OpenArm 2.0: Automated Segmentation of 3D Tissue Structures for Multi-Subject Study of Muscle Deformation Dynamics

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Contributions

- Novel **neural-network-based pipeline for segmentation of 3D muscle and bone structures** from localized 2D ultrasound data of the human arm
- The **OpenArm 2.0 data set**, the first factorial set of **multi-subject, multi-angle, multi-force scans of the arm** with **full volumetric annotation** of the biceps and humerus

Target Application Domains

- **Musculoskeletal simulation**: measurement of individual muscle forces
- **Assistive device control**: extraction of multiple robust control signals for high-DoF prosthesis / exoskeleton control
- **Diagnosis / rehabilitation**: improved measurement and understanding of musculoskeletal deficiency
- **Graphics / animation**: enhanced rendering of muscle shape changes during movement

DOWNLOAD

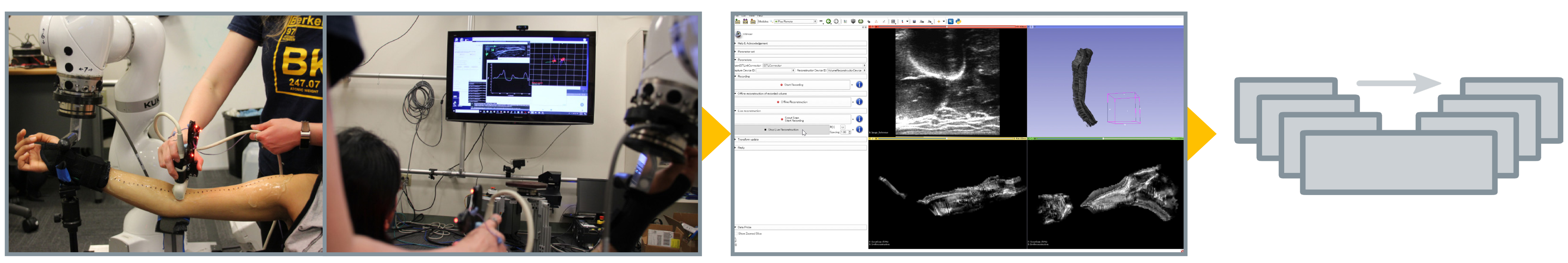
Download all code and data at

`simtk.org/projects/openarm`

Data Set Collection & Specifications

Final Data Processing Pipeline

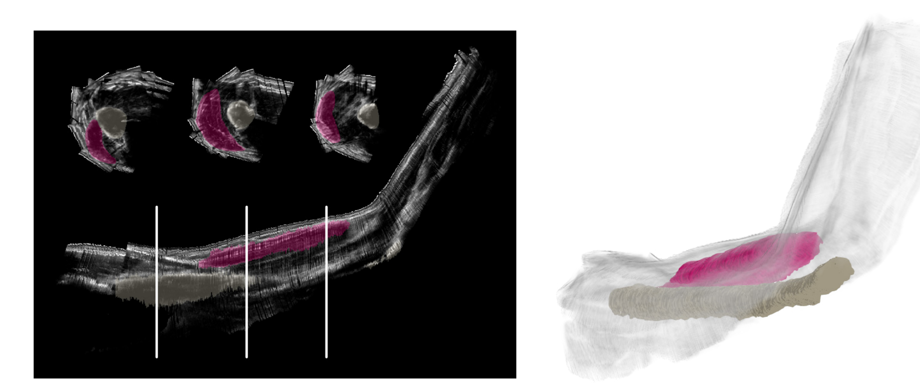
Raw Data Collection via Ultrasound & Motion Capture → **Volumetric Reconstruction** via PLUS Toolkit [1]–[3] → **Tissue Segmentation** via modified U-Net [4]



Full 3D intensity maps of the anterior surface of the arm were assembled from 2D ultrasound data (localized via motion capture) using an adapted version of the first OpenArm experimental protocol [5].

Several improvements were made, including **real-time force tracking and visual feedback** to enable scan collection under arbitrary, repeatable force conditions.

Finalized Tissue Volumes



Data were collected from

10 subjects (+1 partial) at

- 4 elbow angles (*0°, 30°, 60°, 90°*)
- 5 force conditions (*"fully supported", 0/10/30/50% MVC*)

