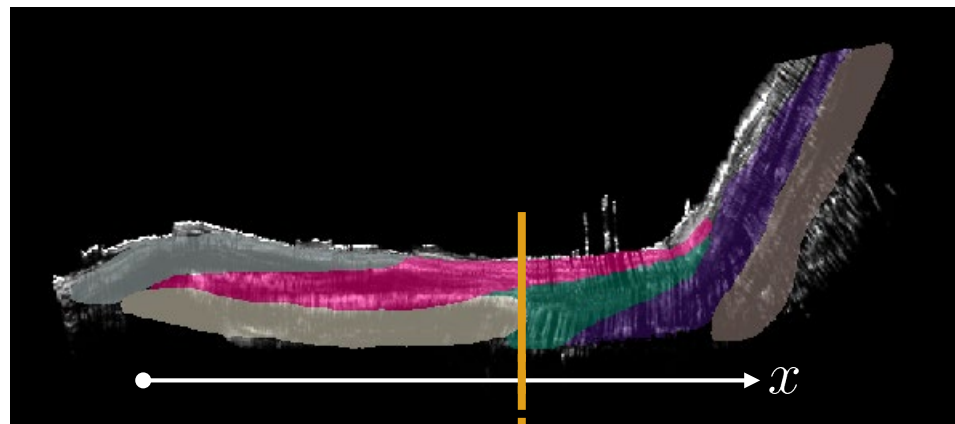
Biceps Cross-Section

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



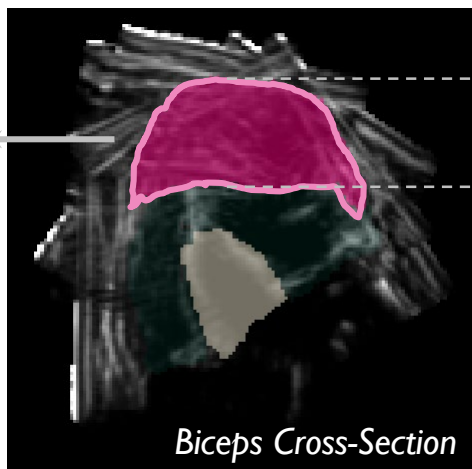
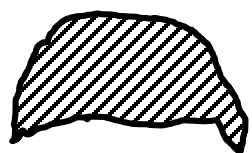
Exploratory Data Analysis: OpenArm 1.0

[Hallock, Kato, Bajcsy, ICRA 2018]

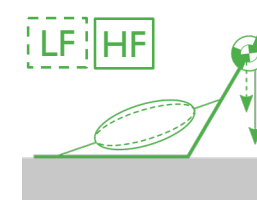
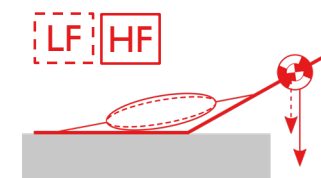
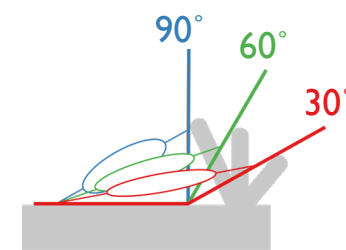
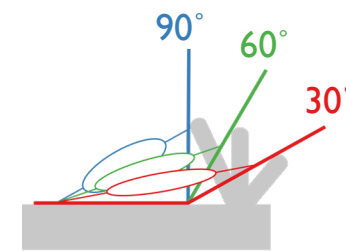
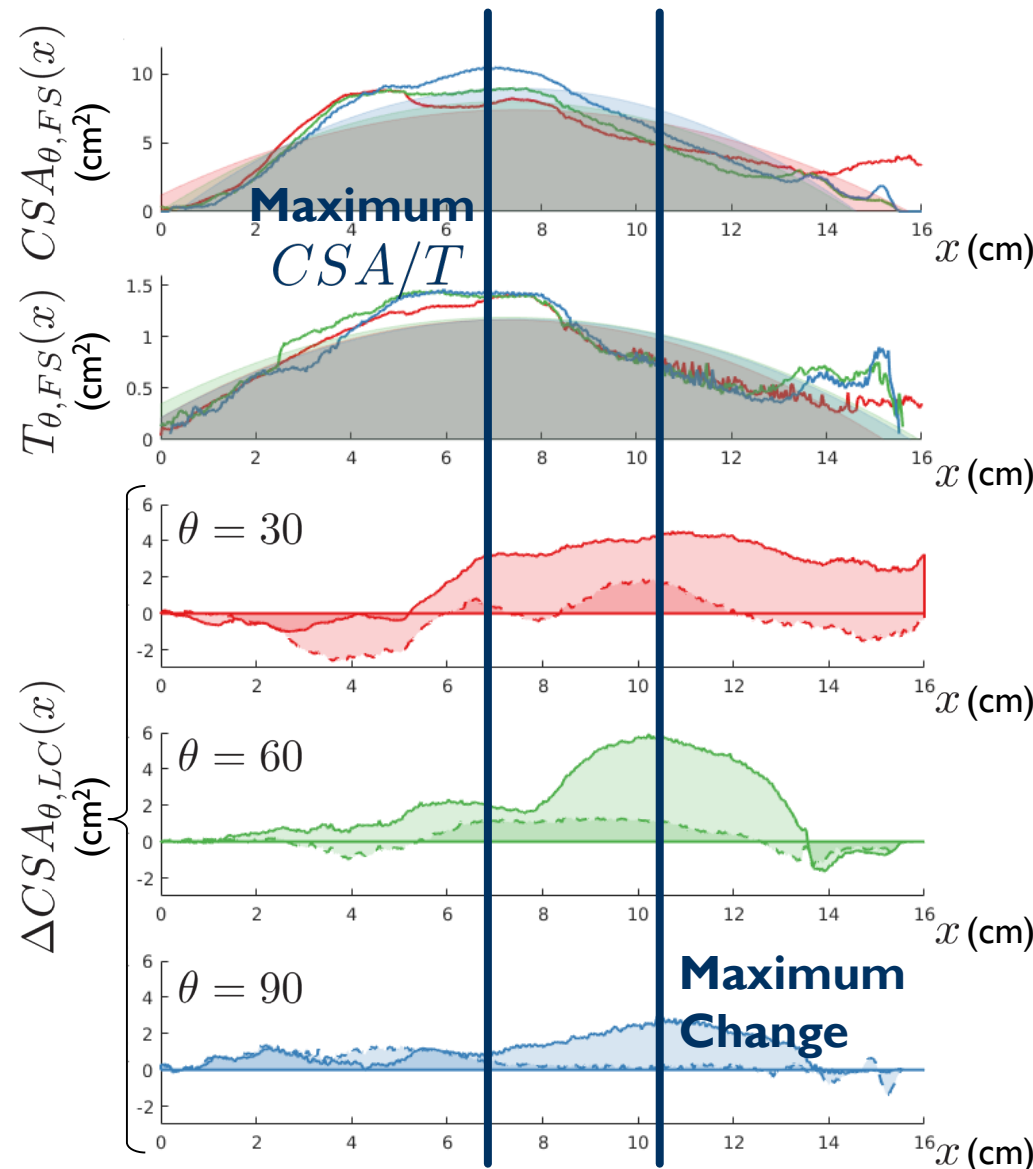


Cross-Sectional Area

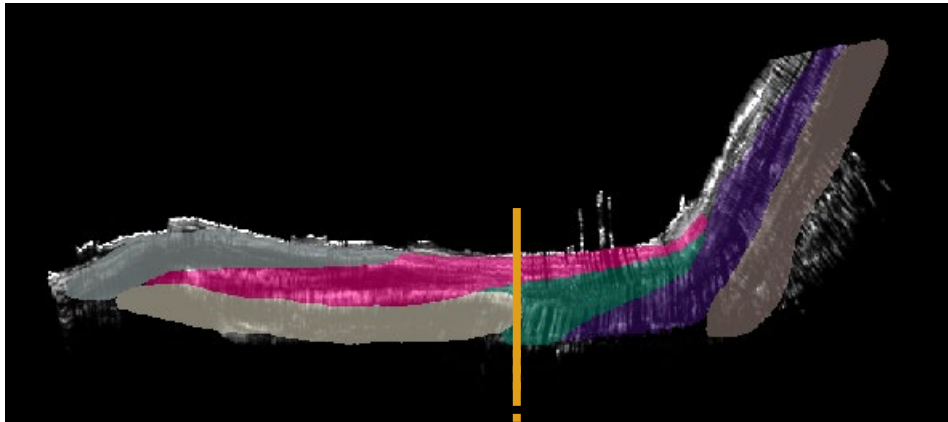
$CSA_{\theta,LC}(x)$



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

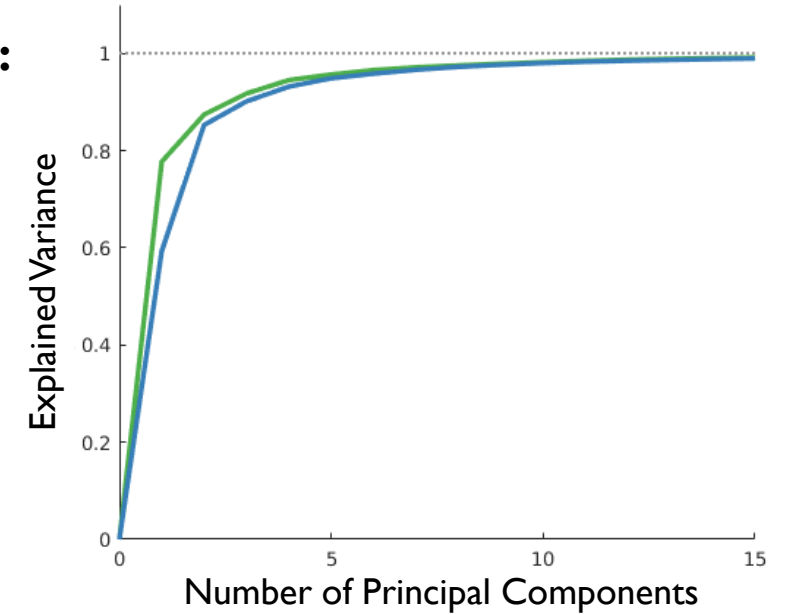


Exploratory Data Analysis: Statistical Shape Modeling



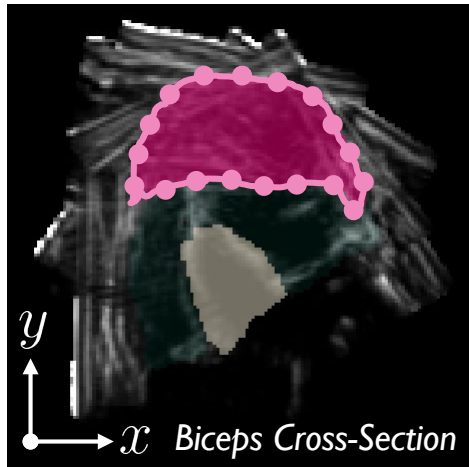
SHAPE DECOMPOSITION :

