A systematic modeling framework for deformation-based muscle force inference

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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

UCB HART Lab APEX
Gamma exoskeleton

PISA-IIT Softhand
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Understanding of Highly Dexterous Movements

Contact juggling, GIPHY

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Introduction & Roadmap
Why measure individual muscle forces?

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Diagnosis and Rehabilitation of Pathology

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

Humans are highly over-actuated, and existing modeling frameworks make significant assumptions about muscle force distribution.
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Muscle Force Inference: State-of-the-Art Shortcomings

Neurological Activation \( \alpha \) via electromyography (EMG)

Contraction Dynamics \( f(\cdot) \)

\[ F_m = f(\alpha) \]
Muscle Force Inference

Neurological Activation $\alpha$

via electromyography (EMG)

Contraction Dynamics $f(\cdot)$

Deformation Dynamics $g(\cdot)$

Muscle Deformation $D = g(F_m)$

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

via ultrasound

Muscle Output Force $F_m = f(\alpha)$
Muscle Force Inference: Our Approach

Deformation Dynamics via ultrasound

Muscle Deformation

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!)
CORE OBJECTIVE

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

**I Exploratory Data Set Generation**

**II Model Development & Validation**

**III Proof-of-Concept Applications**

**Alternate Modalities & Conclusions**
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
Muscle Force Inference: Our Approach

- **Neurological Activation** \( \alpha \)
  - via **electromyography** (EMG)

- **Contraction Dynamics** \( f(\cdot) \)

- **Deformation Dynamics** \( g(\cdot) \)

- **Muscle Deformation**
  
  \[
  D = g(F_m)
  \]

- \( \theta = 25^\circ \) \( \theta = 69^\circ \)

- **What should this model look like?**

**Muscle Output Force**

\[
F_m = f(\alpha) = g^{-1}(D)
\]
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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Deformation Modeling Challenges

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

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)

[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

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:


[Hallock, Kato, Bajcsy, ICRA 2018]
Automated Tissue Segmentation: U-Net

intensity map (2D slice) \[\rightarrow\] \[(2D) \text{ U-Net}\] \[\rightarrow\] output segmentation (2D slice)

[Ronneberger et al. 2015]

[Nozik*, Hallock*, Ho, Mandava, Mitchell, Li, Bajcsy, EMBC 2019]
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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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Automated Tissue Segmentation: Preliminary Results

**Ground Truth**

- **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)

**Registration**

**U-NET**

**U-NET+EA**

**Multi-Subject U-NET+EA**

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

We seek to measure individual muscle forces in vivo via ultrasound based on shape changes under loading.
(Simplified) **Biological Mechanism**

How close is what we observe to the simplified model?
Exploratory Data Analysis: OpenArm 1.0

Cross-Sectional Area $CSA_{\theta,LC}(x)$

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

[Hallock, Kato, Bajcsy, ICRA 2018]
Exploratory Data Analysis: OpenArm 1.0

Cross-Sectional Area $CSA_{\theta,LC}(x)$

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

Biceps Cross-Section

[Illustration of cross-sectional areas and thicknesses for different angles: 30°, 60°, 90°]

[Hallock, Kato, Bajcsy, ICRA 2018]
Exploratory Data Analysis: OpenArm 1.0

Cross-Sectional Area

\[ CSA_{\theta,LC}(x) \]

Thickness

\[ T_{\theta,LC}(x) \]

Biceps Cross-Section

[I1A: Modeling Framework] [Hallock, Kato, Bajcsy, ICRA 2018]
Exploratory Data Analysis: OpenArm 1.0

Cross-Sectional Area
$CSA_{\theta,LC}(x)$

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

Biceps Cross-Section

Maximum
$CSA/T$

Maximum Change

[Hallock, Kato, Bajcsy, ICRA 2018]
Exploratory Data Analysis: Statistical Shape Modeling

SHAPE DECOMPOSITION:

\[ S = \bar{S} + Pb \]

- mean shape
- weight vector
- eigenvectors of covariance

First Shape Modes

- **No Force, Vary Angle**
  - 78% var.
- **30° Angle, Vary Force**
  - 59% var.
Expanded Biological Mechanism

- Multi-muscle dynamics
  - synergies
  - contact forces
Expanded Biological Mechanism

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

- **Geometric complexity**
  - nonlinear, config-specific “line of action”
  - pennation angle
  - tendon/aponeurosis thickness
Expanded Biological Mechanism

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

• **Multi-muscle dynamics**
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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)
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- **Neurological complexity**
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**Expanded Biological Mechanism**

**CHALLENGE:** “One step forward, one step back”

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

**GOAL**

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

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

- feedback vs. feedforward control

I1A: Modeling Framework
(Proposed) **Suite of Models**

**“black box”**

**“white box”**

\[ \tau_{\text{ext}} = r \times F_{\text{ext}} \]

\[ D_{\text{biceps}} \]

\[ F_{\text{biceps}} \]

\[ \theta \]