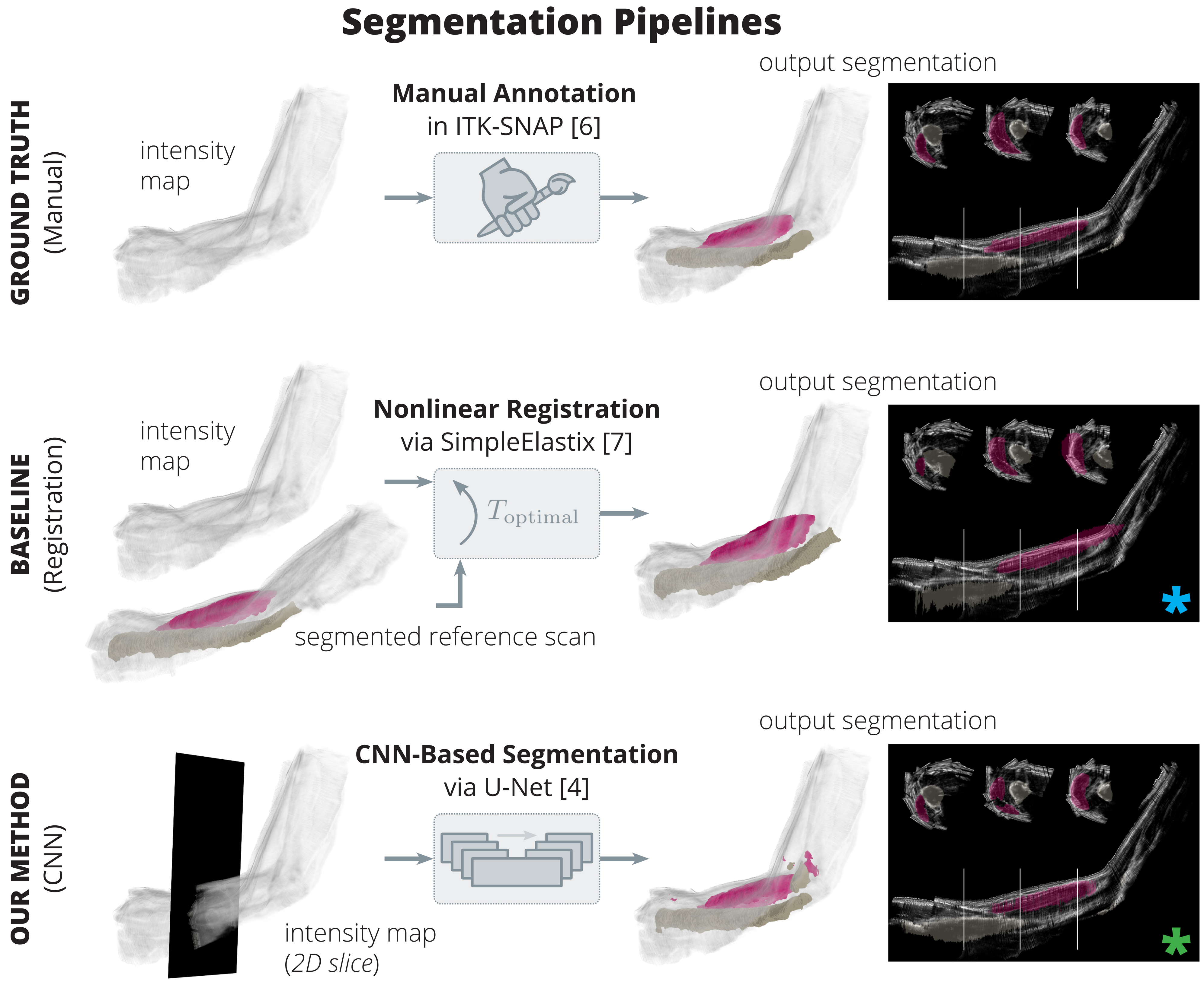
}**20 scans / subject**

automated annotation performed for all scans

ground truth annotation performed for 1 full + 2 partial subject data sets

Automated Tissue Segmentation

Segmentation Pipelines



Segmentation Accuracy by Strategy

	Architecture / Strategy	Accuracy (IoU, *Pixel Accuracy*) same angle, same force, same subject	**new** angle, same force, same subject	same angle, **new** force, same subject	same angle, same force, **new** subject
BASELINE (Registration)	RR	0.431, *0.980*	0.320, *0.970*	0.537, *0.985*	0.244, *0.953*
	RANR	0.722, *0.991*	0.545, *0.980* *	0.450, *0.980*	0.386, *0.960*
OUR METHOD (CNN)	U-NET	0.875, *0.996*	0.593, *0.982*	0.604, *0.988*	0.422, *0.961*
	U-NET+RA	0.929, *0.998*	0.560, *0.984*	0.464, *0.986*	0.393, *0.971*
	U-NET+EA	0.950, *0.999*	0.677, *0.988*	0.573, *0.989*	0.533, *0.978*
	U-NET+RA+EA	0.936, *0.998*	0.577, *0.984*	0.544, *0.988*	0.499, *0.978*
	Multi-Angle U-NET	0.886, *0.997*	0.691, *0.989*	0.614, *0.989*	0.470, *0.972*
	Multi-Angle U-NET+EA	0.906, *0.997*	0.717, *0.989*	0.651, *0.990*	0.523, *0.975*
	Multi-Force U-NET	0.885, *0.997*	0.617, *0.985*	0.770, *0.994*	0.452, *0.972*
	Multi-Force U-NET+EA	0.902, *0.997*	0.682, *0.988*	0.793, *0.994*	0.519, *0.977*
	Multi-Subject U-NET	0.884, *0.997*	0.657, *0.987*	0.536, *0.988*	0.885, *0.995*
	Multi-Subject U-NET+EA	0.908, *0.998*	0.687, *0.989* *	0.565, *0.989*	0.909, *0.996*

