Differentiating Ultrasound-Measured Active and Passive Muscle Deformation via Statistical Shape Modeling

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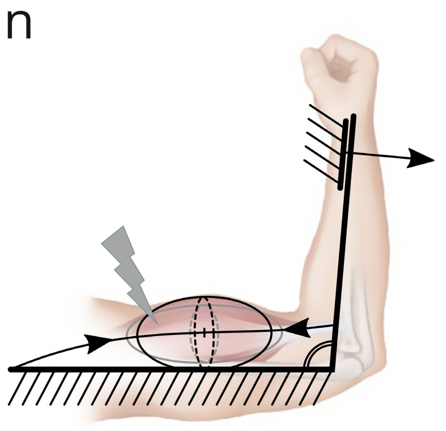
Motivation

- **Quantifying individual muscle forces** has the potential to revolutionize biomechanical study, but no noninvasive methods exist to measure them in real time.
- **Muscle deformation** is a promising signal from which to **infer individual muscle forces** from a single ultrasound scan: when muscles undergo the cross-bridge cycle to stretch the tendon and impart force to the skeleton, they undergo a **shape change**.
- In addition to the force we desire to measure, deformation also reflects passive shape changes due to kinematic configuration and contact dynamics. Thus, **to measure force via deformation, models are needed that account for (and discriminate between) active and passive deformation**.



Contributions

- We **formulate statistical shape models (SSMs) to discriminate between active and passive biceps brachii deformation within a single ultrasound cross section** using the OpenArm 2.0 data set [1].
- Preliminary results indicate that **active deformation may best be quantified by changes in overall cross section size** while **passive deformation may best be quantified by measures of shape**.

Data Set

Deformation data were analyzed from the **OpenArm 2.0** data set [1], which consists of **3D segmented ultrasound scans** of the **biceps brachii** and humerus:

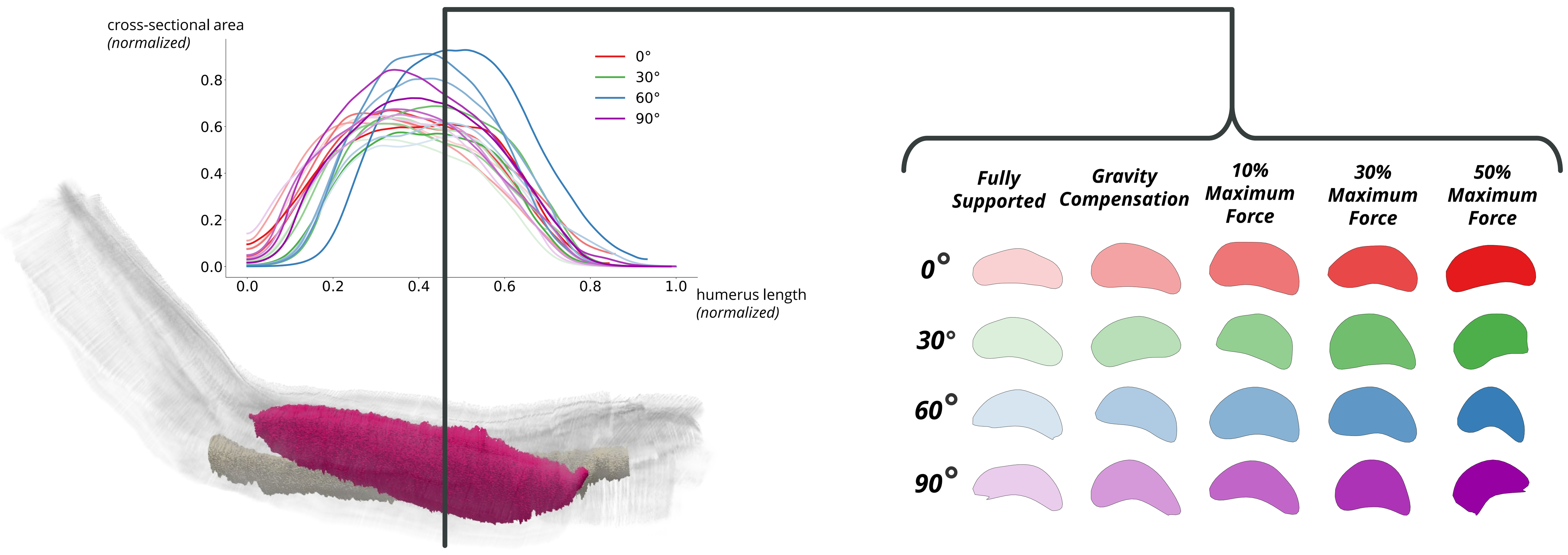
- from 11 subjects;
- at 4 elbow angles;
- under 5 different loading conditions at each angle.

