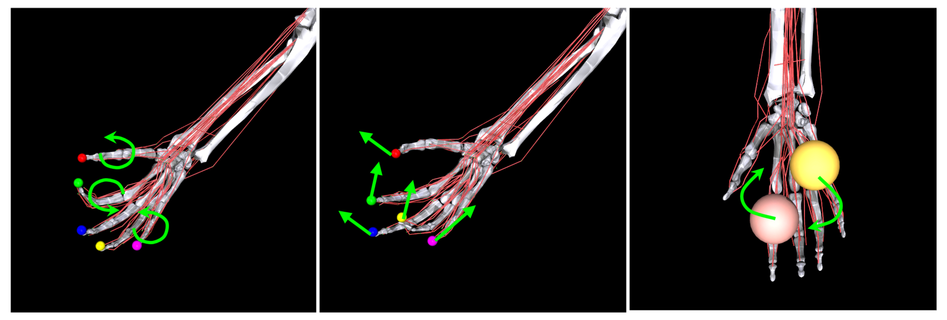
emg2tendon: From sEMG Signals to Tendon Control in Musculoskeletal Hands

Sagar Verma
email: sagar@micropilot.org

Anthropomorphic Hands



- Tendon-driven robotic hands closely mimic human biomechanics.
- Offer high dexterity for tasks like grasping, manipulation, and teleoperation.
- Better compliance and energy efficiency than joint-controlled designs.
- Direct one-to-one mapping with human motion aids imitation learning.
- Widely applicable to prosthetics, surgery, rehabilitation, and HRI.

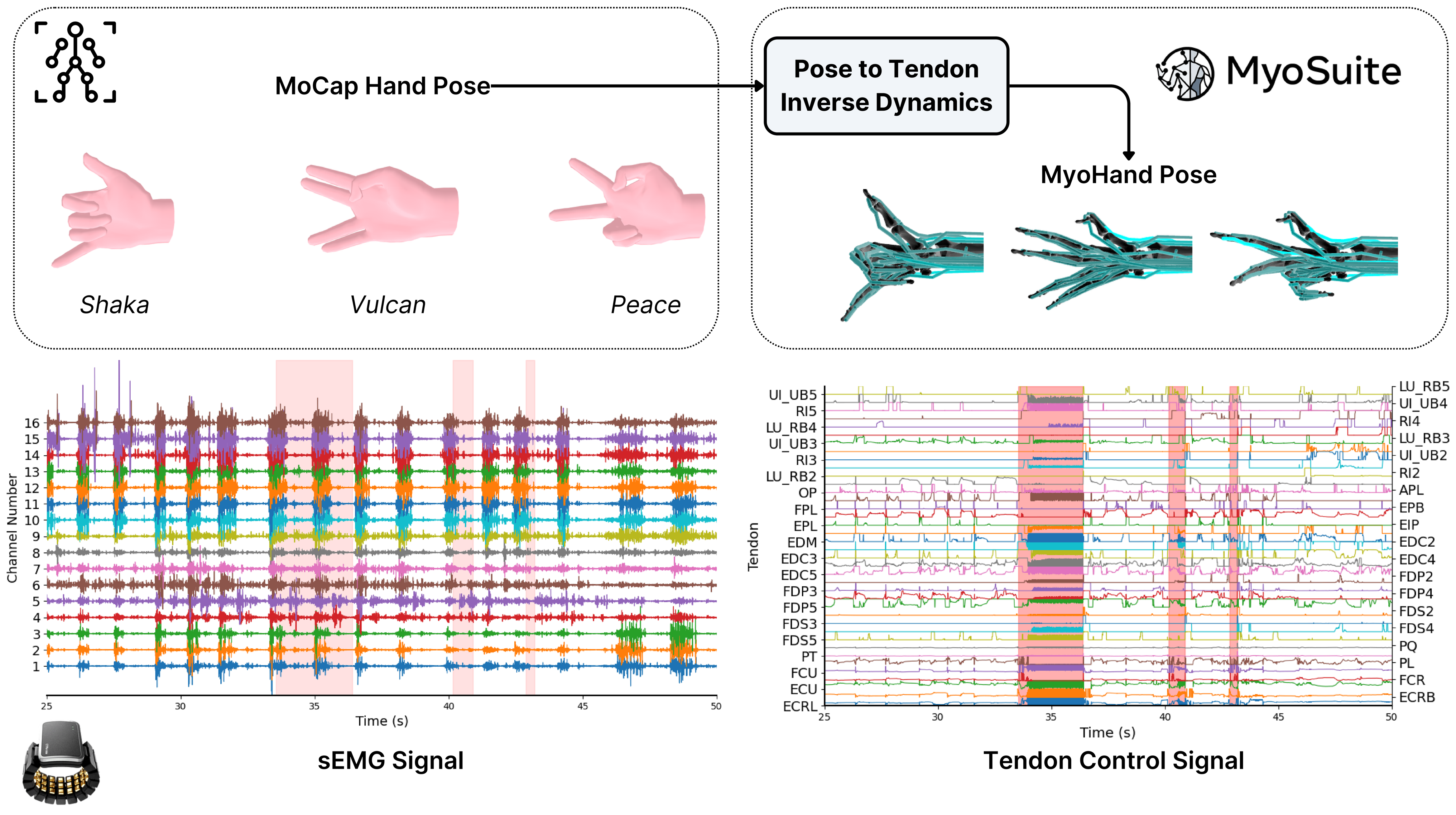
Pose From Vision

- Visual tracking suffers from occlusions and field-of-view limitations.
- Marker-based MoCap systems are impractical for real-world use.
- Depth/RGB sensors introduce noise and require careful alignment.
- Labeling from vision datasets often lacks tendon-level granularity.