**Musculoskeletal Dynamics**

\[ D_{\text{biceps}} \]

\[ \theta \]

\[ \tau_{\text{ext}} \]
(Proposed) **Suite of Models**

- **“black box”**
- **“white box”**
- **“model free” baseline**

Musculoskeletal Dynamics

\[ \tau_{ext} = r \times F_{ext} \]

\[ \tau_{ext} = f_0(\theta, D_{biceps}) \]

**IIB: Model Development**
(Proposed) **Suite of Models**

```
“black box”
“model free” baseline
+ multi-muscle dynamics
```

**Musculoskeletal Dynamics**

**Biceps Contraction Dynamics**

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

**Force Distribution Model**

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

\[ \tau_{\text{ext}} = r \times F_{\text{ext}} \]

\[ \sum F_{\text{biceps}} = D_{\text{biceps}} \]

\[ F_{\text{biceps}} \]

\[ \theta \]

\[ r \]

\[ F_{\text{ext}} \]

\[ m \]

\[ g \]

MUSCULOSKELETAL DYNAMICS

BICEPS CONTRACTION DYNAMICS

FORCE DISTRIBUTION MODEL

\[ \sum F_{\text{biceps}} \]

\[ D_{\text{biceps}} \]

\[ \theta \]

\[ r \]

\[ F_{\text{ext}} \]

\[ m \]

\[ g \]
(Proposed) **Suite of Models**

```
Musculoskeletal Dynamics
```

```
Biceps Contraction Dynamics
```

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

```
\tau_{\text{ext}} = r \times F_{\text{ext}}
```

```
D_{\text{biceps}}
```

```
F_{\text{biceps}}
```

```
\theta
```

```
\tau_{\text{biceps}}
```

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

```
[assumed]
```

```
[measured]
```

```
"black box" + multi-muscle baseline" white box"
```

```
"model free" baseline
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```
"white box"
```