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



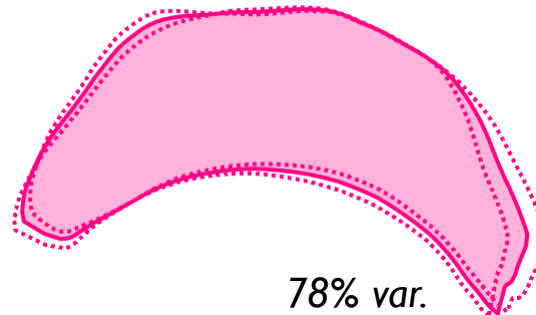
Shape

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

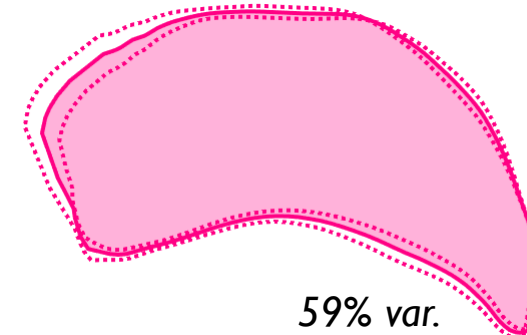


First Shape Modes

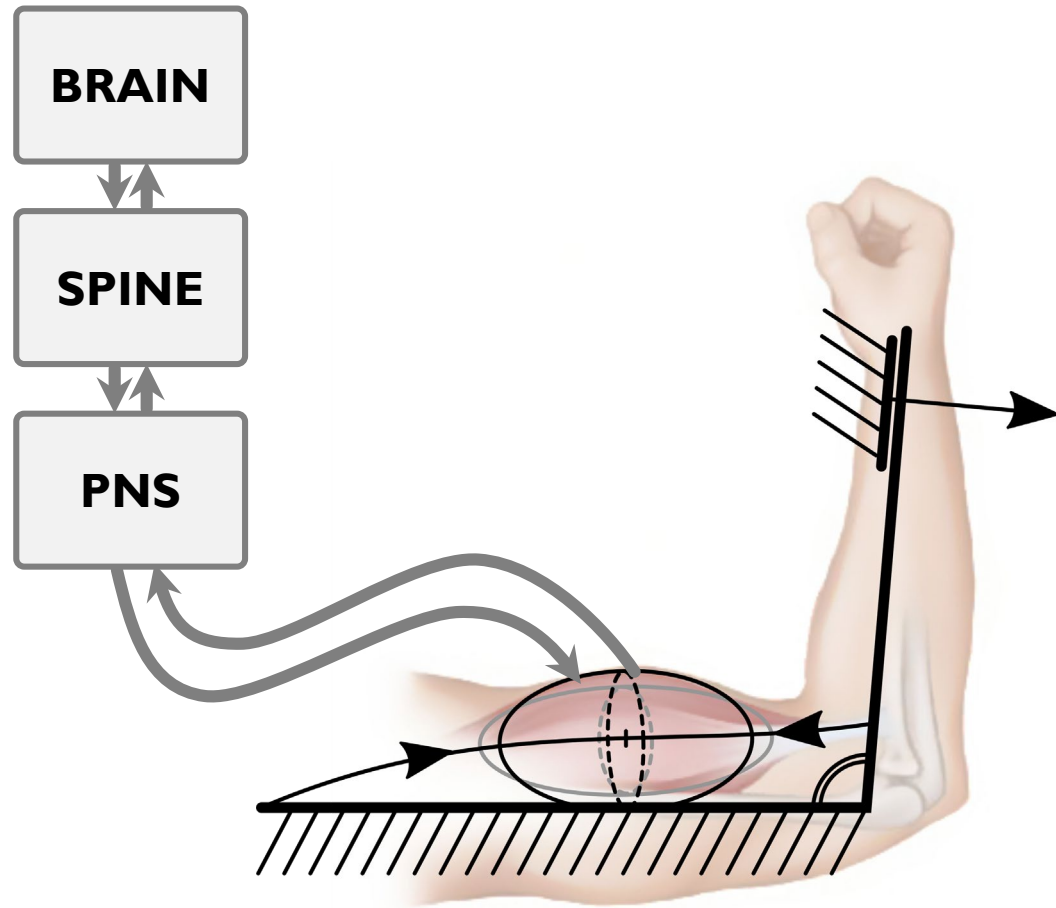
No Force, Vary Angle



30° Angle, Vary Force



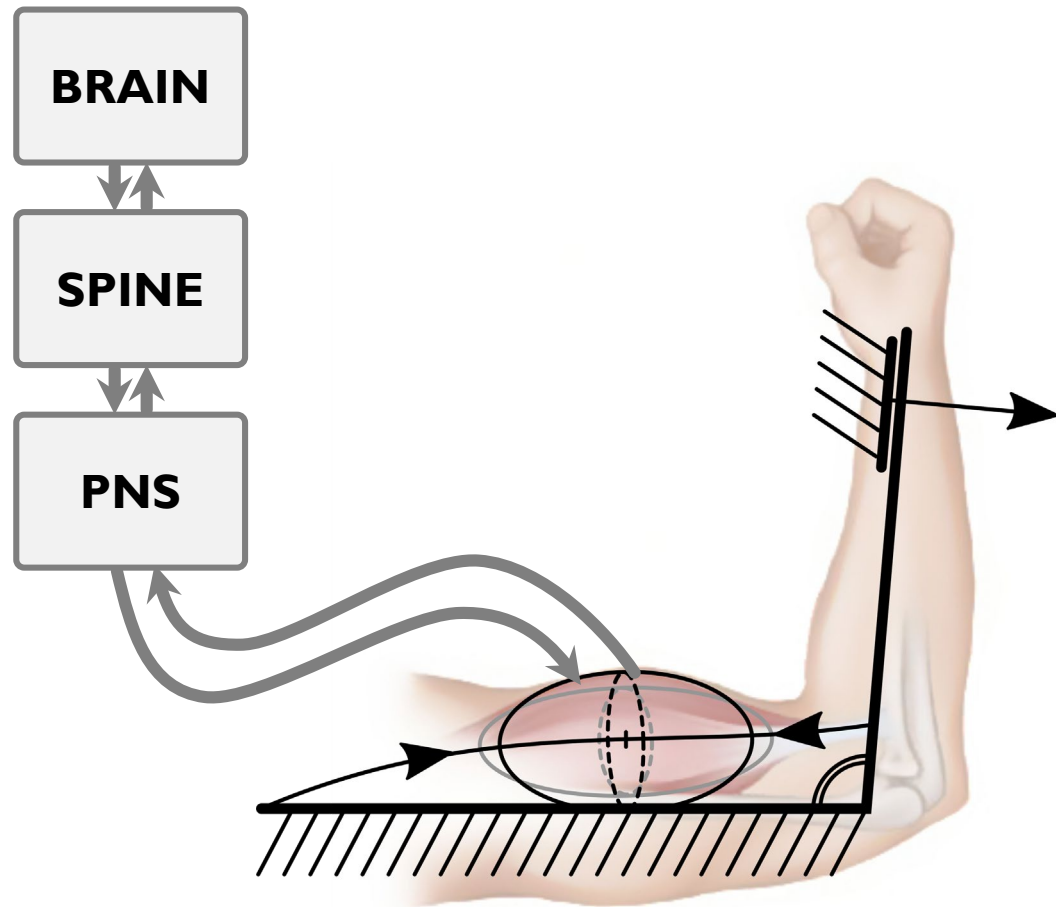
Expanded Biological Mechanism



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



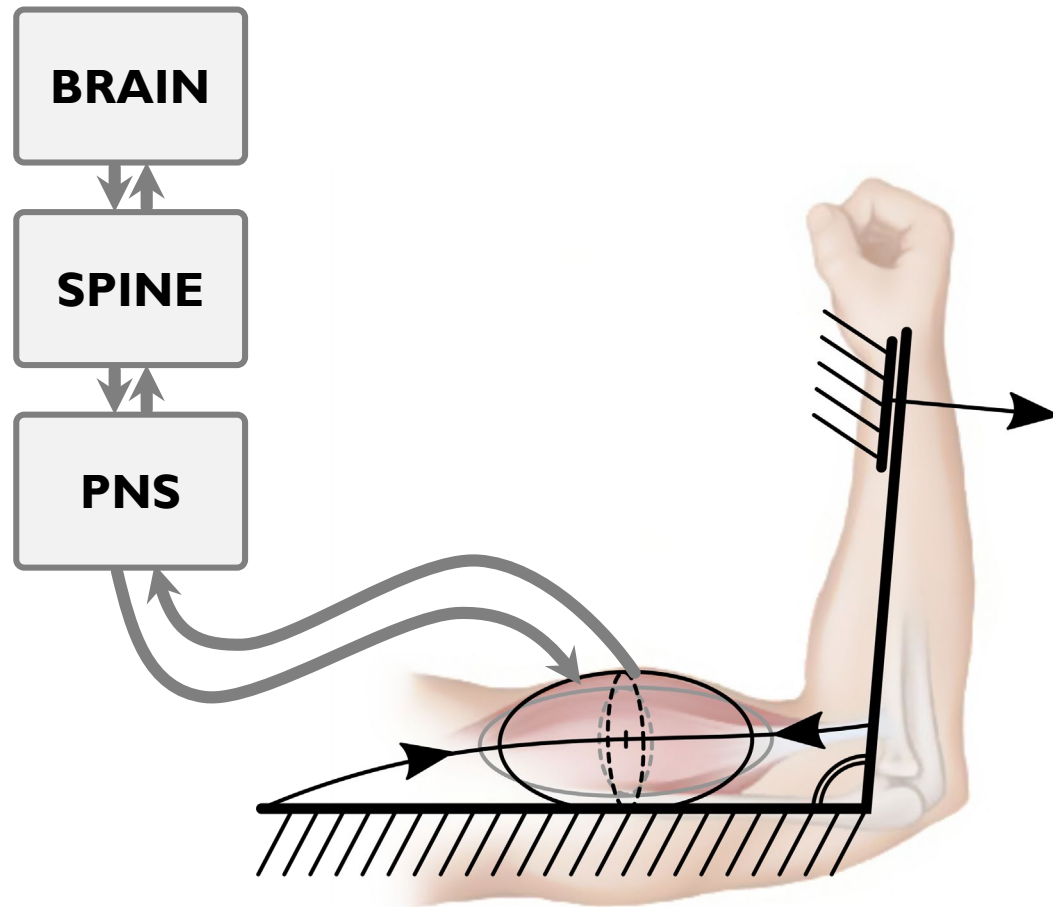
Expanded Biological Mechanism



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



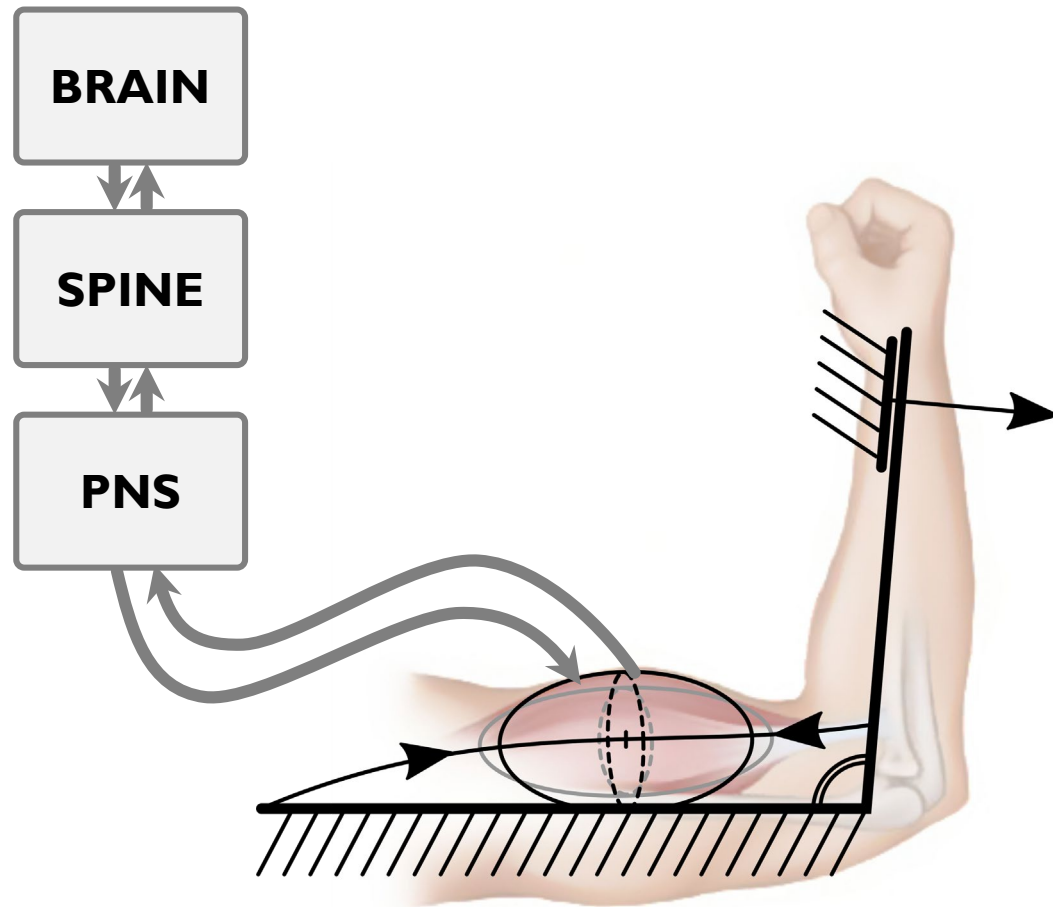
Expanded Biological Mechanism



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



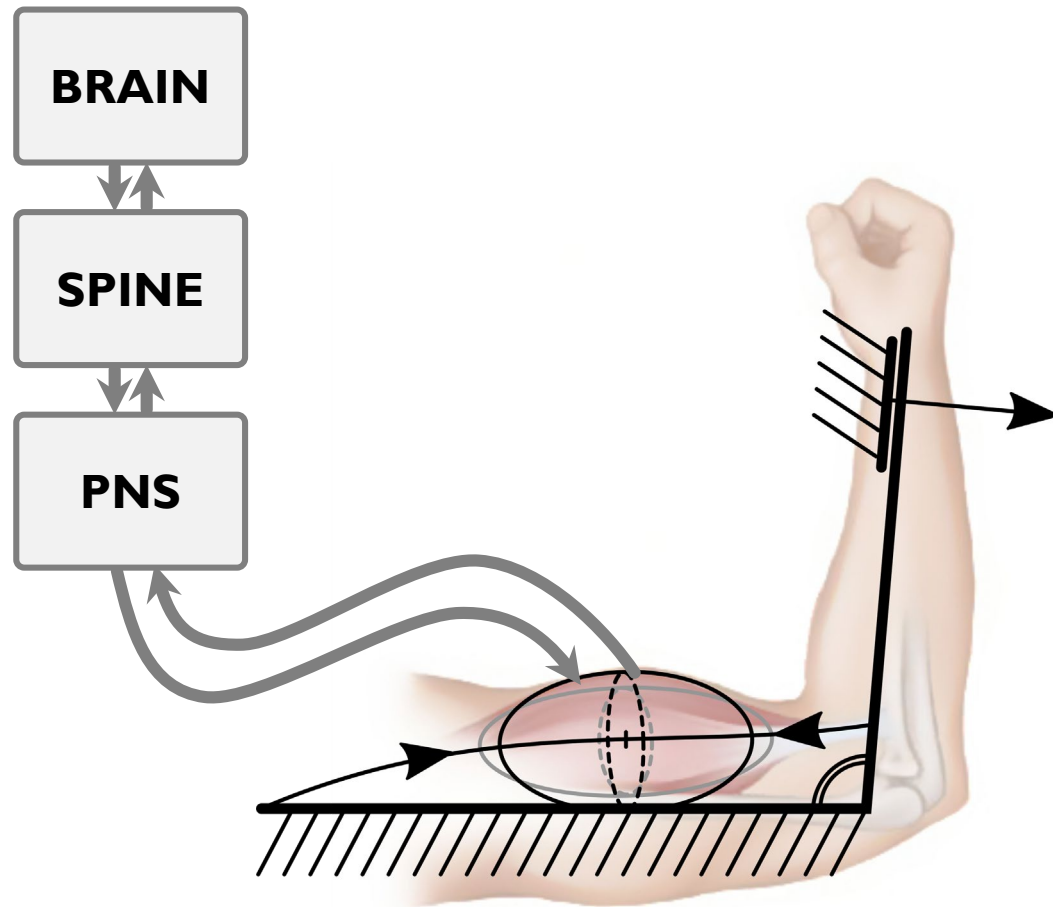
Expanded Biological Mechanism



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



Expanded Biological Mechanism



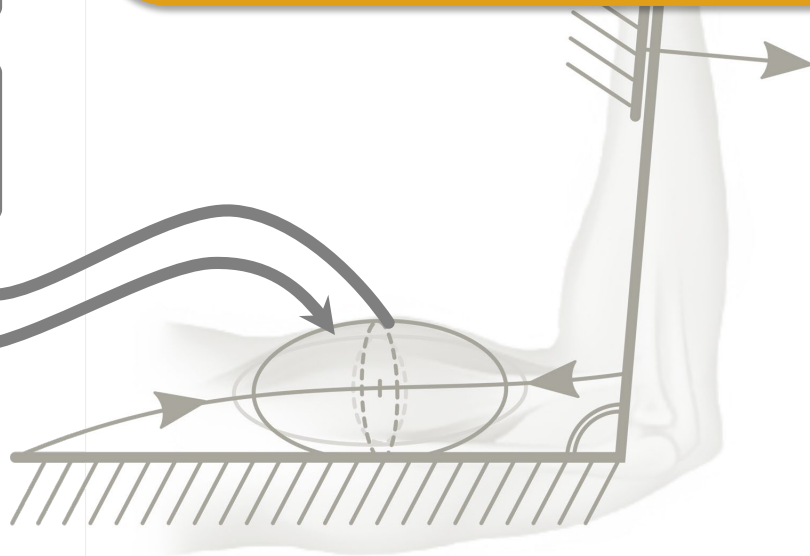
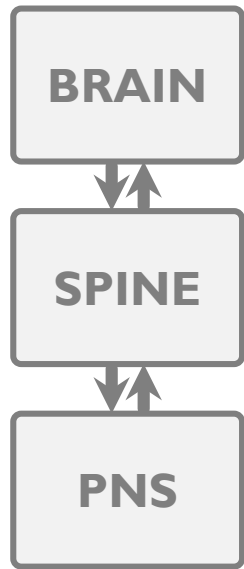
- **Multi-muscle dynamics**
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Expanded Biological Mechanism

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.



- **Mechanical complexity**
 - fiber type (I or II)
 - hysteresis
 - concentric vs. eccentric contraction
 - fatigue
- **Neurological complexity**
 - motor unit distribution
