

# Finger Joint Angle and Gesture Estimation Under Dynamic Hand Position Using a Soft Printed Electrode Array

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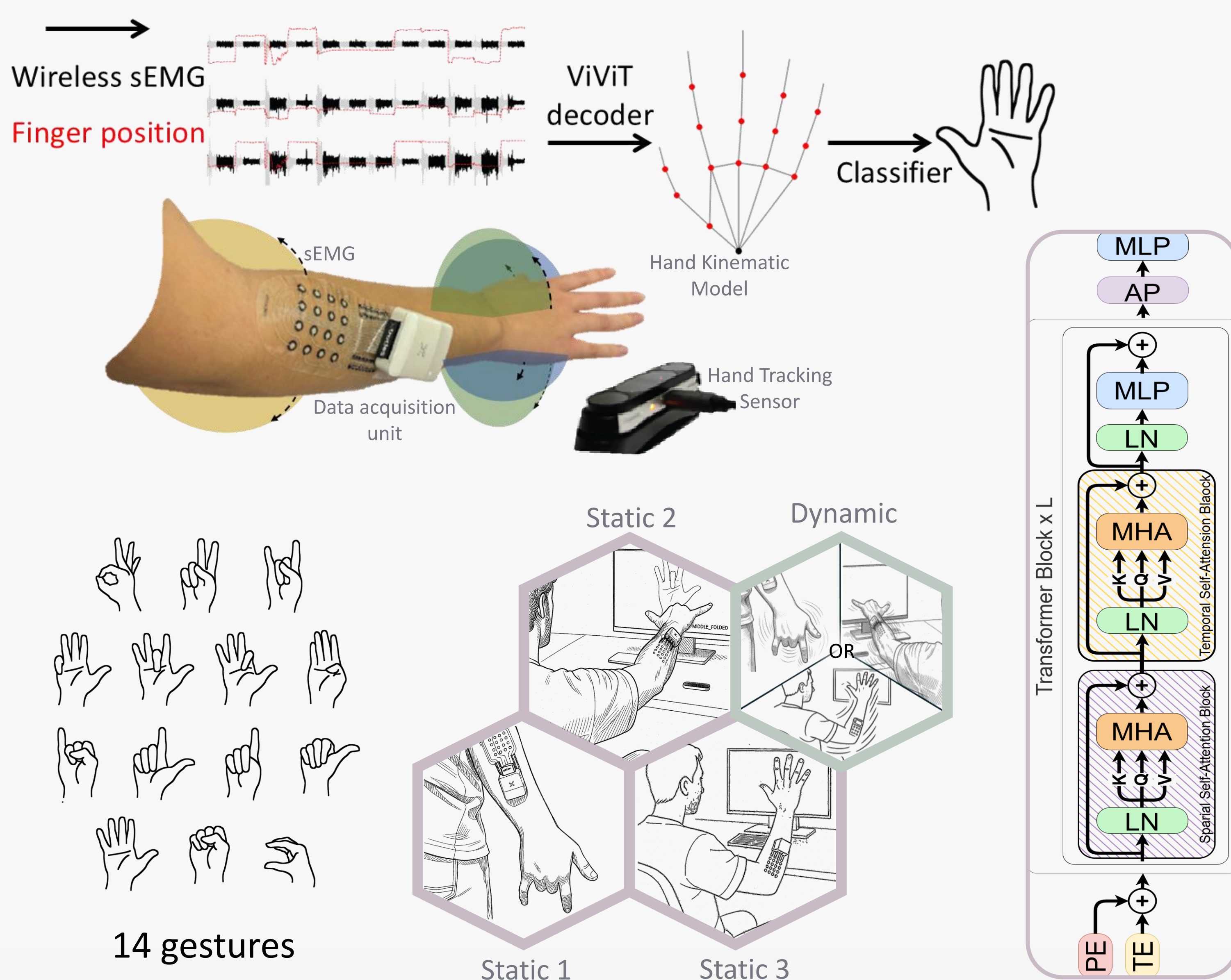
# INTRODUCTION

Gesture recognition using forearm muscle surface electromyography (sEMG) signals are gaining a lot of attention, but current methods often fail when the hand is not held still. This study addresses this limitation with a novel wireless sEMG system and Video-Vision-Transformer (ViViT) model.