Data from a single exemplar subject (Sub1) were analyzed in this initial study.

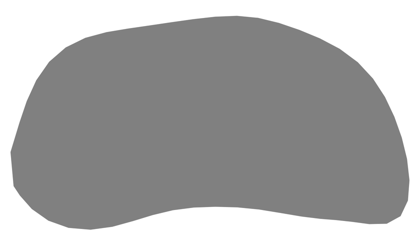
Data Processing & Scan Selection

Scans at all conditions were aligned to a consistent humerus position via a combination of automated processes and manual alignment to identified landmarks.

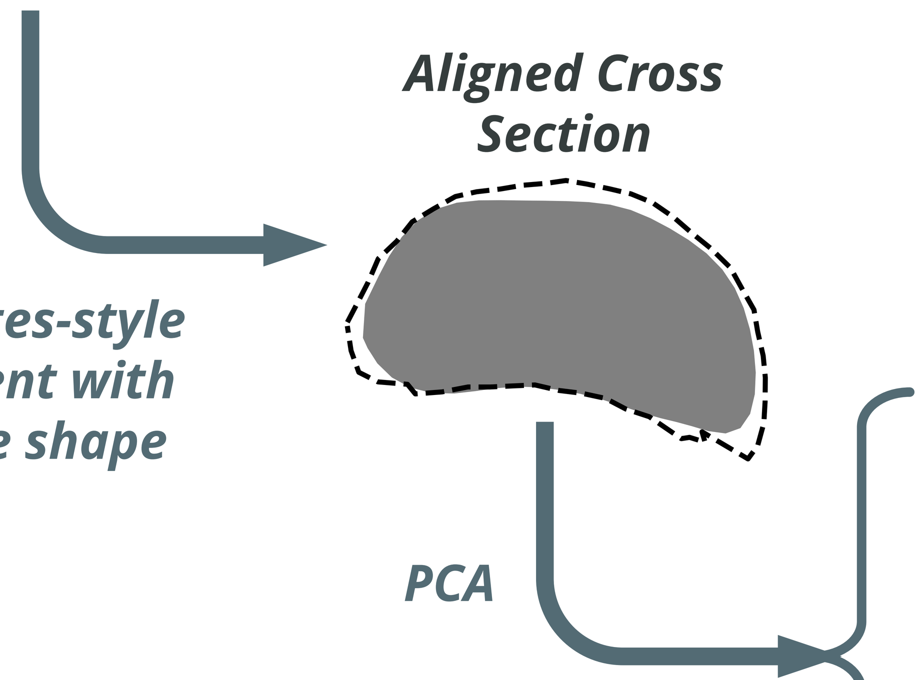
The cross section with the **most linear relative change across conditions** (i.e., most consistent signal, averaged across angle conditions) was selected for analysis. This was found to be at 45% of the length of the humerus, measured distal to proximal (i.e., elbow to shoulder).



Analysis & Results



On each examined cross section, a **modified Procrustes analysis** (where only the translational and rotational transformations were used) [2] was used to remove non-shape-associated variation while **retaining size variations**.