 - tetanic vs. subtetanic contraction
 - feedback vs. feedforward control



Expanded Biological Mechanism

CHALLENGE: “One step forward, one step back”

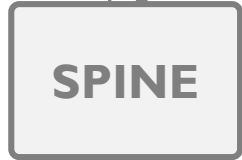
The more closely we attempt to model biological mechanisms, the more values and parameters we must assume based on literature.

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

“black box”

“white box”

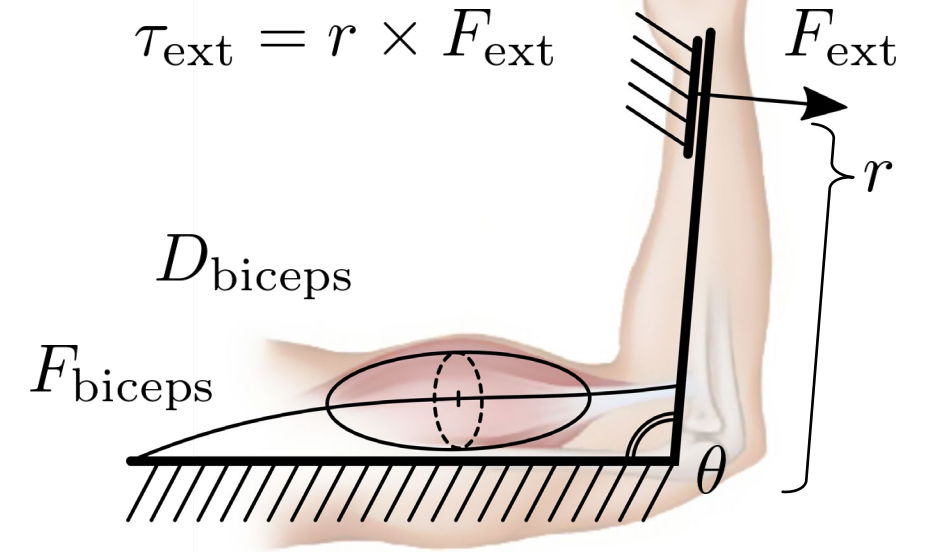


Musculoskeletal Dynamics

D_{biceps}

θ

τ_{ext}

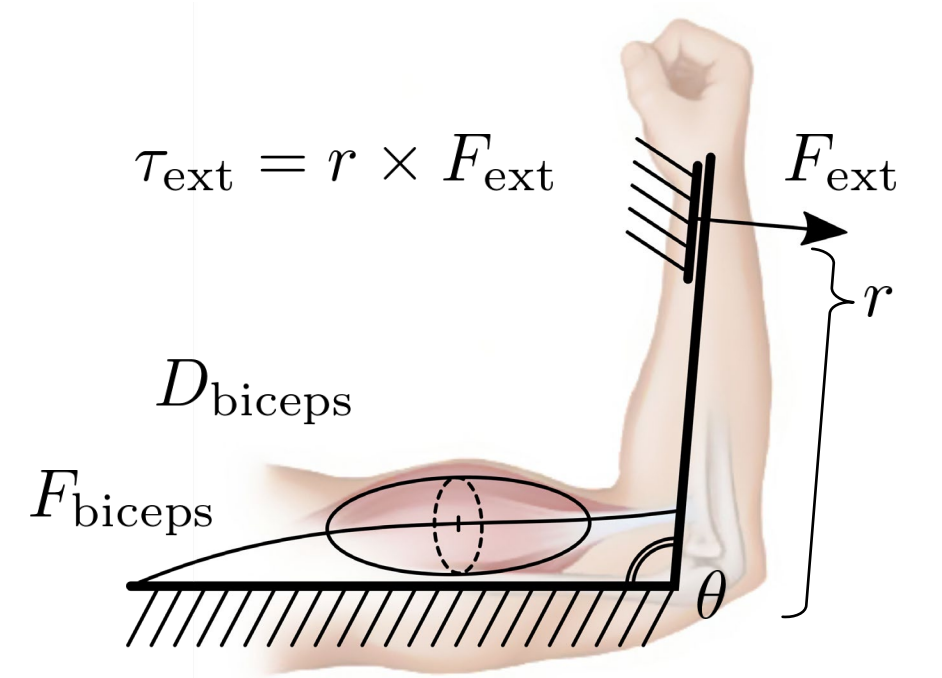
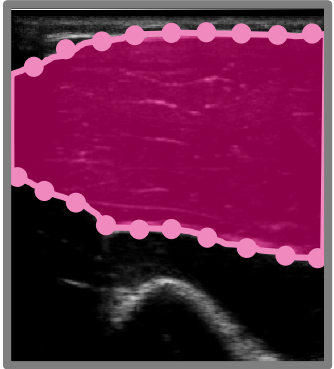


(Proposed) Suite of Models

“black box”

“white box”

“model free”
baseline



Musculoskeletal Dynamics

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

D_{biceps}

θ

τ_{ext}



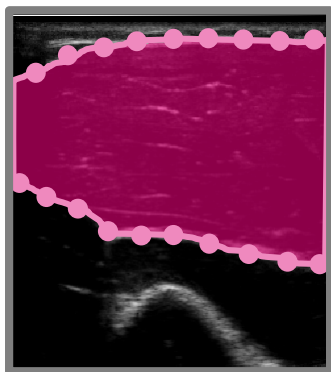
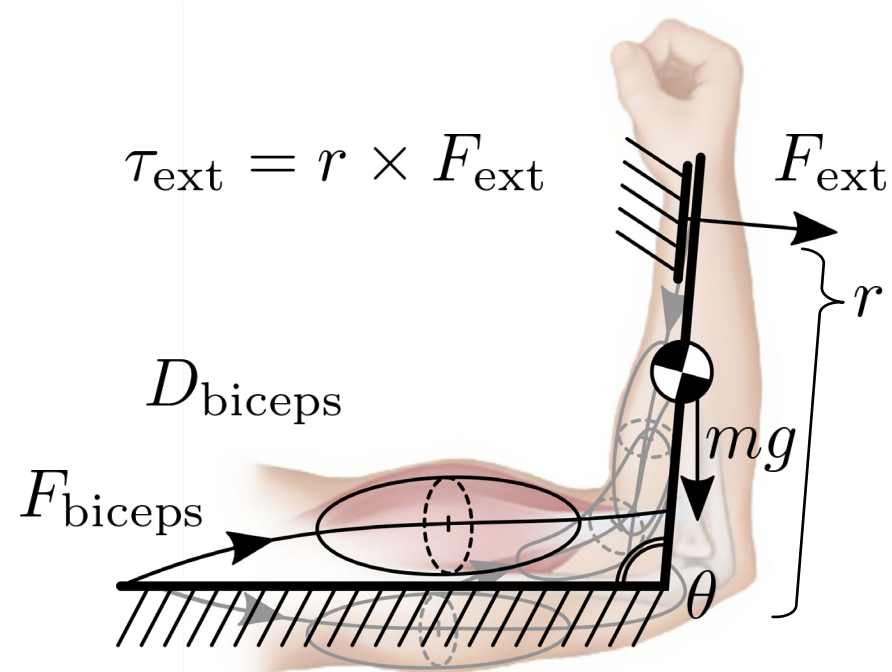
(Proposed) Suite of Models

“black box”

“white box”

“model free”
baseline

+ multi-muscle
dynamics



Musculoskeletal Dynamics

Biceps Contraction Dynamics

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

Force Distribution Model

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

[assumed]

[measured]

$c(\cdot)$



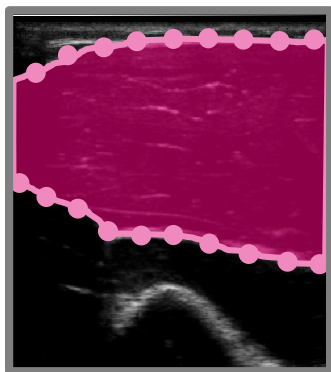
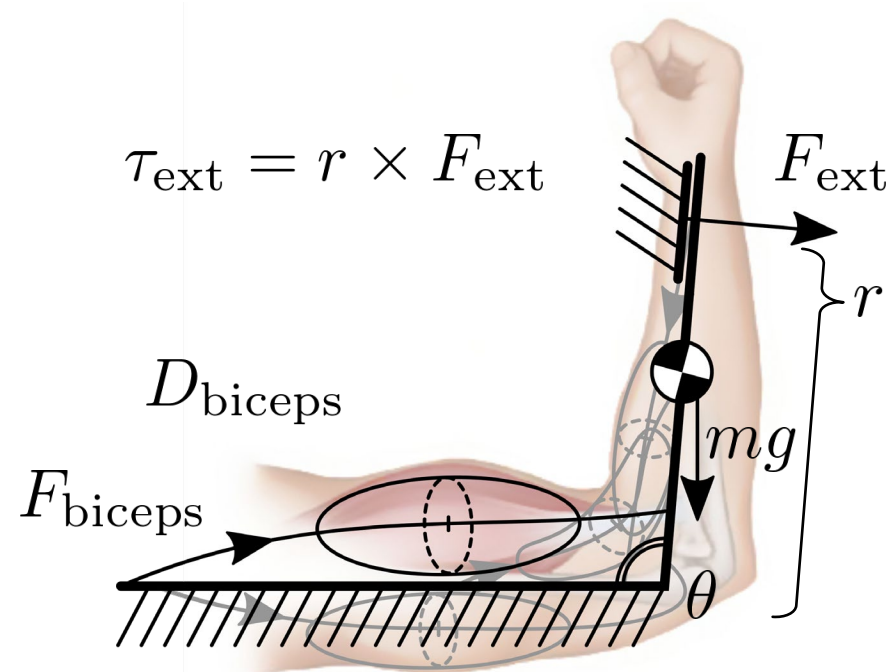
(Proposed) Suite of Models