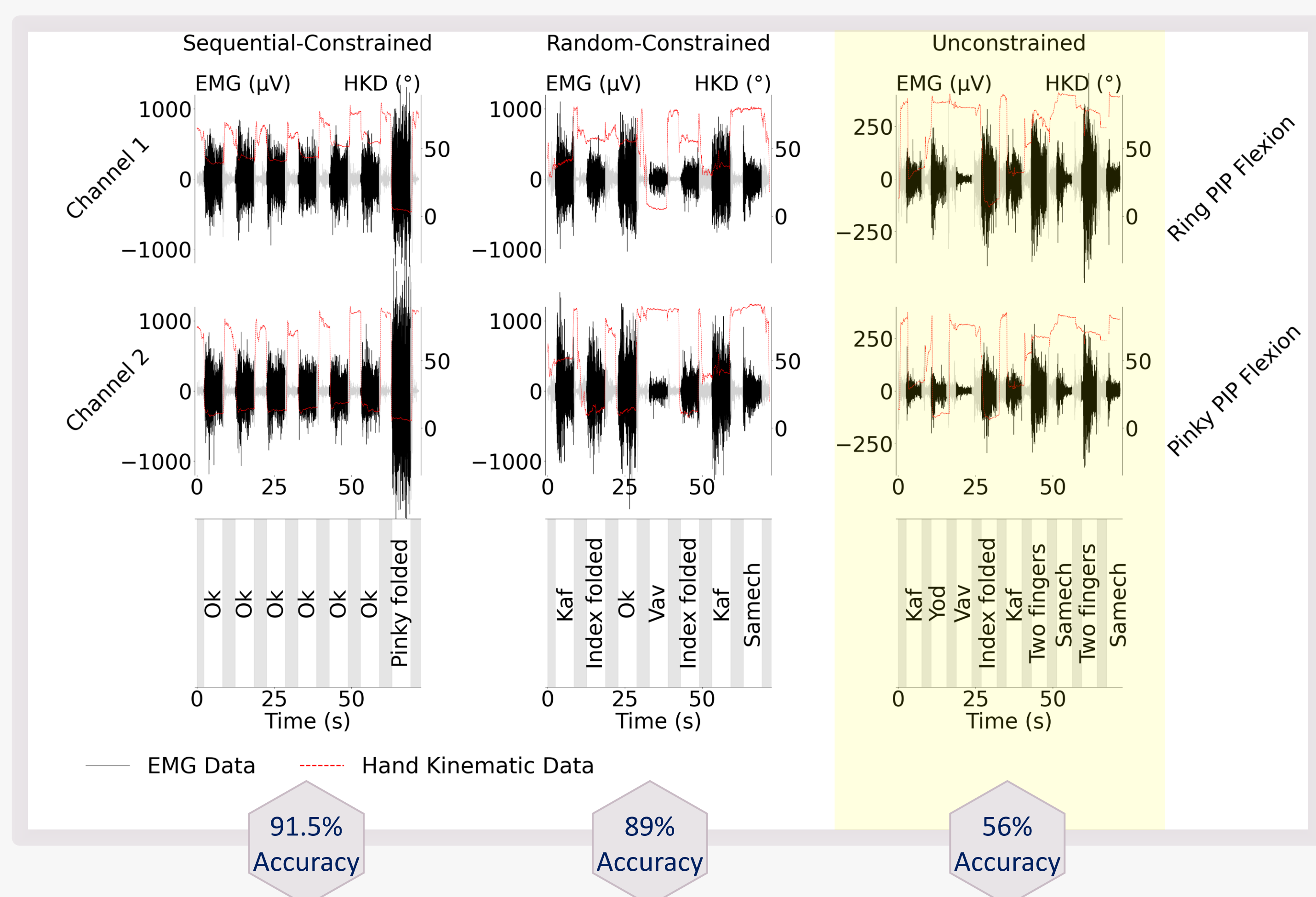
The proposed approach successfully identifies static finger gestures even while the user's hand is in motion. This breakthrough in separating gestures from motion-related noise is a significant step toward more robust, real-world applications in prosthetics, virtual reality, and human-machine interfaces.

## THE PARADIGM

Sixteen healthy adults (aged 21–30) performed seven repetitions of 14 finger gestures. Each gesture was held for 5 s with a 3 s rest in between. The experiment was conducted under four settings, including three different “Static” settings and a “Dynamic” setting, simulating real-world conditions where participants moved their arm freely (within the sensor's range). No instructions were given regarding gesture force.