Contributions

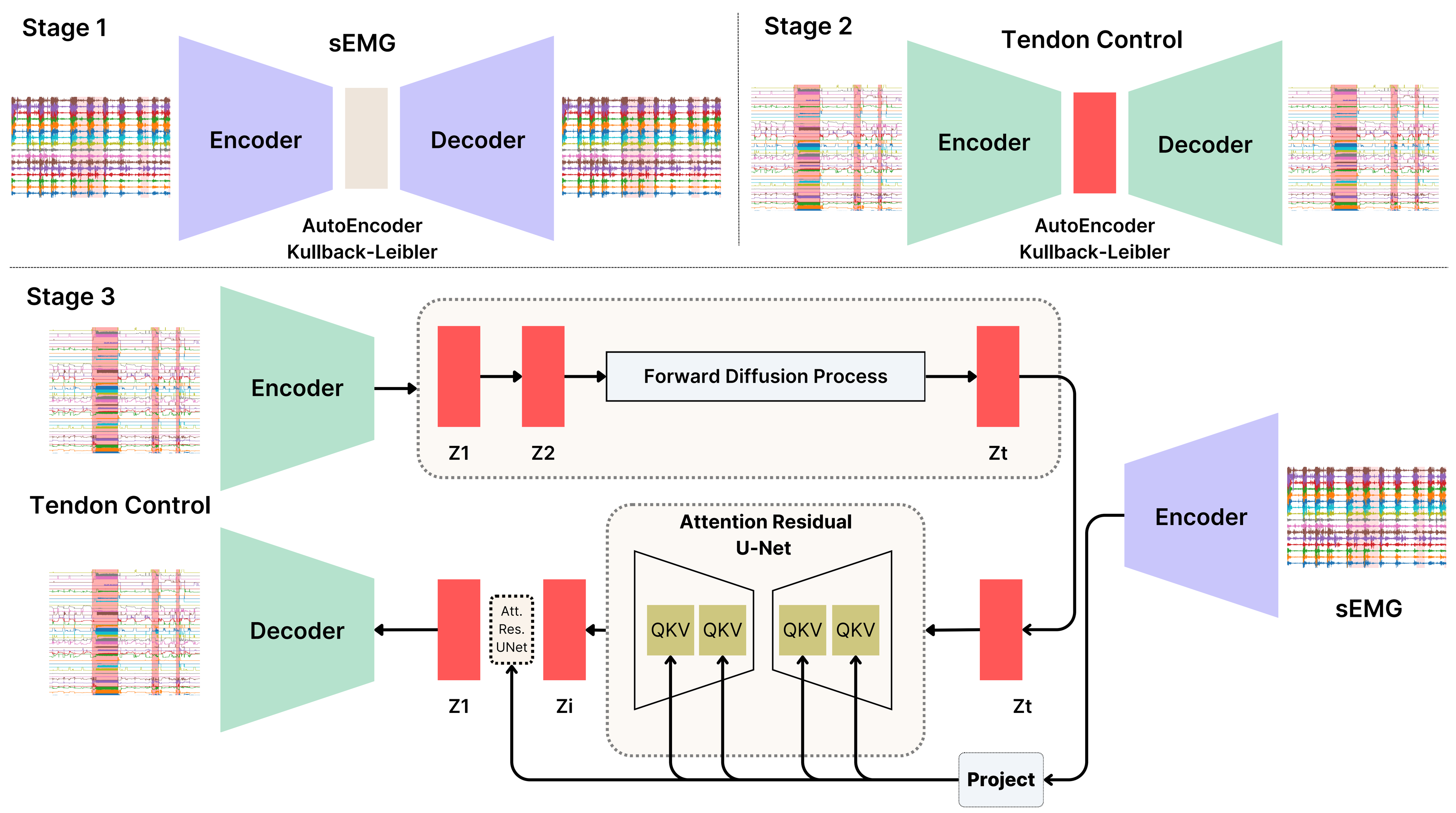
- First large-scale EMG-to-Tendon dataset (193 users, 370 hours, 29 stages).
- Introduced conditional latent diffusion model (CLDM) for EMG→tendon learning.
- Extensive benchmarking across EMG→pose, tendon→pose, and EMG→tendon.
- Simulation pipeline using MyoSuite MyoHand for tendon inverse dynamics.
- Demonstrated tendon signals as effective intermediate representations.

Converting Pose to Tendon Controls



Motion capture hand poses are converted into tendon control signals using inverse dynamics in the MyoHand model. Each frame is mapped to 39 tendon forces via QP-based biomechanical modeling.

Mapping sEMG to Tendon Controls



Conditional Latent Diffusion Model (CLDM) encodes sEMG and tendon control signals in a shared latent space. A U-Net-based diffusion model reconstructs tendon control signals conditioned on muscle activations.

Observations

- CLDM outperforms TDS, NeuroPose, and SensingDynamics across tasks.
- Best pose error: 11.3° (EMG→Pose), 10.8° (Tendon→Pose).
- Best tendon control error: 0.201 RMSE, 0.139 MAE.
- Physics-informed simulation further improves accuracy.
- Two-step EMG→Tendon→Pose modeling is more accurate than direct EMG→Pose.
- Diffusion models handle temporal variability and user heterogeneity better.

References

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5. **Liu et al.**, *NeuroPose: EMG Wearable Pose Tracking*, in *Proceedings of the Web Conference (WWW)*, 2021.

Code and Author Information

Project Page

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