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Biceps Contraction Dynamics
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```
F_{\text{biceps}} = f_1(\theta, D_{\text{biceps}})
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"white box"
```
(Proposed) Suite of Models

Musculoskeletal Dynamics

Biceps Contraction Dynamics

Muscle Deformation

\[ D_{\text{biceps}} \]

\[ \ell_m = f_2(\theta, D_{\text{biceps}}) \]

Tendon Dynamics

\[ F_{\text{biceps}} = F_t \approx k \Delta \ell_t \]

\[ \approx k \Delta (\ell_{\text{MTU}} - \ell_m) \]

\[ \ell_{\text{MTU}} \]

\[ k \]

\[ r_{\text{biceps}}(\cdot) \]

Force Distribution Model

Muscle Geometry

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

\[ \tau_{\text{ext}} = r \times F_{\text{ext}} \]

\[ \ell_t = \ell_{\text{MTU}} - \ell_m \]

\[ D_{\text{biceps}} \]

\[ \ell_m \]

\[ m \]

\[ g \]

\[ F_{\text{biceps}} \]

\[ \theta \]

\[ \tau_{\text{brach}}, \tau_{\text{brachrad}}, \tau_{\text{triceps}}, \tau_{\text{mg}} \]
(Proposed) Suite of Models

Musculoskeletal Dynamics

Biceps Contraction Dynamics

**Muscle Deformation**

\[
\ell_m = f_2(\theta, D_{\text{biceps}})
\]

**Tendon Dynamics**

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

**Force Distribution Model**

\[
\tau_{\text{ext}} = r \times F_{\text{ext}} \\
\ell_t = \ell_{\text{MTU}} - \ell_m
\]

**Muscle Geometry**

\[
F_{\text{biceps}} = r_{\text{biceps}}(\theta) \times F_{\text{biceps}}
\]

**Tendon**

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

**Baseline**

“black box”

“model free” baseline

Tendon + multi-muscle dynamics

+ MTU dynamics

“white box”
(Proposed) Suite of Models

Musculoskeletal Dynamics

**Biceps Contraction Dynamics**

- **Muscle Deformation**
  \[ D_{\text{biceps}} \triangleq A_m \]
  \[ \ell_m \approx T_\theta \left[ \frac{3V_m}{4A_m} \right] \]

- **Tendon Dynamics**
  \[ F_{\text{biceps}} = F_t \approx k \Delta \ell_t \]
  \[ \approx k \Delta (\ell_{MTU} - \ell_m) \]

**Force Distribution Model**

- **Muscle Geometry**
  \[ \tau_{\text{biceps}} = r_{\text{biceps}}(\theta) \times F_{\text{biceps}} \]

\[ \tau_{\text{ext}} = r \times F_{\text{ext}} \]
\[ \ell_t = \ell_{MTU} - \ell_m \]

\[ D_{\text{biceps}} \]

\[ \ell_m \]

\[ \ell_{MTU} \]

\[ k \]

\[ r_{\text{biceps}}(\cdot) \]

\[ \tau_{\text{brach}}, \tau_{\text{brachrad}}, \tau_{\text{triceps}}, \tau_{mg} \]
Model Validation

Direct, Invasive Force Measurement

Consistency Across Sensors

AMG

“tapping tendons”

cine DENSE MRI

[Salmons 1969]
[Sherif et al. 1983]
[Hoffer et al. 1989]
[Barnes & Pinder 1974]
[Harrison 2017]
[Zhong et al. 2008]
[Martín et al. 2018]

[Salmons 1969]
[Yager 1972]
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
Points along the muscle fascia can be **reliably tracked in real time** via Lucas-Kanade optical flow.
Real-Time Device Control: Robot Teleoperation

\[
\begin{align*}
\theta_u & \quad + \\ & \quad \text{PD Controller} \quad k_P, k_D \\
\theta_r & \quad - \\ & \quad \theta_r
\end{align*}
\]
Real-Time Device Control: Baseline sEMG Control
Real-Time Device Control: Proposed Control

$F_{\text{des}} \propto D_{\text{biceps}}$

$k_P, k_D \propto \alpha_{\text{diff}}$

$\theta_u \quad \theta_r$

PD Controller

$F_{dy}$

$F_r$

$\theta_r$
Real-Time Device Control: Proposed Control

Proof-of-Concept Application: ball catching!

\[ F_{\text{des}} \propto D_{\text{biceps}} \]

\[ k_P, k_D \propto \alpha_{\text{diff}} \]

PD Controller

\[ k_P, k_D \]

\[ F_{\text{dy}} \]

\[ F_r \]

\[ \theta_r \]
In Vivo Muscle Force Inference: State-of-the-Art

Joint Angles / Velocities: \( \{\theta, \dot{\theta}\} \)

Joint Torques: \( \{\tau\} \)

Muscle Output Forces: \( \{F_m\} \)

Inverse Dynamics

Cost Function (e.g., minimum total energy, sEMG matching)

[e.g., OpenSIM, AnyBody]

IIB: Extant Framework Evaluation
Deformation-Enhanced In Vivo Muscle Force Inference

\[
\{\theta, \dot{\theta}\} \xrightarrow{\text{Inverse Dynamics}} \{\tau\} \xrightarrow{\text{Cost Function}} \{F_m\} = \{\ldots, F_{\text{biceps}}, \ldots\}
\]

Cost Function (e.g., minimum total energy, sEMG matching)

[e.g., OpenSIM, AnyBody]
Deformation-Enhanced In Vivo Muscle Force Inference

**FORWARD DYNAMICS**

Joint Angles / Velocities

\[ \{\theta, \dot{\theta}\} \]

**COST FUNCTION**

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

Muscle Output Forces

\[ \{\tau\} \]

Muscle Output Forces

\[ \{F_m\} = \{\ldots, F_{\text{biceps}}, \ldots\} \]

**INVERSE DYNAMICS**

**FORWARD DYNAMICS**

Muscle Output Forces

\[ \{F_m\} \]

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

EEG, ECoG
nerve cuff electrodes
(s)EMG

BRAIN
SPINE
PNS

III: Proof-of-Concept Applications
Future Directions: Closing the Loop

EEG, ECoG

BRAIN

SPINE

PNS

erve cuff electrodes

muscular dystrophy

(s)EMG

cerebral palsy

Parkinson’s stroke

ALS

SCI

cerebral palsy

Parkinson’s stroke

ALS

SCI

muscular dystrophy

(s)EMG

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III: Proof-of-Concept Applications
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**.
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Alternate Modalities & Conclusions
Muscle Force Inference: AMG

Muscle Deformation

\[ D = g(F_m) \]

Vibration Dynamics

\[ V = h(F_m) \]

Muscle Output Force

\[ F_m = f(\alpha) = g^{-1}(D) = h^{-1}(V) \]

Neurological Activation \( \alpha \) via electromyography (EMG)

Contraction Dynamics

\[ f(\cdot) \]

Deformation Dynamics

\[ g(\cdot) \]

Vibration Dynamics

\[ h(\cdot) \]

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

AMG amplitude $A \propto \# \text{activated muscle fibers}$

AMG frequency $\nu \propto \text{mean fiber force}$

$F_m \propto A \nu$

- 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.

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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.)

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**II Model Development & Validation**

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

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**III Proof-of-Concept Applications**

A proof-of-concept control application demonstrating the utility of this technology

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Alternate Modalities & Conclusions
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List of Publications