## THE NOVELTY OF THE DATA

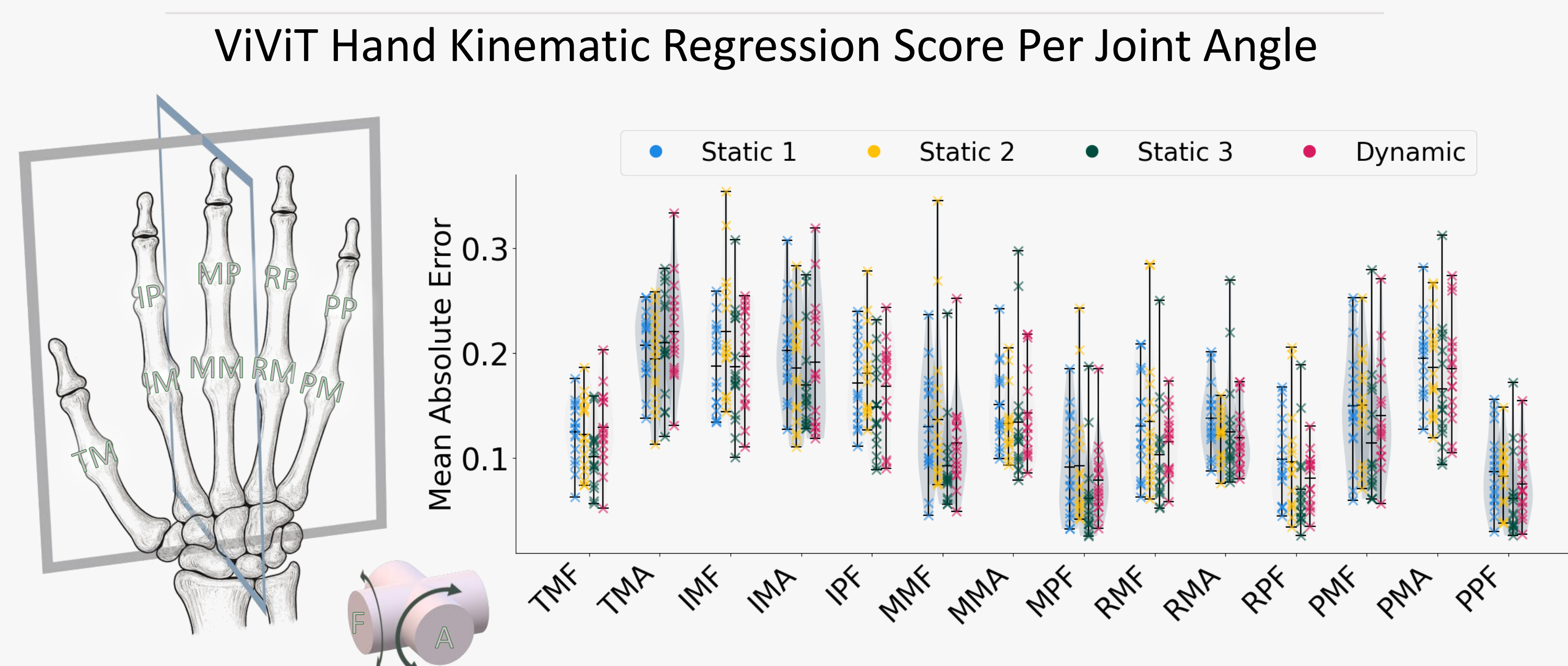


**Figure 1.** sEMG and hand-kinematic signals during unconstrained gestures (left) and during force-plus-rest instructions delivered in random (middle) or sequential (right) order. Black solid lines are sEMG signals from two electrode channels; red dashed lines overlay the corresponding joint-angle trajectories. Dark horizontal bands mark the active gesture periods, and gray regions indicate transitions.