“black box”

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Musculoskeletal Dynamics

Biceps Contraction Dynamics

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

Force Distribution Model

Muscle Geometry

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

[assumed]

[measured]

$$\tau_{\text{ext}} = \tau_{\text{biceps}} + \tau_{\text{brach}} + \tau_{\text{brachrad}} + \tau_{\text{triceps}} + \tau_{\text{mg}}$$



(Proposed) Suite of Models

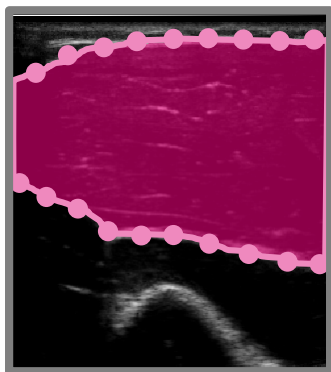
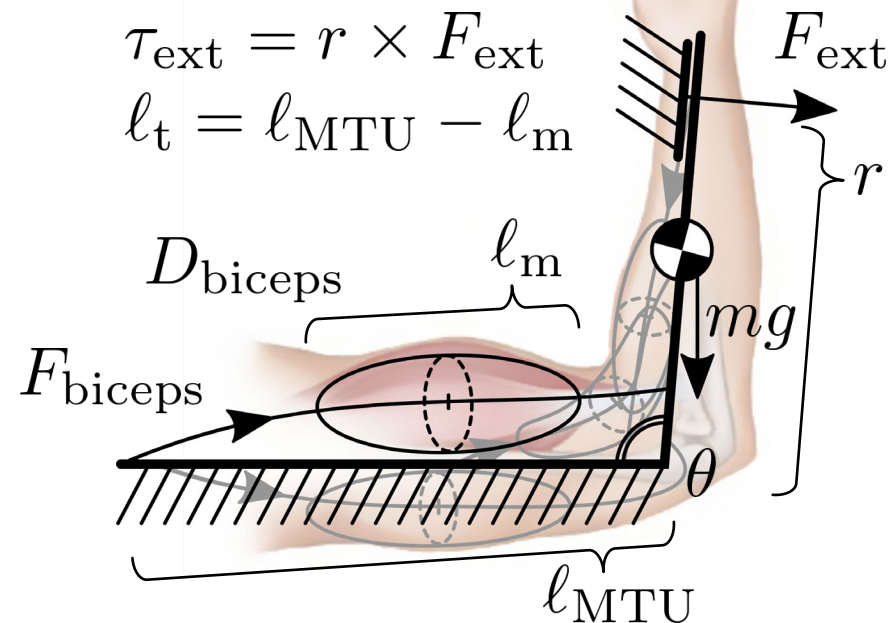
“black box”

“white box”

“model free”
baseline

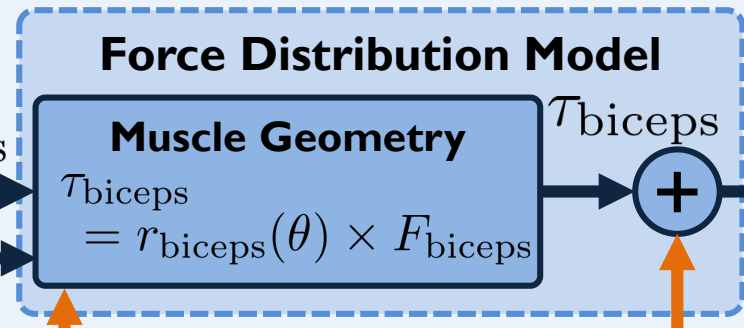
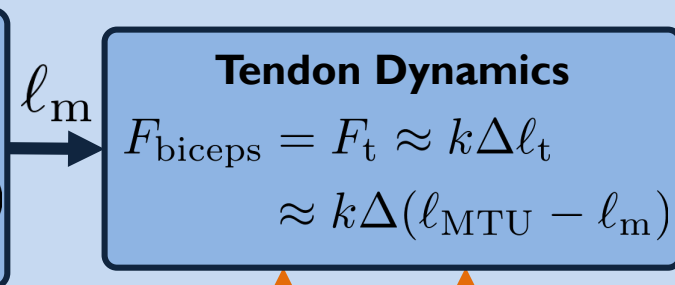
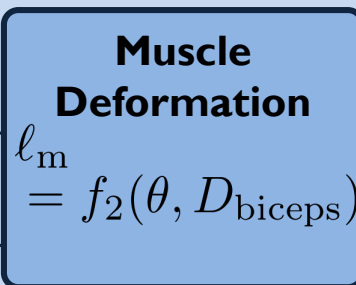
+ multi-muscle
dynamics

+ **MTU**
dynamics



Musculoskeletal Dynamics

Biceps Contraction Dynamics



[assumed]
[measured]

ℓ_{MTU}

k

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

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



(Proposed) Suite of Models

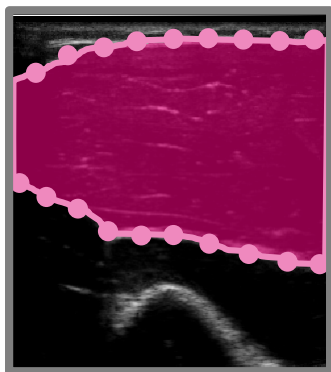
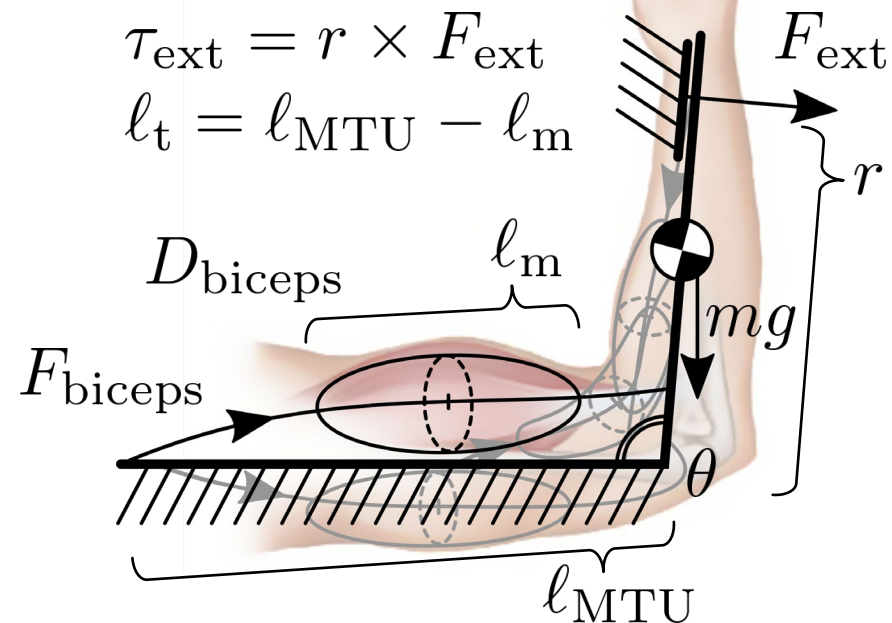
“black box”

“white box”

“model free”
baseline

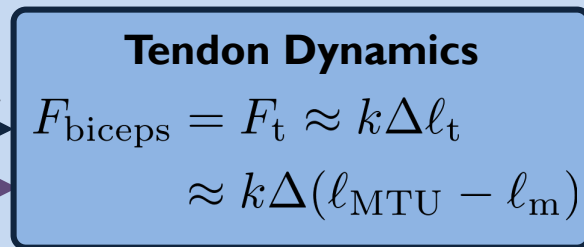
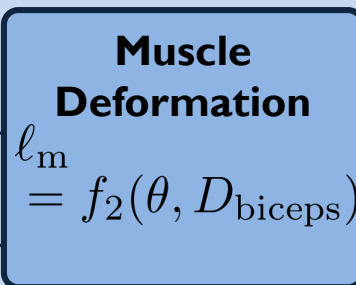
+ multi-muscle
dynamics

+ **MTU**
dynamics

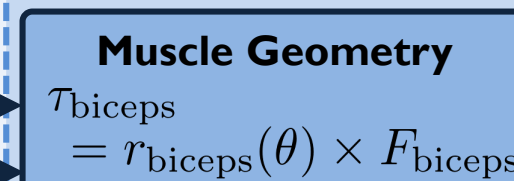


Musculoskeletal Dynamics

Biceps Contraction Dynamics



Force Distribution Model



[assumed]
[measured]

τ_{biceps}

τ_{ext}

ℓ_{m}

ℓ_{MTU}

k

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

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



(Proposed) Suite of Models

“black box”

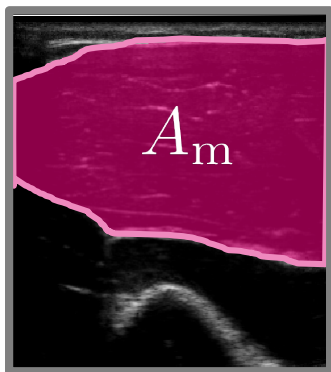
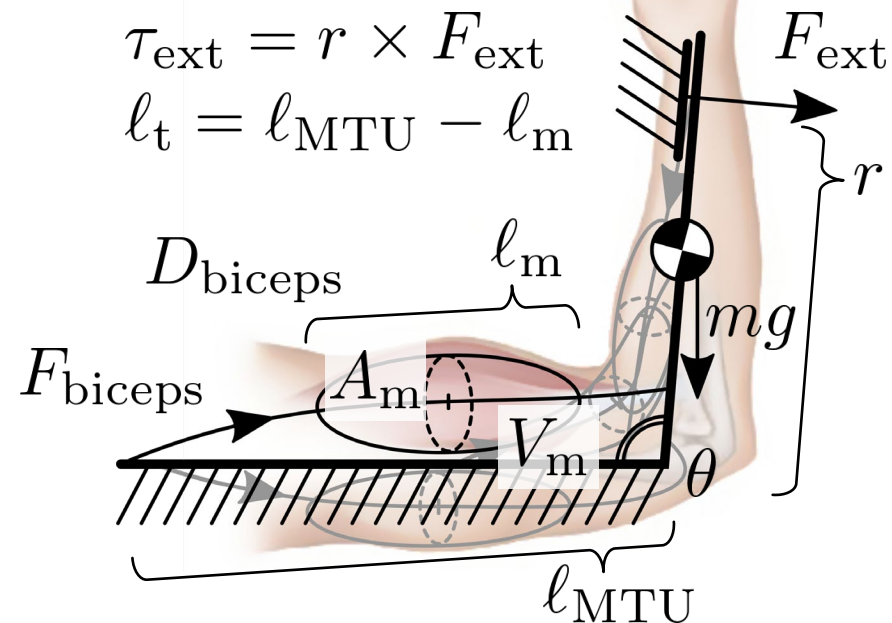
“white box”

“model free”
baseline

+ multi-muscle
dynamics

+ MTU
dynamics

+ ellipsoidal
kinematics



Musculoskeletal Dynamics

Biceps Contraction Dynamics

Muscle Deformation

$$\ell_m \approx T_\theta \left[\frac{3V_m}{4A_m} \right]$$

Tendon Dynamics

$$F_{\text{biceps}} = F_t \approx k \Delta \ell_t \approx k \Delta (\ell_{\text{MTU}} - \ell_m)$$

Force Distribution Model

Muscle Geometry

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

[assumed]

[measured]

$$D_{\text{biceps}} \triangleq A_m$$

θ

V_m

ℓ_m

ℓ_{MTU}

k

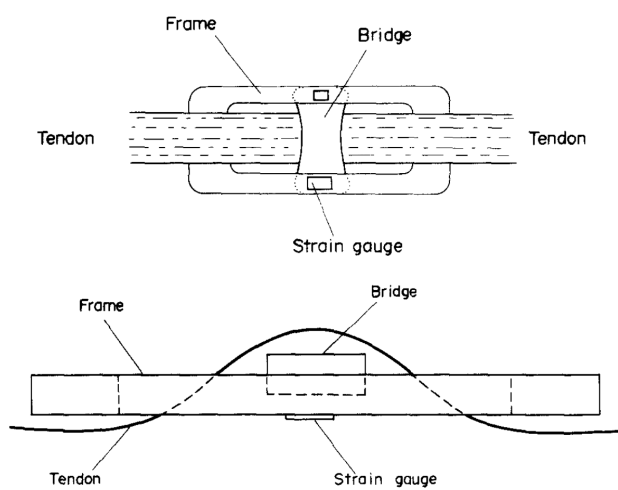
$r_{\text{biceps}}(\cdot)$

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



Model Validation

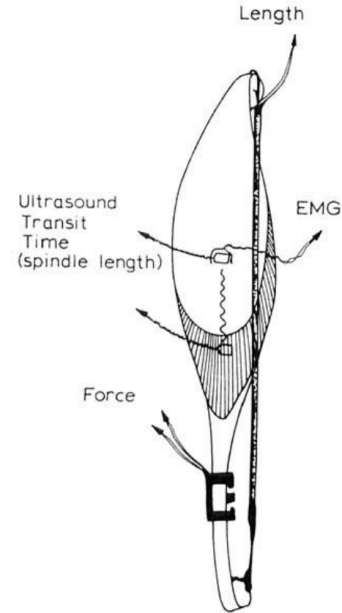
Direct, Invasive Force Measurement



[Barnes & Pinder 1974]



