Sensor-Driven Musculoskeletal Dynamic Modeling

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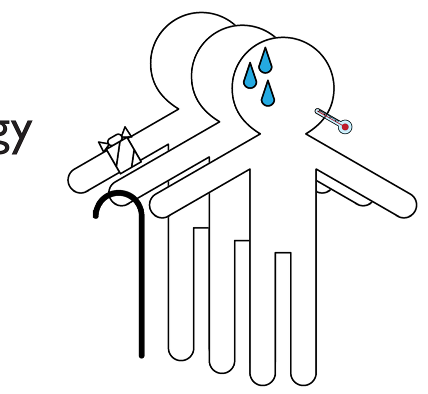
Objective

Create a musculoskeletal model of the human arm that:
- has appropriate level of abstraction (is as simple as possible while accommodating dynamically- and medically-relevant pathologies)
- is trainable/customizable using non-invasive sensing
- can be used in an exoskeletal control system using non-invasive, wearable sensing
- has no reliance on literature values or population measures

Motivation

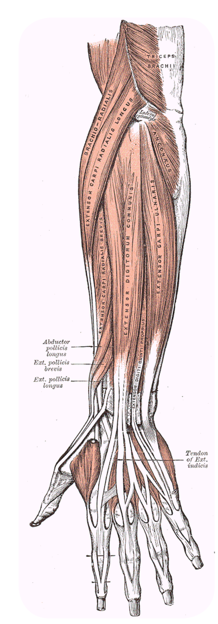
Creation of descriptive human dynamical modeling framework is hampered by:
- **reliance on population-based models** that fail to account for variation/pathology
- **system complexities** at every level of abstraction
  - single muscle force-length-velocity relation is poorly understood
  - *in vivo*, muscles act in aggregate
  - non-invasive sensing is limited



At the same time, **kinematics alone are insufficient** to diagnose and treat musculoskeletal pathologies and create assistive devices (e.g., exoskeletons): **dynamics must be modeled**.

State of the Art

Current modeling frameworks are built using:
- cadaver / *ex vivo* studies (human and animal)
- population measures
- model fitting/optimization w/ additional assumptions (e.g., gait cycle, optimal energy consumption)
- aggregate "average human" population models (e.g., OpenSim [1], AnyBody [2])

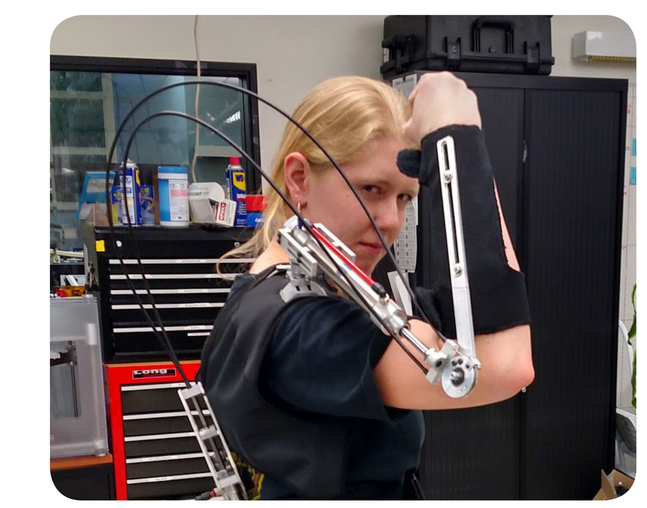


Assumptions

Assume ability to measure:
- **skeletal kinematics** (motion capture, IMU, electrogoniometer)
- **morphological parameters**
  - muscle/tendon/bone volumes, insertion points (ultrasound - dynamic, MRI - static)
  - limb link masses (force plates using method in [3])
- **contact forces** (force plates, force-torque sensors)
- **muscle "activation"** (sEMG - aggregate, dimensionless)
- peripheral signals - blood oxygenation (NIRS), metabolic effort (O_2 consumption mask)

Approach

Develop a modeling framework informed by
- **sensor capability**
- kinematic/dynamic **parameters of interest**



Gamma exoskeleton, developed in the HART Lab.