## CONCLUSIONS

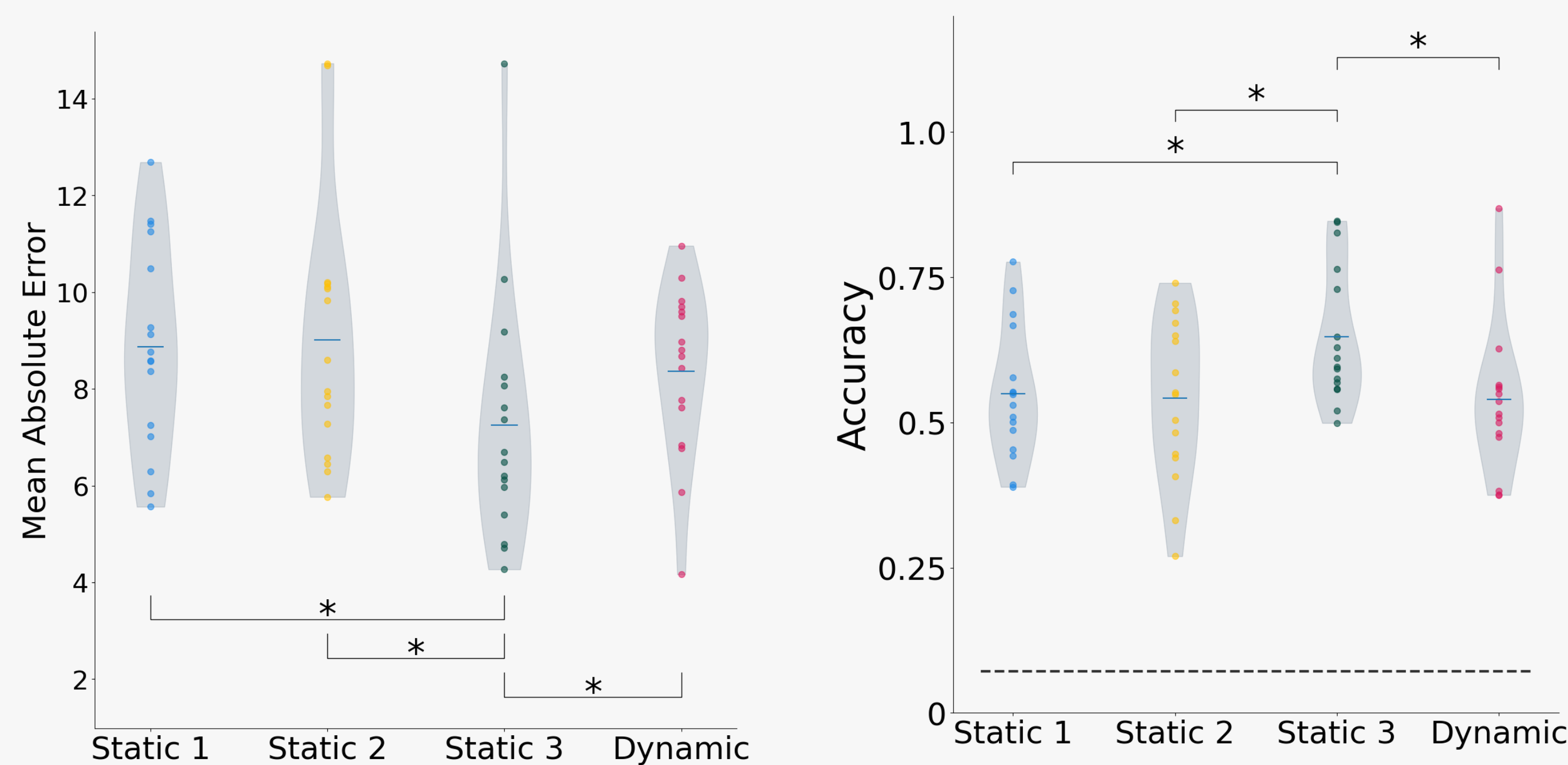
We paired soft, wireless 16-electrode sEMG with a Video-Vision-Transformer to decode finger joint angles during freely moving arm. Despite unconstrained conditions, the model of the best performing subject reached 87 % accuracy, showing that fine finger kinematics can be recovered in real-world conditions. Moreover, ViViT model outperforms other network architectures (CNN, CNN+LTSM, FC). Finally, this study advances gesture recognition by evaluating performance in settings that simulate natural behaviour versus those under traditional, controlled laboratory protocols.