[Sherif et al. 1983]



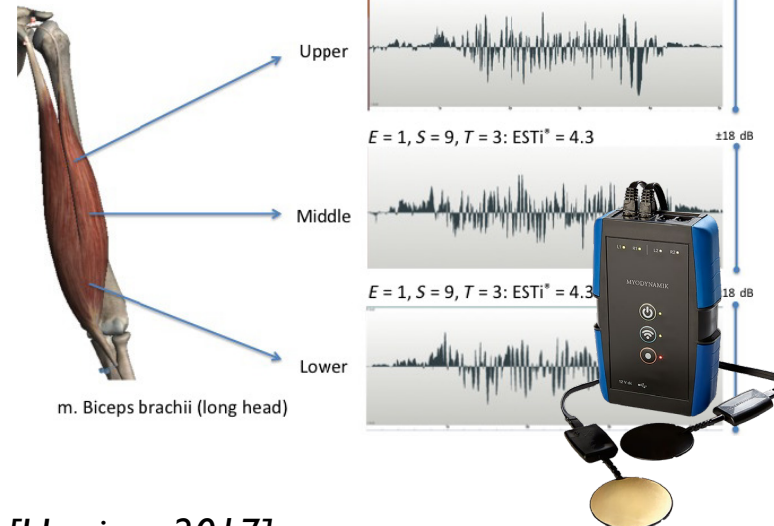
[Hoffer et al. 1989]

[Salmons 1969]

[Yager 1972]

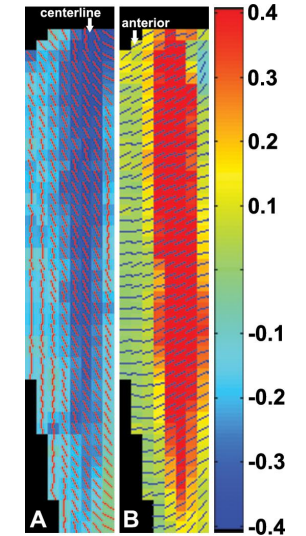
Consistency Across Sensors

AMG



[Harrison 2017]

cine DENSE MRI

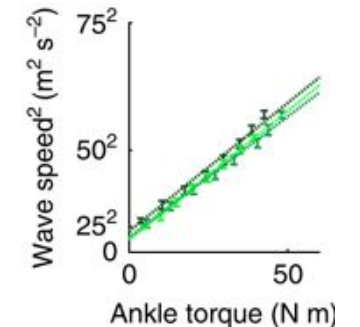
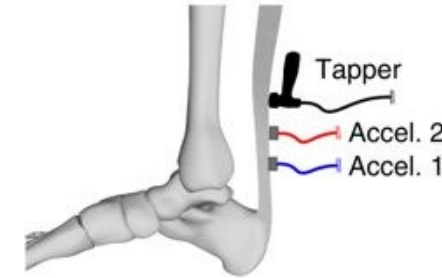


[Zhong et al. 2008]

“tapping tendons”



[Martin et al. 2018]

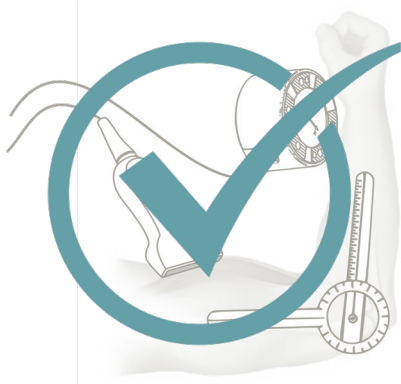


Roadmap

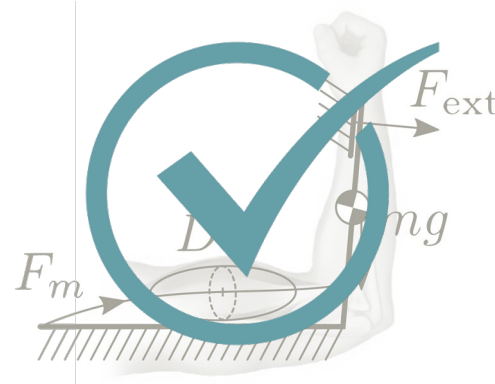
CORE OBJECTIVE

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

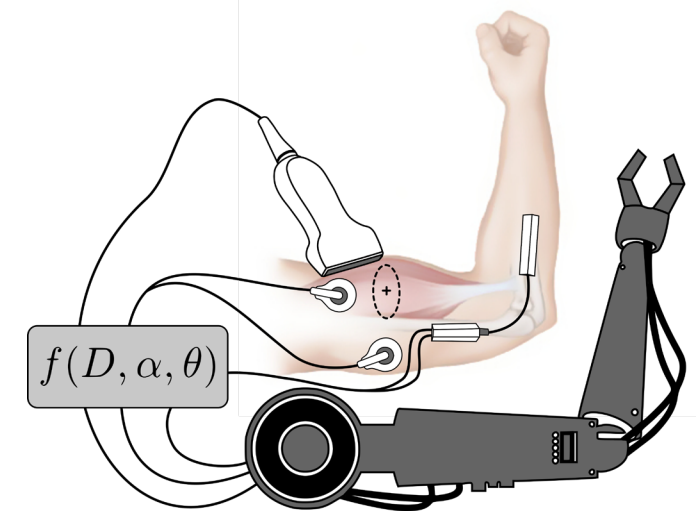
I Exploratory Data Set Generation



II Model Development & Validation



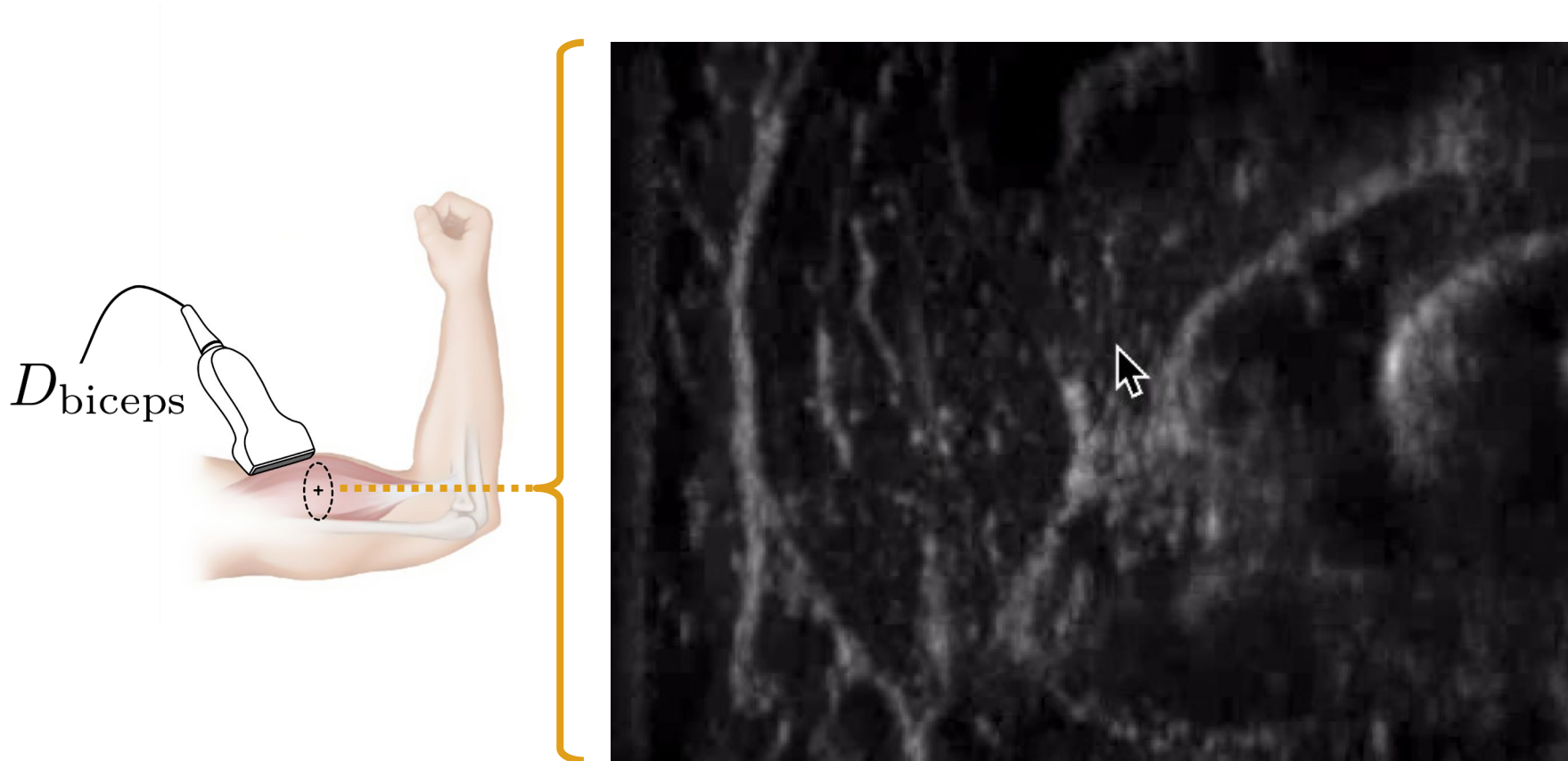
III Proof-of-Concept Applications



Alternate Modalities & Conclusions



Preliminary Deformation Signal Tracking

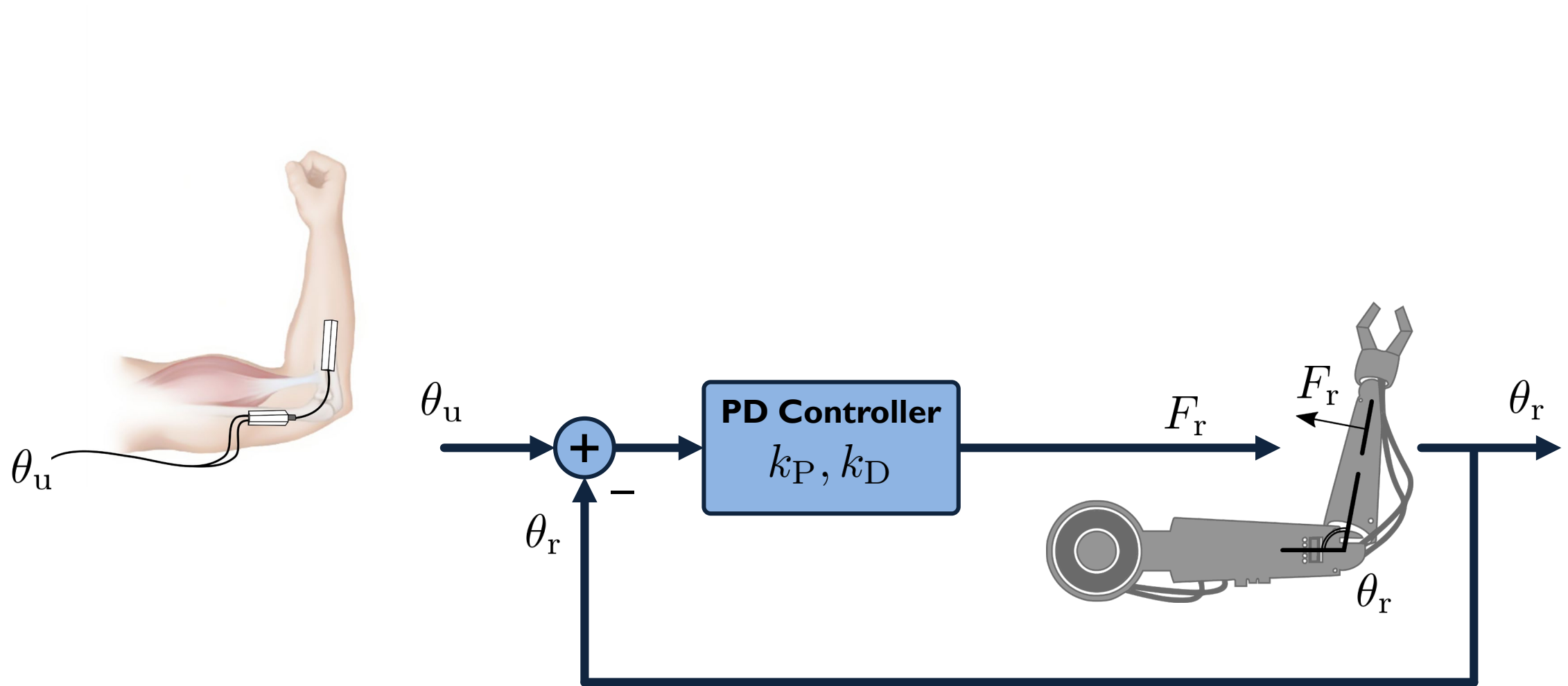


Points along the muscle fascia can be **reliably tracked in real time** via Lucas-Kanade optical flow.