Training Accuracy *"memorization baseline"* **Validation Accuracy** *BEST* *WORST*

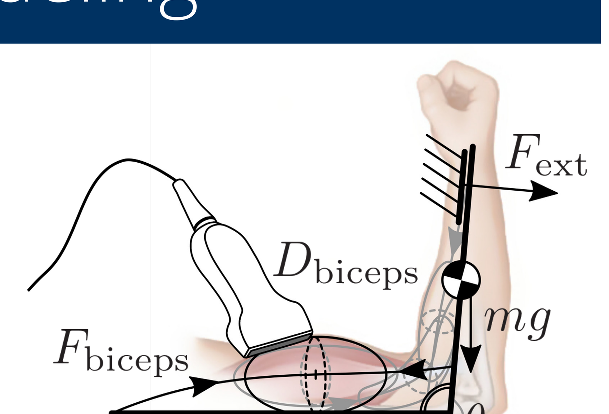
Our CNN-based segmentation method results in **more accurate tissue segmentation than baseline registration-based methods**, especially when networks are trained on **elastically augmented data** [8] from **multiple subjects**.

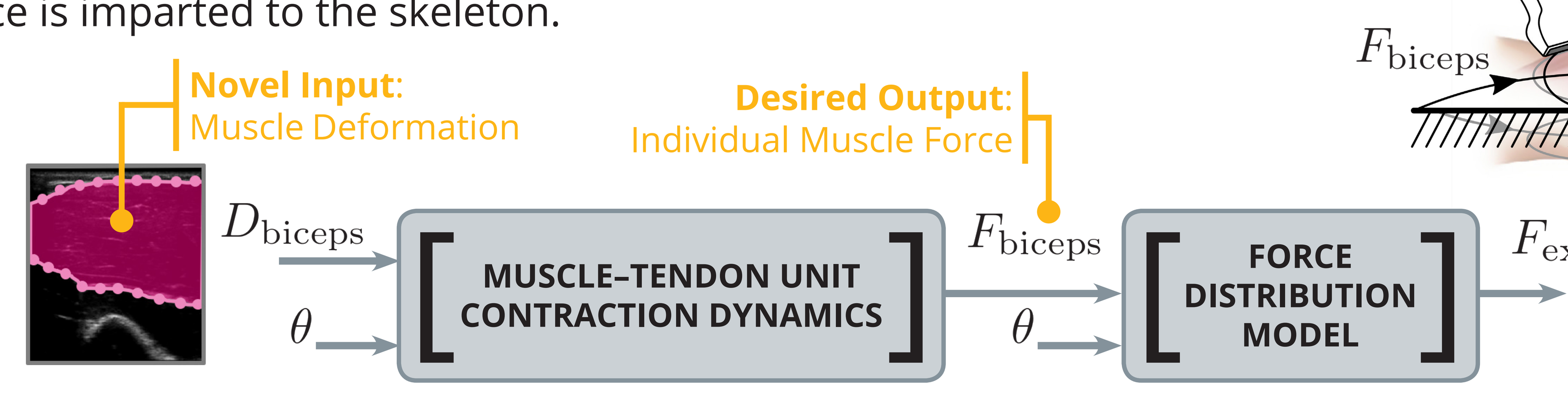
Registration-based methods result in significant errors **along the entire length of the muscle**, while our CNN-based methods reliably segment the muscle belly, with errors **primarily at muscle ends**. Our method thus results in **faster manual cleanup time** when it is necessary for applications requiring higher accuracy.

Segmenting new subjects remains more difficult than segmenting new angle and force conditions; thus, we are **actively working to improve accuracy** by training **subject-specific networks** on **more comprehensive data sets**.

Current Work: Muscle Force Modeling

CORE HYPOTHESIS: **Individual muscle force can be inferred from muscle deformation, which can be detected via ultrasound.** This relationship can be measured and quantified because changes in muscle shape reflect changes in tendon length, and therefore tendon stiffness, the mechanism by which force is imparted to the skeleton.





We are building a **principled suite of models** that make varying trade-offs between **collected data** and (possibly unreliable) **literature values** in a quantifiable manner, ranging from "black box" to "white box".

Acknowledgments / Sponsors / References

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