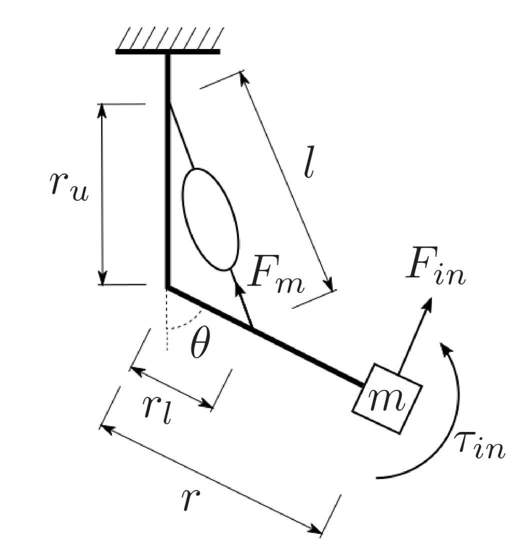
Simplified Initial Model (static)

Assuming muscle force-length relation

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

and normalized muscle activation and length

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



the dynamics relation of each $(\bar{a}, \tau, \theta)$ pair is described by

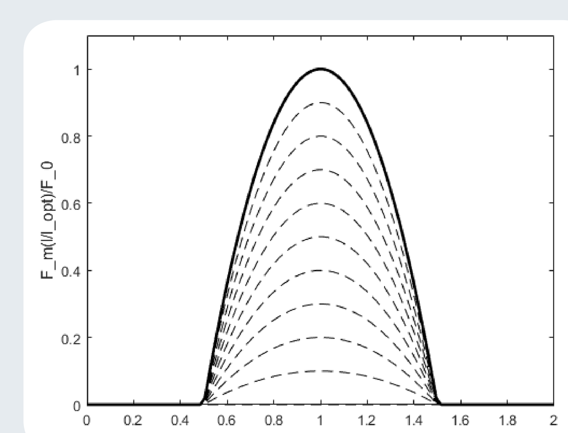
$$\begin{bmatrix} \tau_1 \\ \vdots \\ \tau_n \end{bmatrix} = \begin{bmatrix} \tau_{in,1} + rF_{in,1} - \frac{1}{2}mg\sin\theta_1 r \\ \vdots \\ \tau_{in,n} + rF_{in,n} - \frac{1}{2}mg\sin\theta_n r \end{bmatrix} = F_0 r_l r_u \begin{bmatrix} \frac{l_1}{l_{opt}^2}\sin\theta_1\bar{a}_1 & \frac{1}{l_{opt}}\sin\theta_1\bar{a}_1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

i.e., $T = WB$.

Model Validation

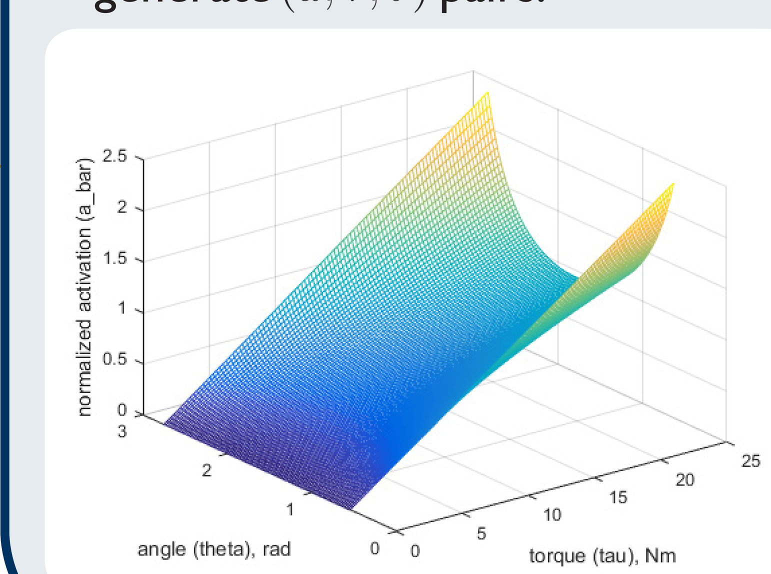
Hypothesize Approximate System

- Set morphological parameters to approximate biceps
- Assume 2nd-order approx. for force-length curve [4]:



Generate Synthetic Data

Based on morphological model, generate $(\bar{a}, \tau, \theta)$ pairs:



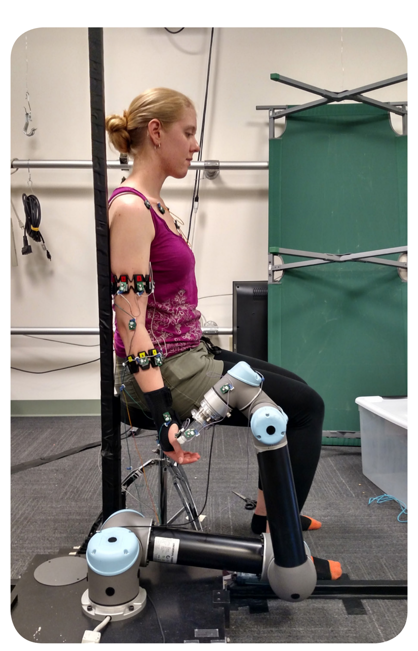
Add Noise + Recover System Function via Least Squares

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

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

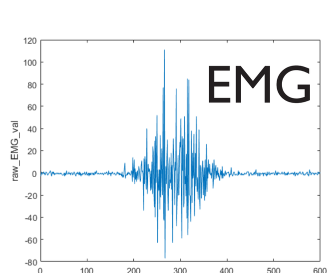
To verify system's validity:
- condition number of W
- numerical computation of base parameters [5]

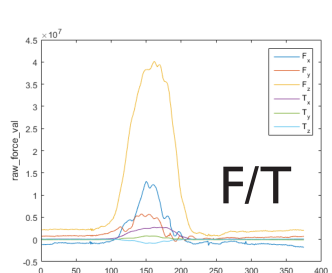
Preliminary Results



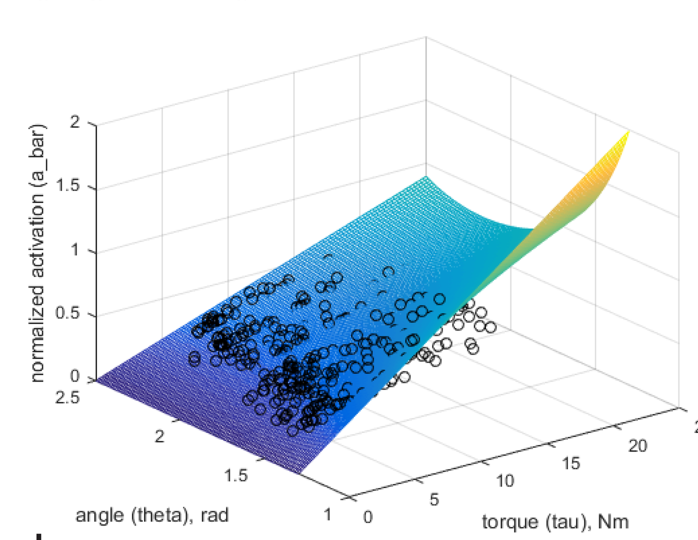
Experimental setup. Subject pressed upward on F/T sensor mounted to UR5 robot with varying levels of effort at varying angles while sEMG data were gathered from Myo arm bands.

Data: ~400 × { EMG, F/T, θ } for single subject





- $(\bar{a}, \tau, \theta)$ pairs generated using normalized and filtered EMG, normalized and summed force (taking the max. sample value for each), and measured angle (within range of optimal angle as defined by [6])
- least squares optimization used to recover force-length relation



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

The generated **surface is qualitatively reasonable** and fits the data well, and the predicted **force-length relation is biologically reasonable**.

Current/Future Work

To refine the above framework, are currently working to:
- incorporate **more extensive data**: multi-channel EMG, additional sensors for better morphological parameter estimation
- incorporate **multiple muscles** (extensors and additional flexors)
- **hybridize model** (agonist/antagonist w/ different system functions)
- **add muscle dynamics** (e.g., Hill model)

[1] Delp, S.L. et al. "OpenSim: open-source software to create and analyze dynamic simulations of movement."
[2] The AnyBody Modeling System. Aalborg, Denmark: AnyBody Technology, 2015.
[3] Matthew, R.P. et al. (2016) "Generating physically realistic kinematic and dynamic models from small data sets." *IEEE EMBC*.
[4] Gordon, A.M. et al. (1966) "The variation in isometric tension with sarcomere length in vertebrate muscle fibers." *Journal of Physiology* 185:170-192.
[5] Khalil, W. & Dombre, E. (2004) "Numerical computation of the base parameters (Appendix 5)." *Modeling, Identification & Control of Robots*.
[6] Chang, Y.W. et al. (1999) "Optimum length of muscle contraction." *Clinical Biomechanics* 14(8):537-42.

Further information can be found in:
Hallock, L.A. et al. (2016) "Sensor-Driven Musculoskeletal Dynamic Modeling." UC Berkeley EECS, Tech. Rep. UCB/EECS-2016-66.