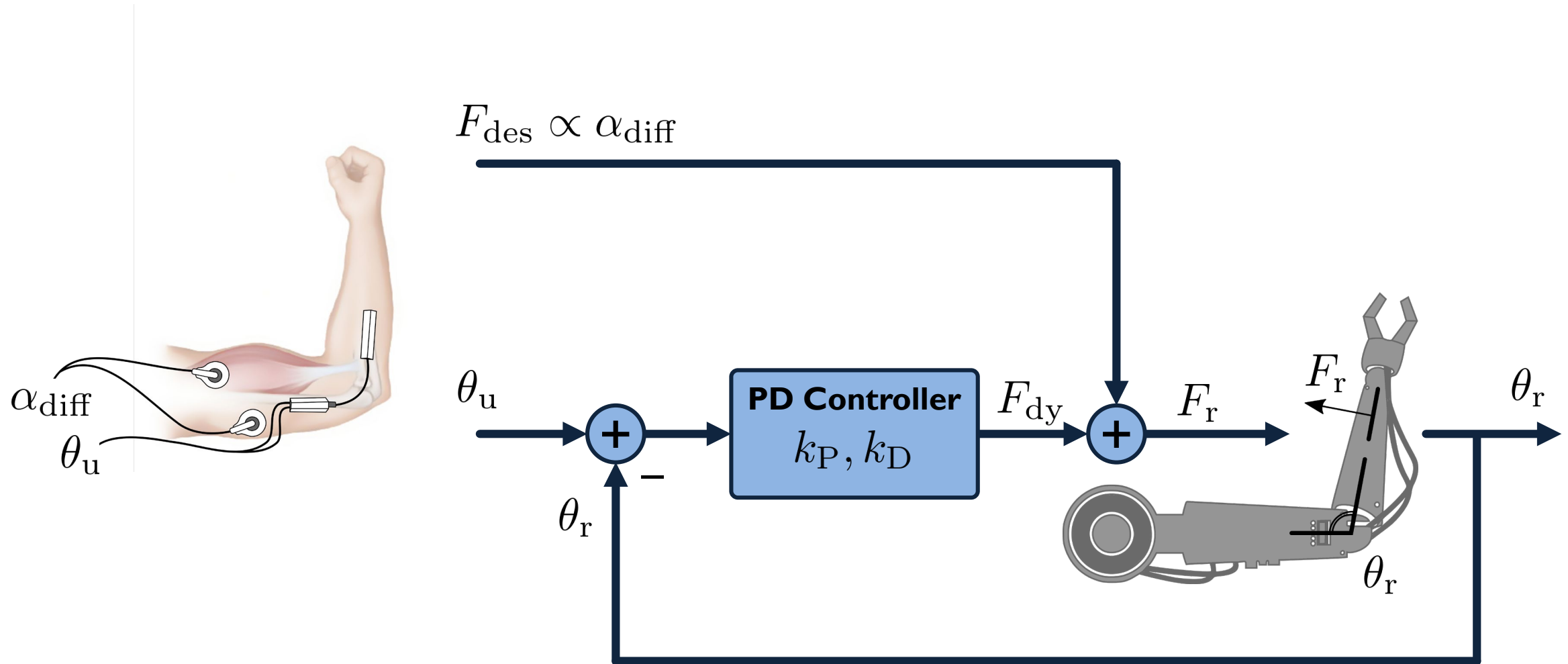
[Schwartz, Velu]



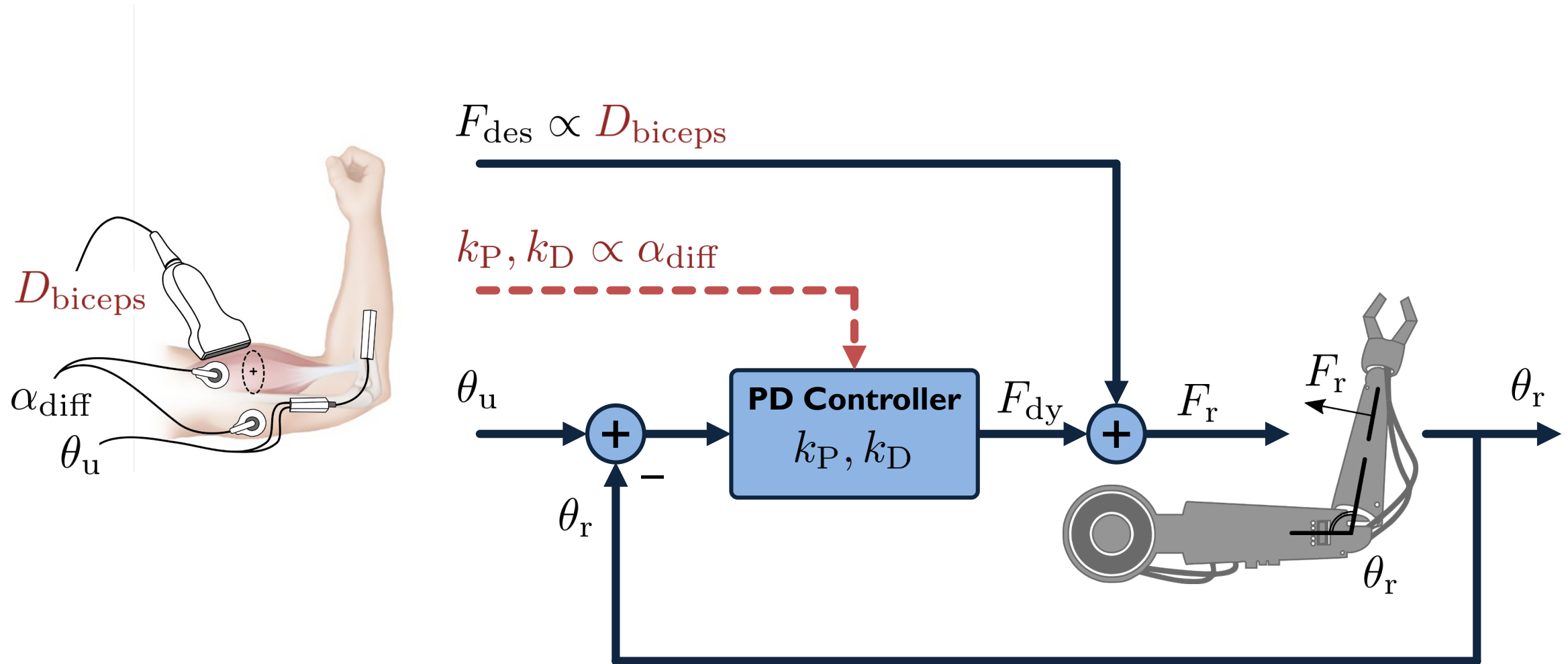
Real-Time Device Control: Robot Teleoperation



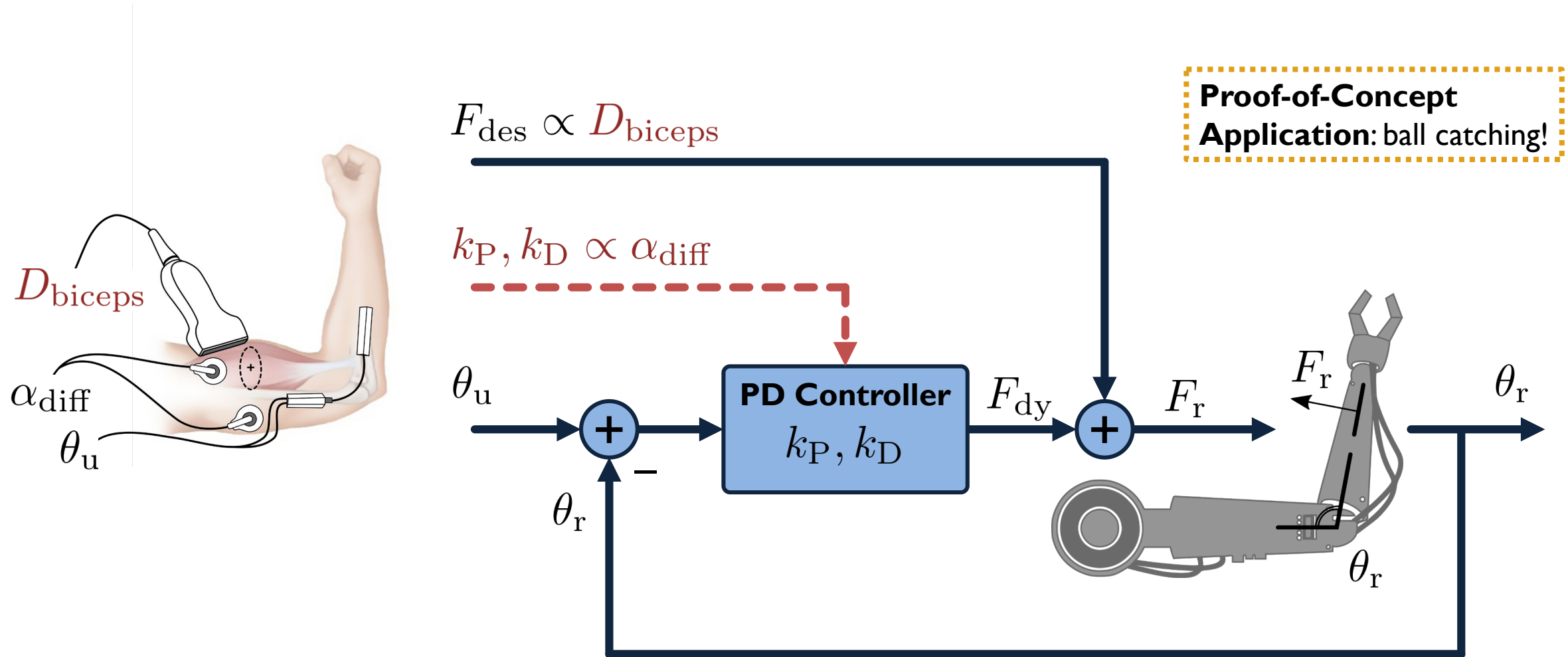
Real-Time Device Control: Baseline sEMG Control



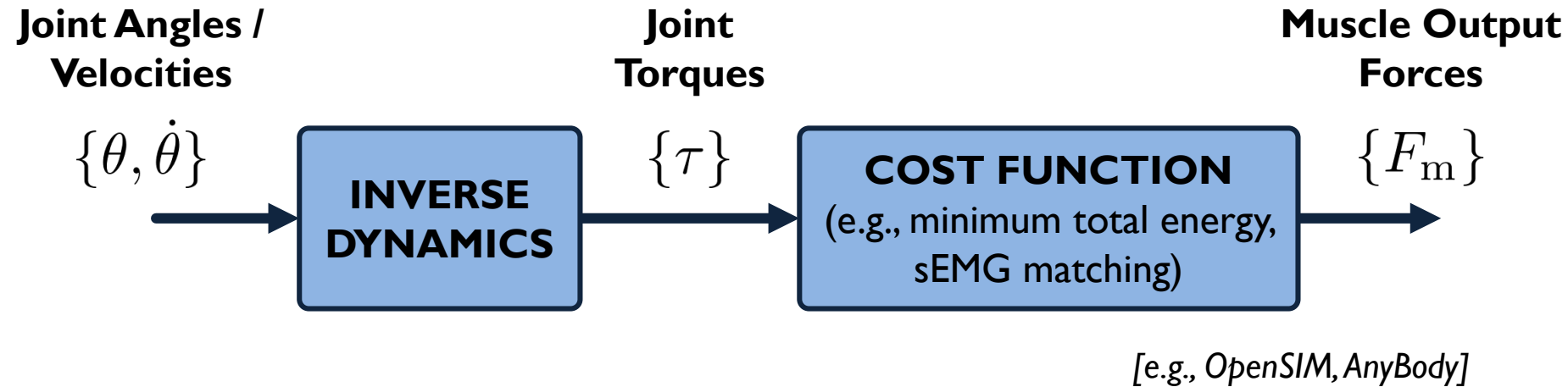
Real-Time Device Control: Proposed Control