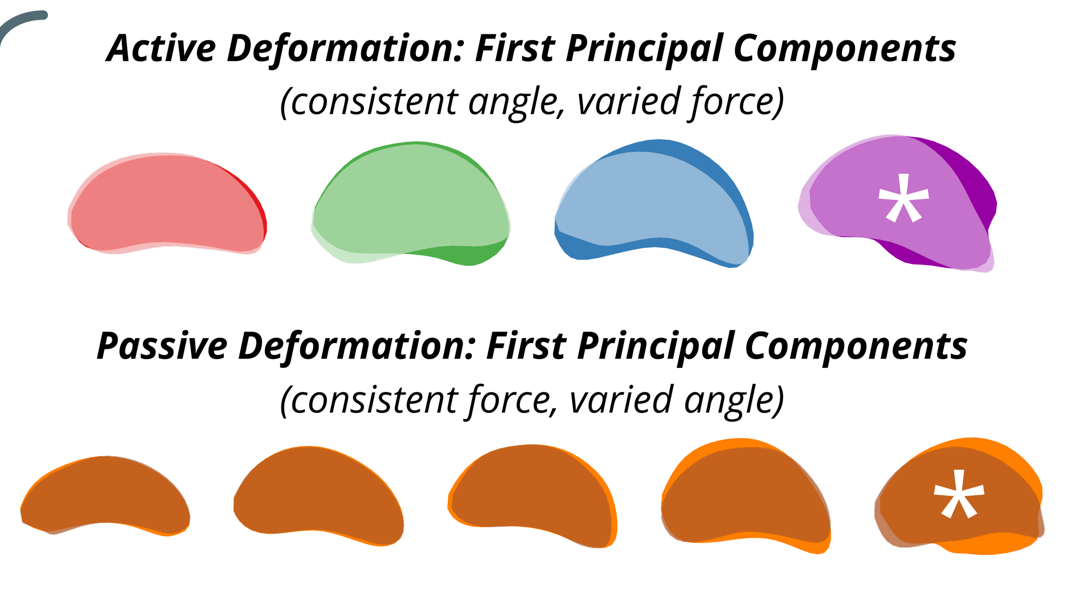


Active deformation results in a **more global size change.** This type of deformation **may best be quantified by a measure of scale** such as cross-sectional area.

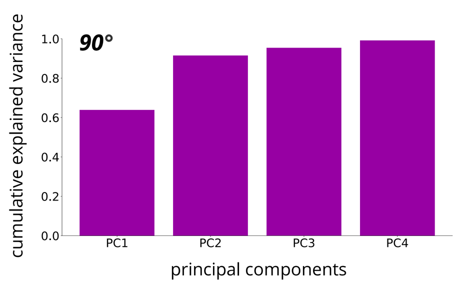
Passive deformation results in **more localized shape changes.** The difference in cross-sectional area between the two contours is extremely small, suggesting that **changes in shape**, such as eccentricity, **may be useful in quantifying this type of deformation.**

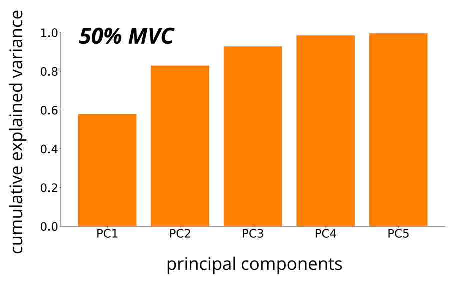
Principal Component Analysis (PCA) was applied separately to scans **varying only in force** and **only in kinematic configuration.**

A **statistical shape model (SSM)** [2] was built for each group to **reveal shape features linked to active and passive deformation**.



*In these cases, noisy point correspondence leads to some unpredictable shape variations.





PCA reveals **that the underlying dimensionality of muscle cross section deformation is low**, supporting the computational feasibility of using deformation signals in **real-time modeling and control applications**.

95% reconstruction is possible with **as few as 3 principal components.**

Conclusions & Future Work

- Preliminary results **support the feasibility of SSM as a tool to identify active and passive muscle deformation signals**, indicating that SSM-based deformation models, once fitted to individual bodies and muscles, could be used to **more accurately describe internal muscle forces** without the optimization-based techniques relied on by current musculoskeletal modeling frameworks [3] [4].
- Future work aims quantify and validate our preliminary insights in additional subjects and muscles, to ultimately build **personalized real-time models of muscle force output** and **ultrasound-based control schemes for assistive robots** based on active muscle deformation.

Acknowledgments / Sponsors / References

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[2] C. Lindner, "Automated Image Interpretation Using Statistical Shape Models," in Statistical Shape and Deformation Analysis, G. Zheng, S. Li, and G. Székely, New York, NY, USA: Academic Press, 2017.

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[4] V. Caggiano, H. Wang, G. Durandau, M. Sartori, and V. Kumar, "MyoSuite -- A contact-rich simulation suite for musculoskeletal motor control," presented at 4th Annual Learning for Dynamics & Control Conference, Palo Alto, California, United States, Jun. 23-24, 2022, doi: 10.48550/arXiv.2205.13600.

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