## RESULTS



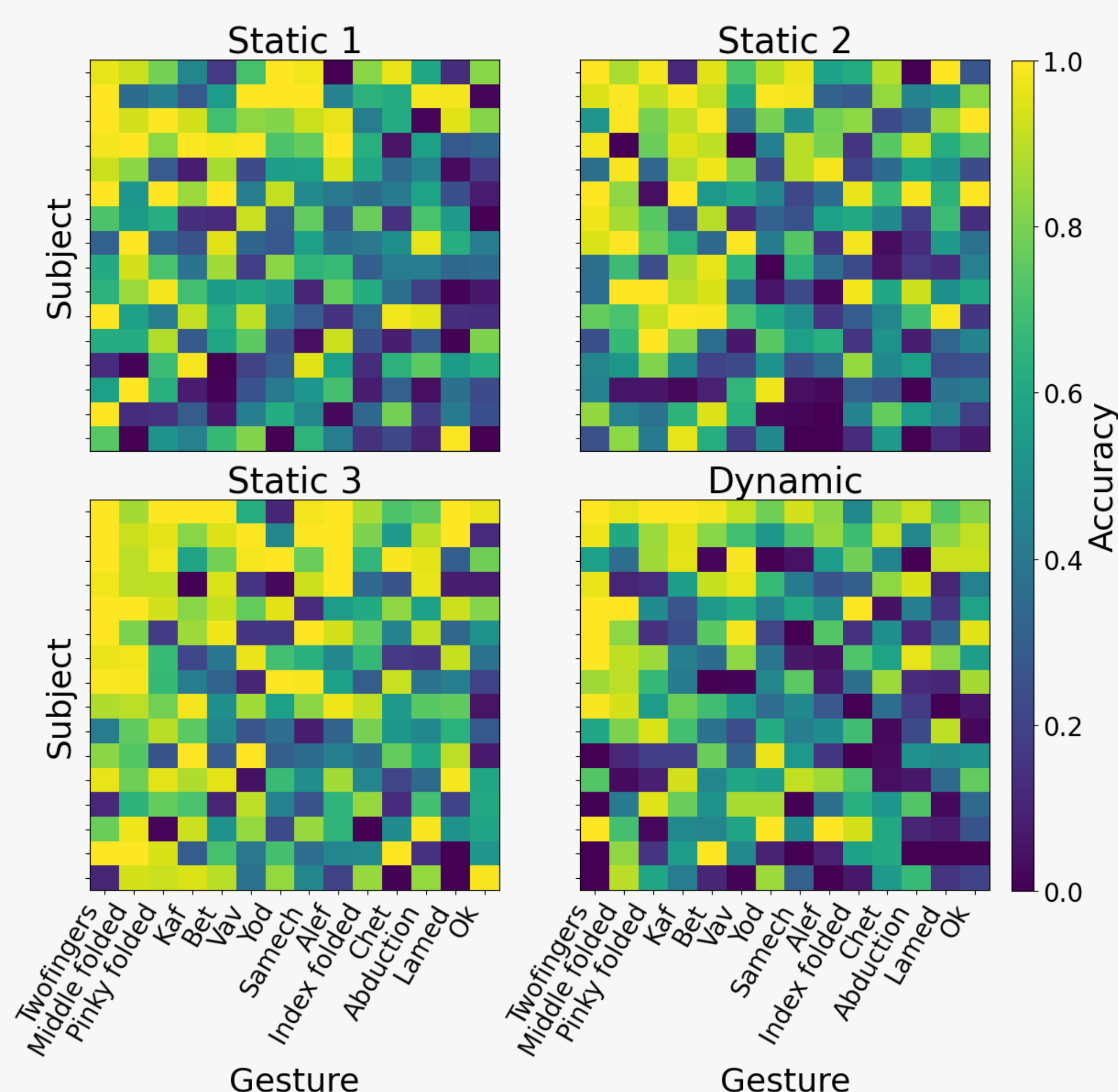
**Figure 2.** Finger joint angle prediction: Normalized error between joint angle values from the model's output and motion sensor measurements.

## ViViT Performance



**Figure 3.** (Left) Mean absolute error of the joint angles for each setting, (Right) Distribution of average classification accuracy per subject for each condition. (\*) significance level using paired t-test  $p < 0.05$ .

## Inter-Subject Gesture Recognition Across Static & Dynamic Settings



**Figure 4.** Accuracy per subject per gesture.

	ViViT	CNN+LSTM	CNN	FC
Static 1	55% $\pm$ 11%	40% $\pm$ 18%	31% $\pm$ 15%	19% $\pm$ 10%
Static 2	54% $\pm$ 14%	44% $\pm$ 16%	30% $\pm$ 12%	23% $\pm$ 10%
Static 3	65% $\pm$ 12%	48% $\pm$ 17%	40% $\pm$ 12%	28% $\pm$ 9%
Dynamic	54% $\pm$ 13%	36% $\pm$ 17%	29% $\pm$ 10%	22% $\pm$ 8%

**Table 1.** Accuracy across settings and models with equal parameter counts, 14 gestures, 16 subjects (mean  $\pm$  SD)

Detailed methods: JoVe article

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