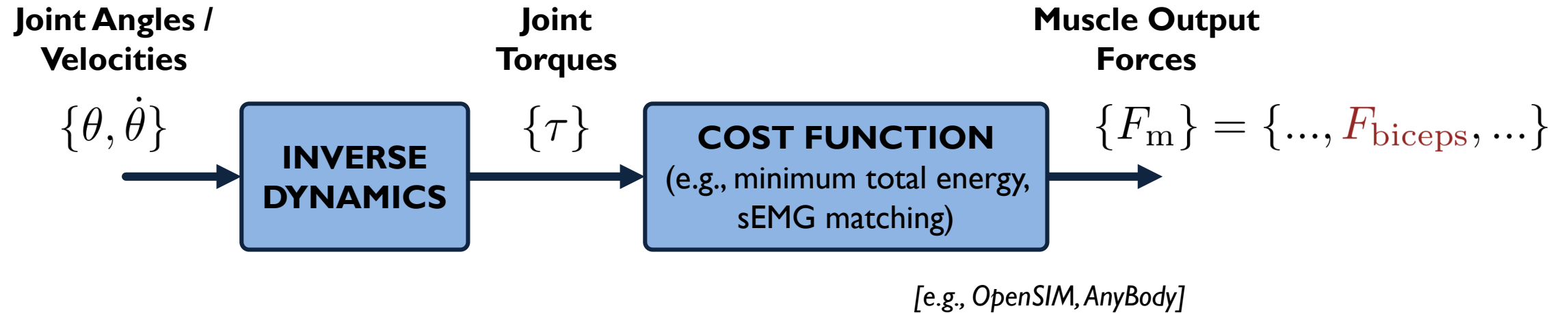
Real-Time Device Control: Proposed Control



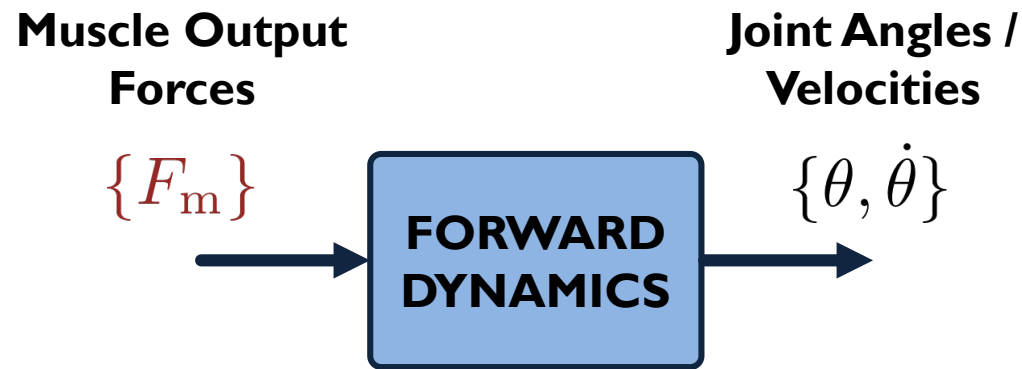
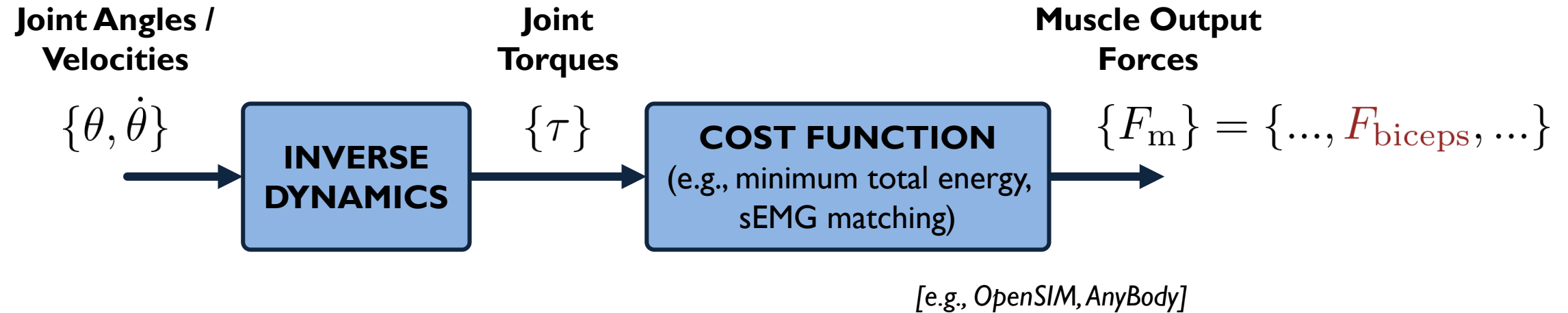
In Vivo Muscle Force Inference: State-of-the-Art



Deformation-Enhanced In Vivo Muscle Force Inference



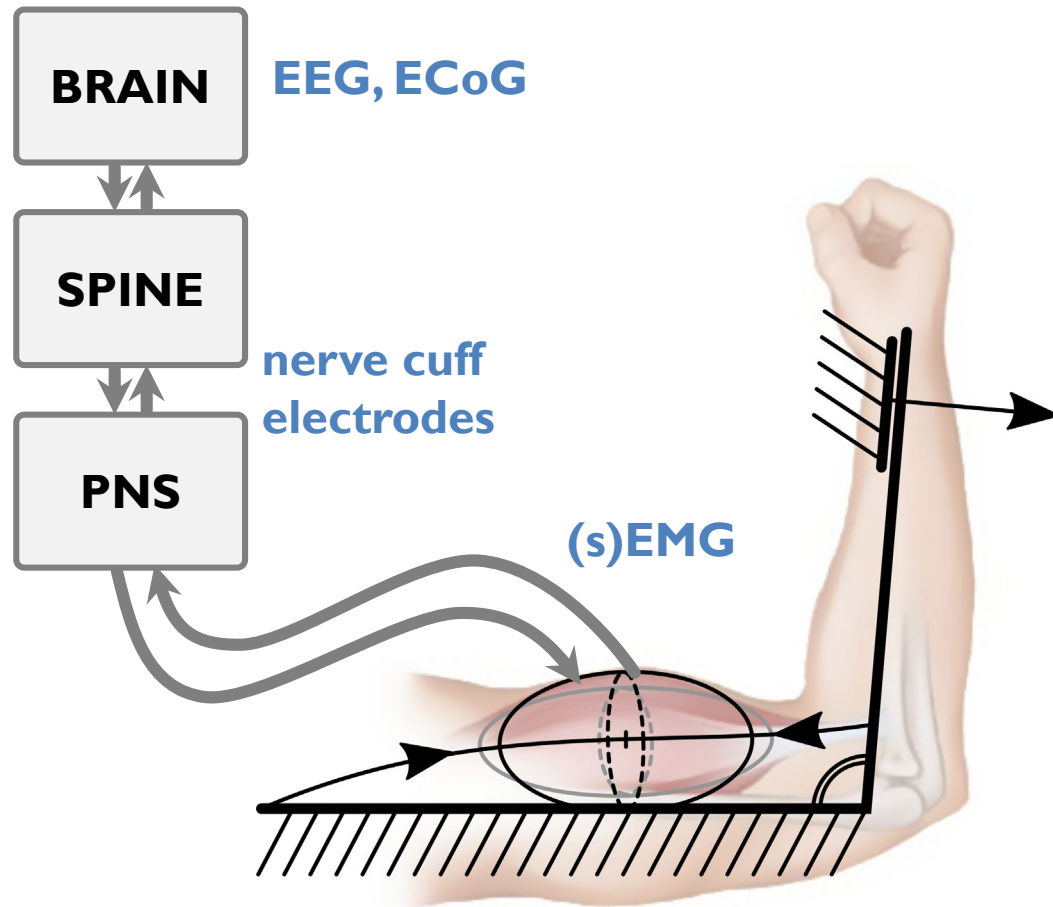
Deformation-Enhanced In Vivo Muscle Force Inference



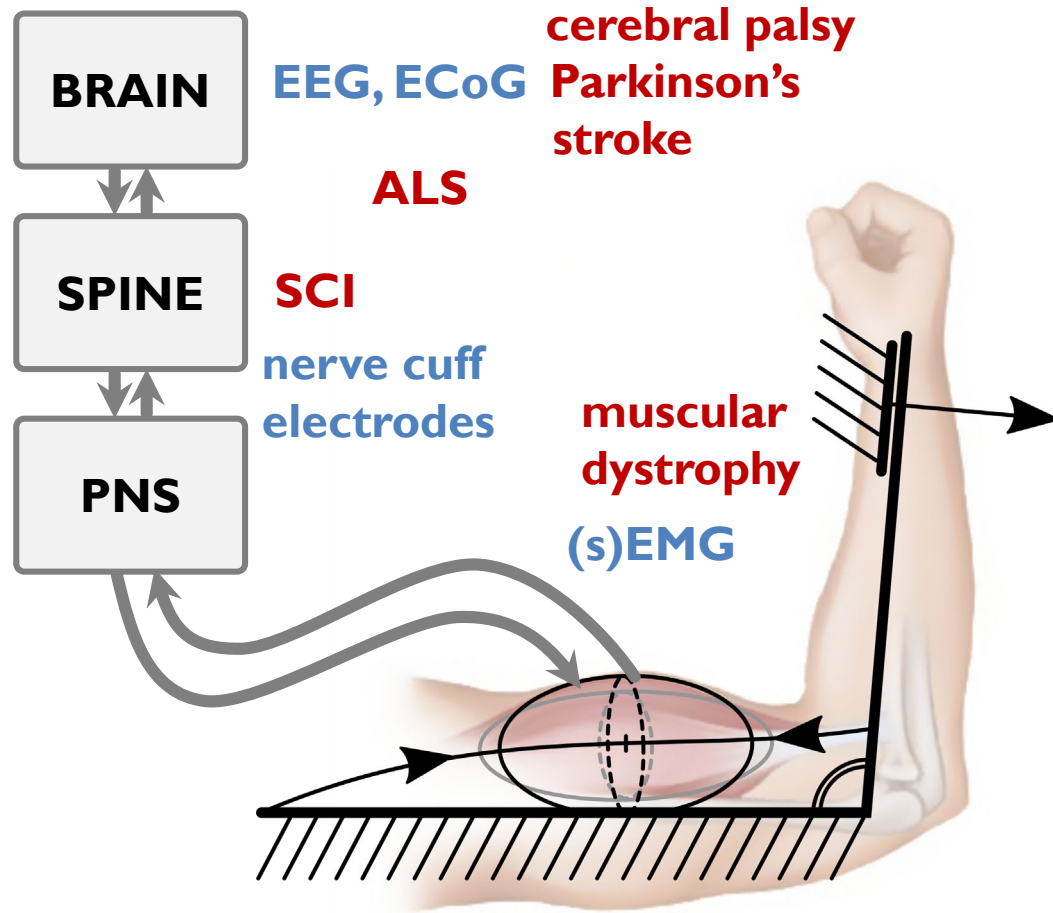
Measuring individual muscle forces allows for **probing / validating current ID inference models** and **developing FD measurement systems** with reasonable behavior.



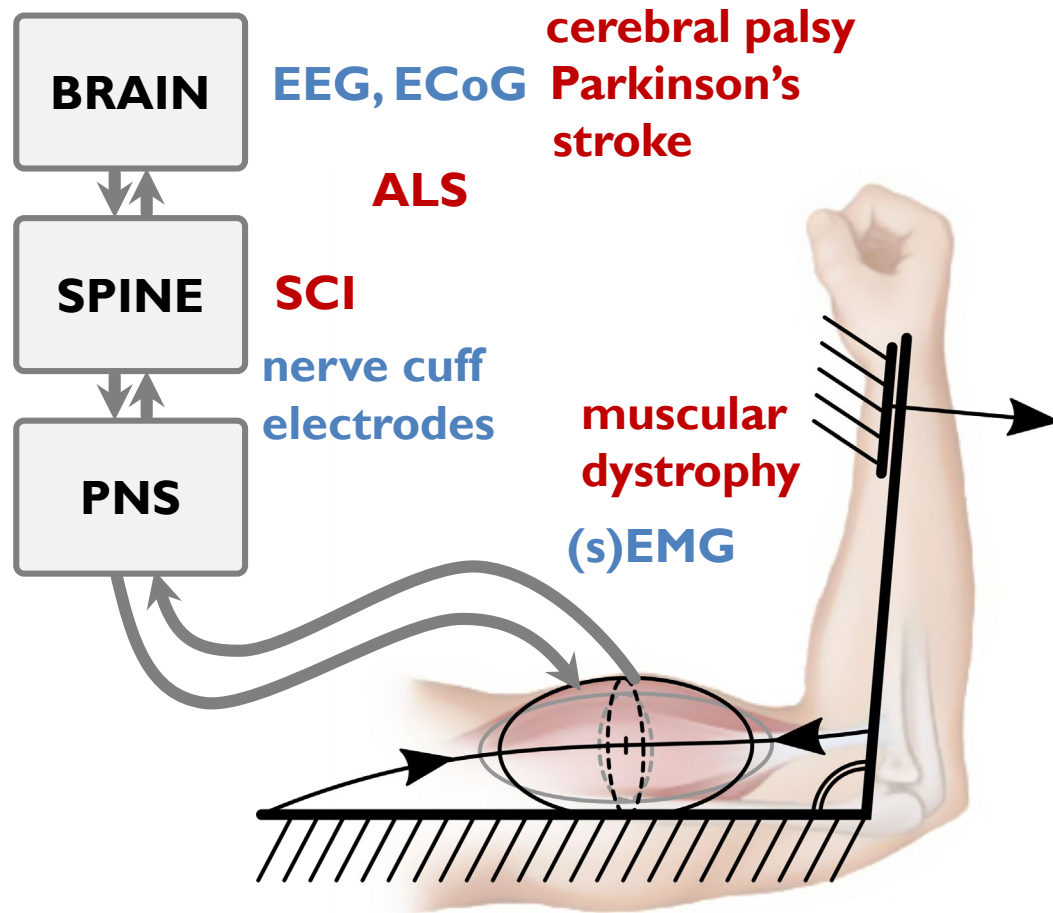
Future Directions: Closing the Loop



Future Directions: Closing the Loop



Future Directions: Closing the Loop



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**.

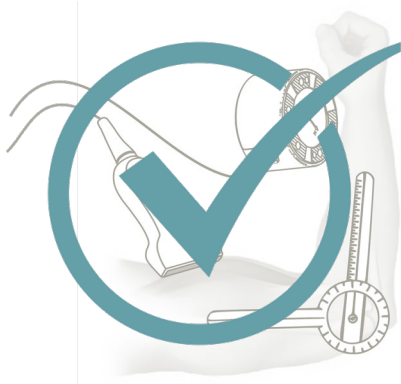


Roadmap

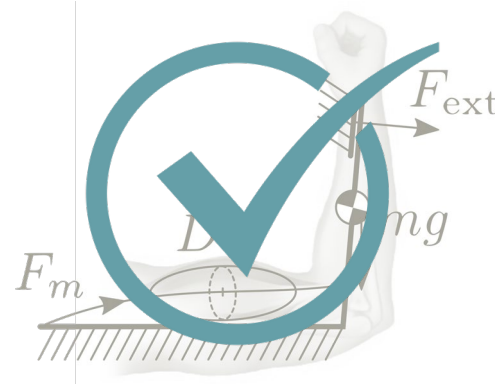
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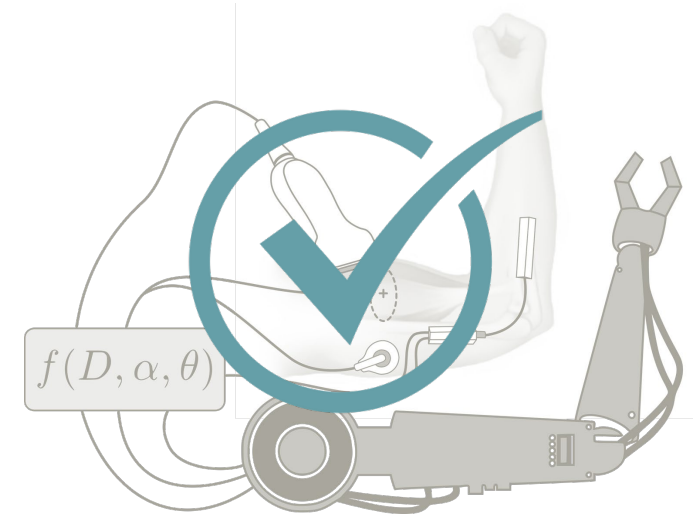
I Exploratory Data Set Generation



II Model Development & Validation



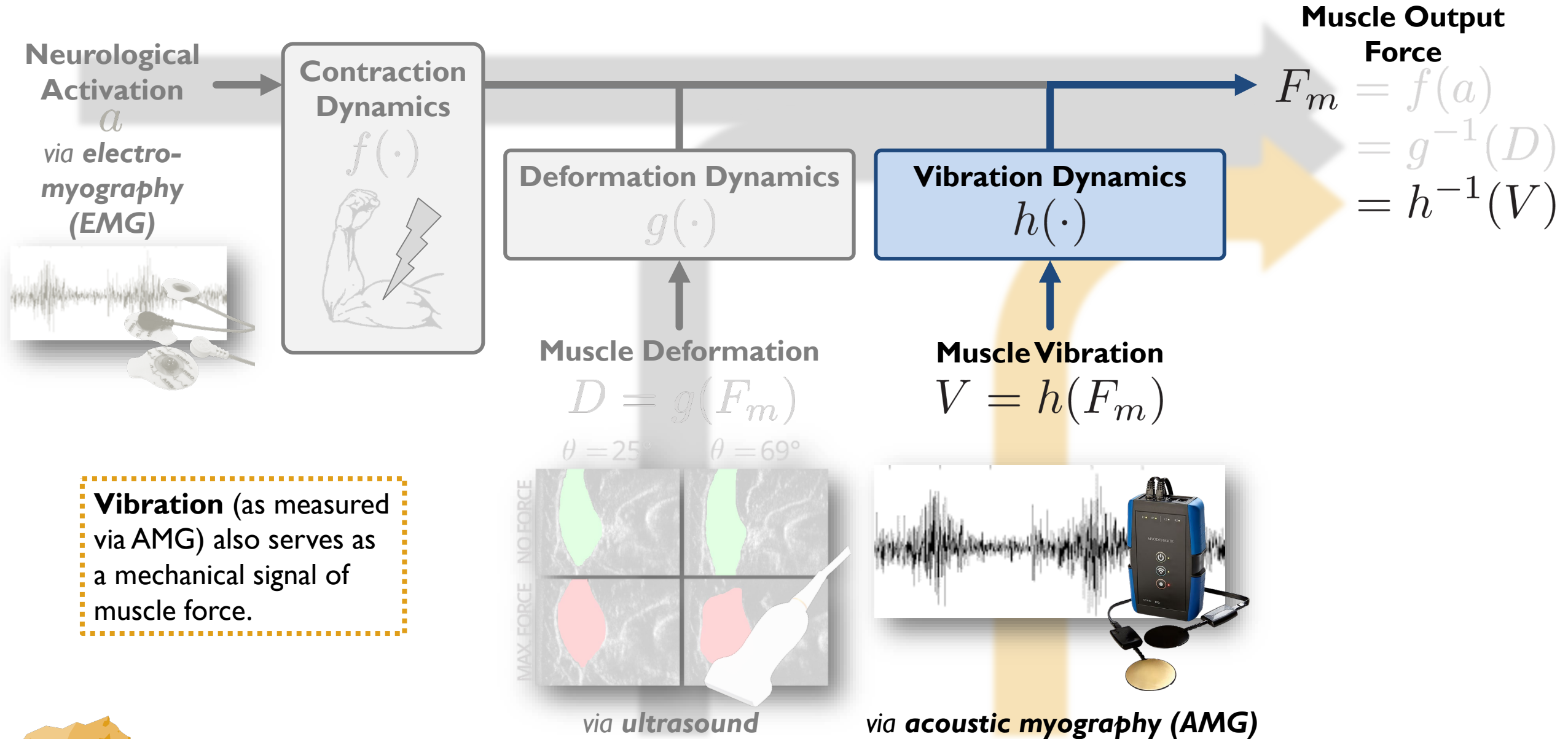
III Proof-of-Concept Applications



Alternate Modalities & Conclusions



Muscle Force Inference: AMG



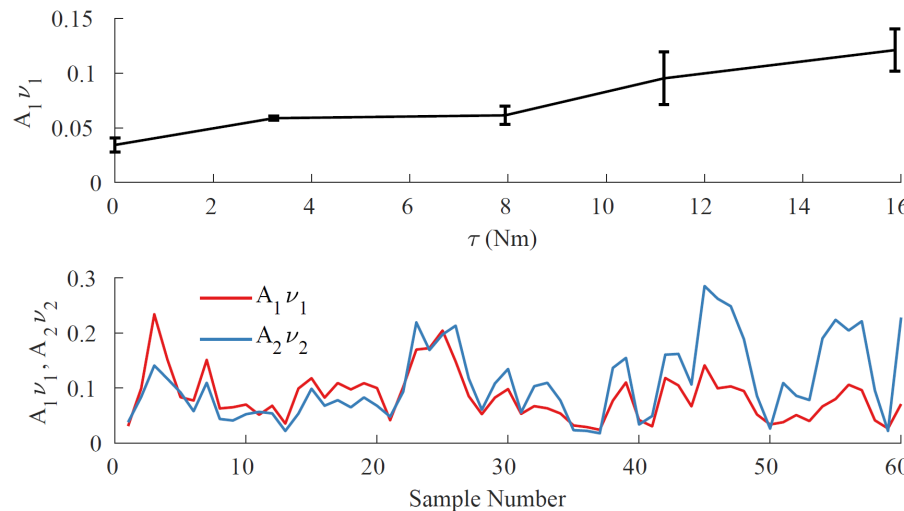
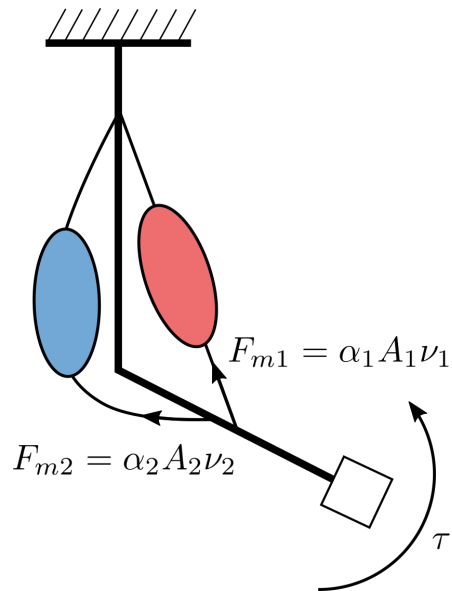
Preliminary AMG-Force Model

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]

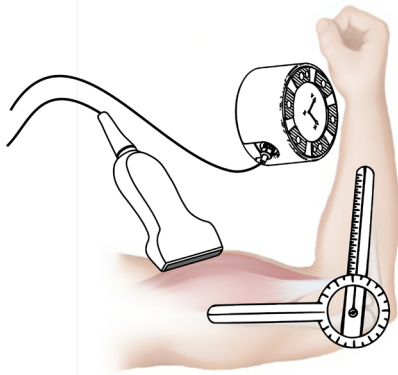


Roadmap: Recap

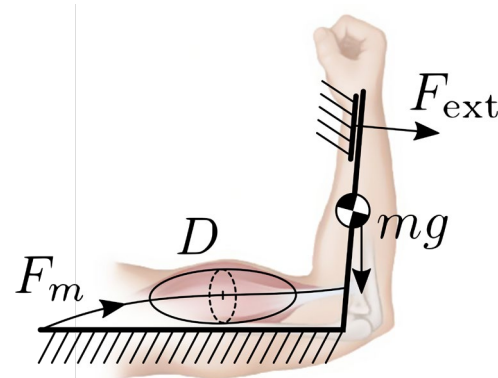
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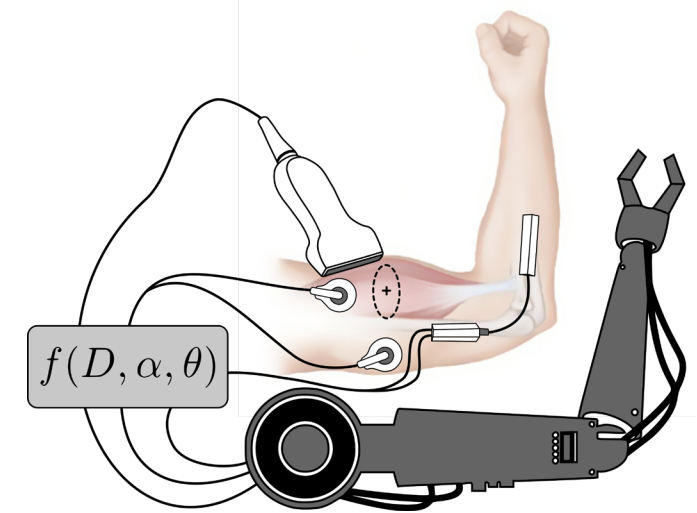
I Exploratory Data Set Generation



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

$$f(D, \alpha, \theta)$$

Alternate Modalities & Conclusions



Acknowledgments & Sponsors

THANKS TO:

Ruzena Bajcsy

Claire Tomlin

Robert Full

Hannah Stuart

Neville Hogan

Gregorij Kurillo

Akira Kato

Sara Fridovich-Keil

Jeffrey Zhang

Daniel Ho

Ian McDonald

Yonatan Nozick

Sai Mandava

Chris Mitchell

Thomas Li

David Wang

Sachiko Matsumoto

Nandita Iyer

Stella Seo

Prerana Kiran

Shivani Sharma

Michelle He

Evan Shu

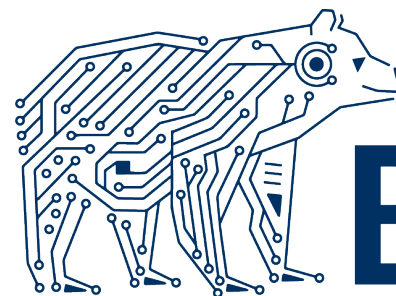
Jason Liu

Aaron Sy

Amanda Schwartz

Akash Velu

SIEMENS



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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)

