emg2qwerty: A Large Dataset with Baselines for Touch Typing using Surface Electromyography

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Reality Labs, Meta

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Pioneering Human-Computer Interface for AR/VR Paradigm

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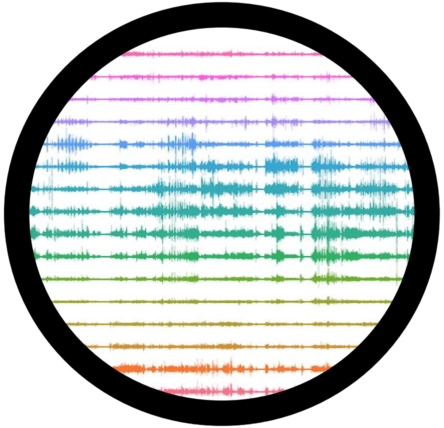

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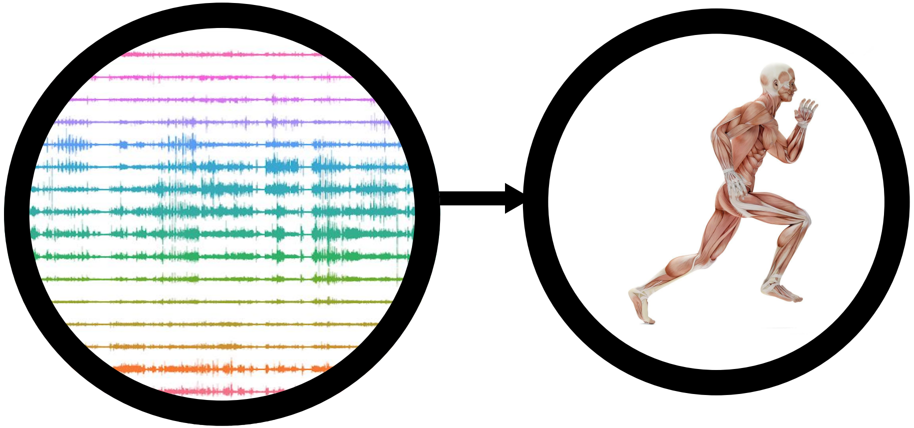

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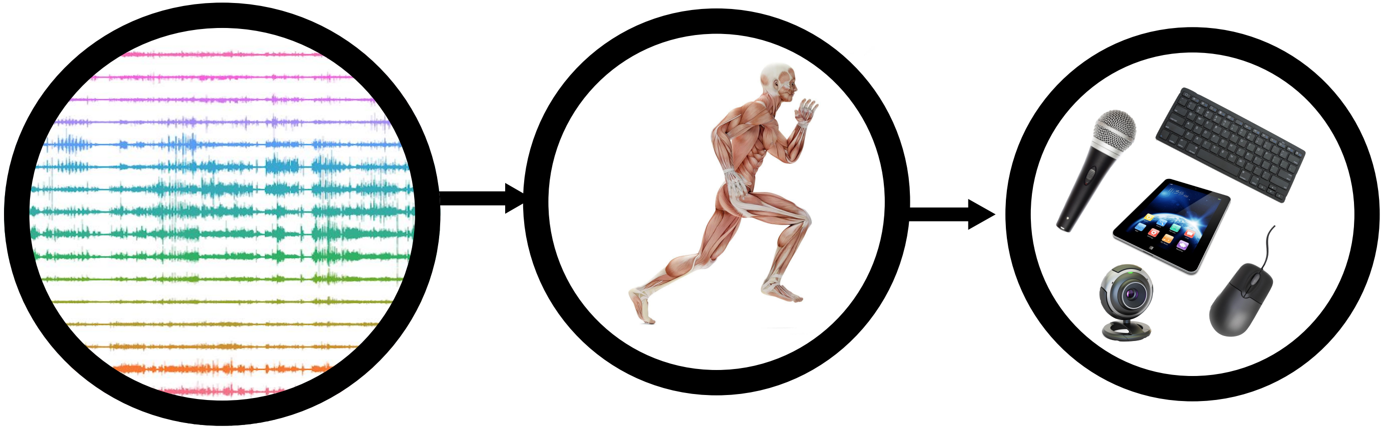

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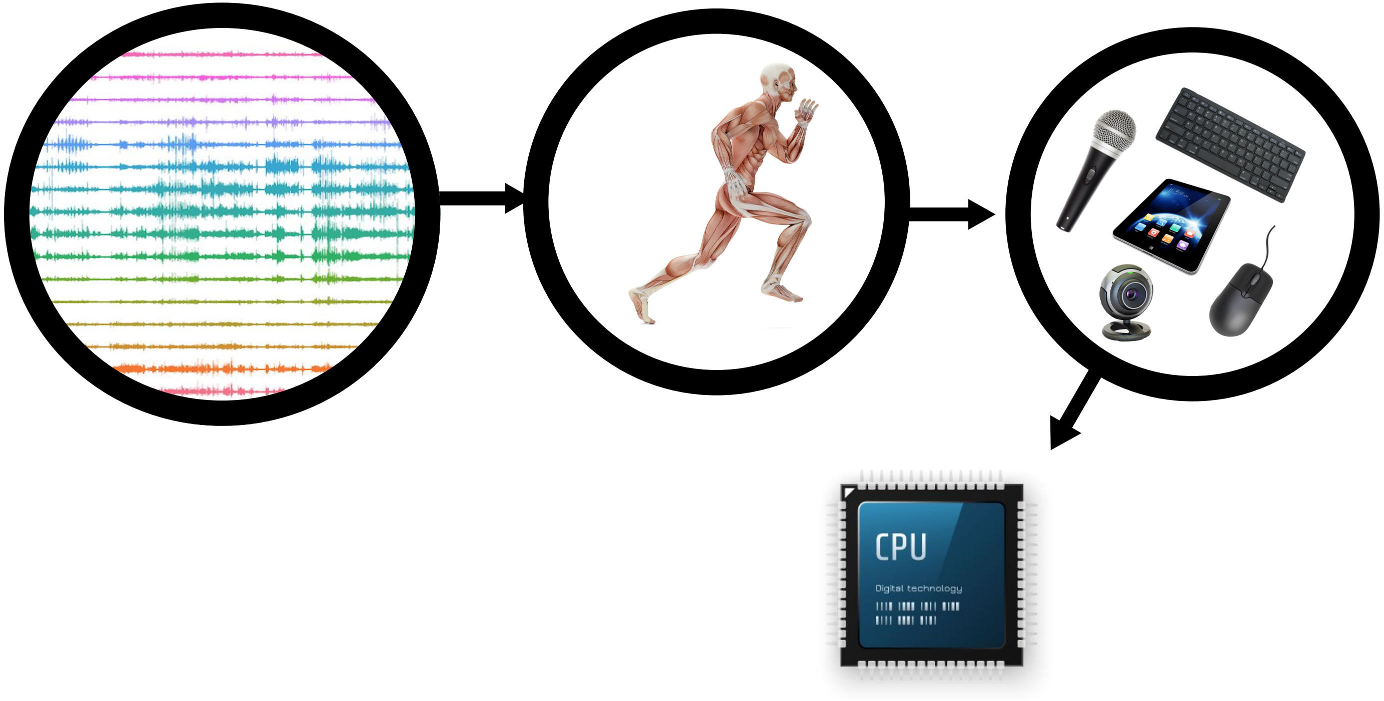

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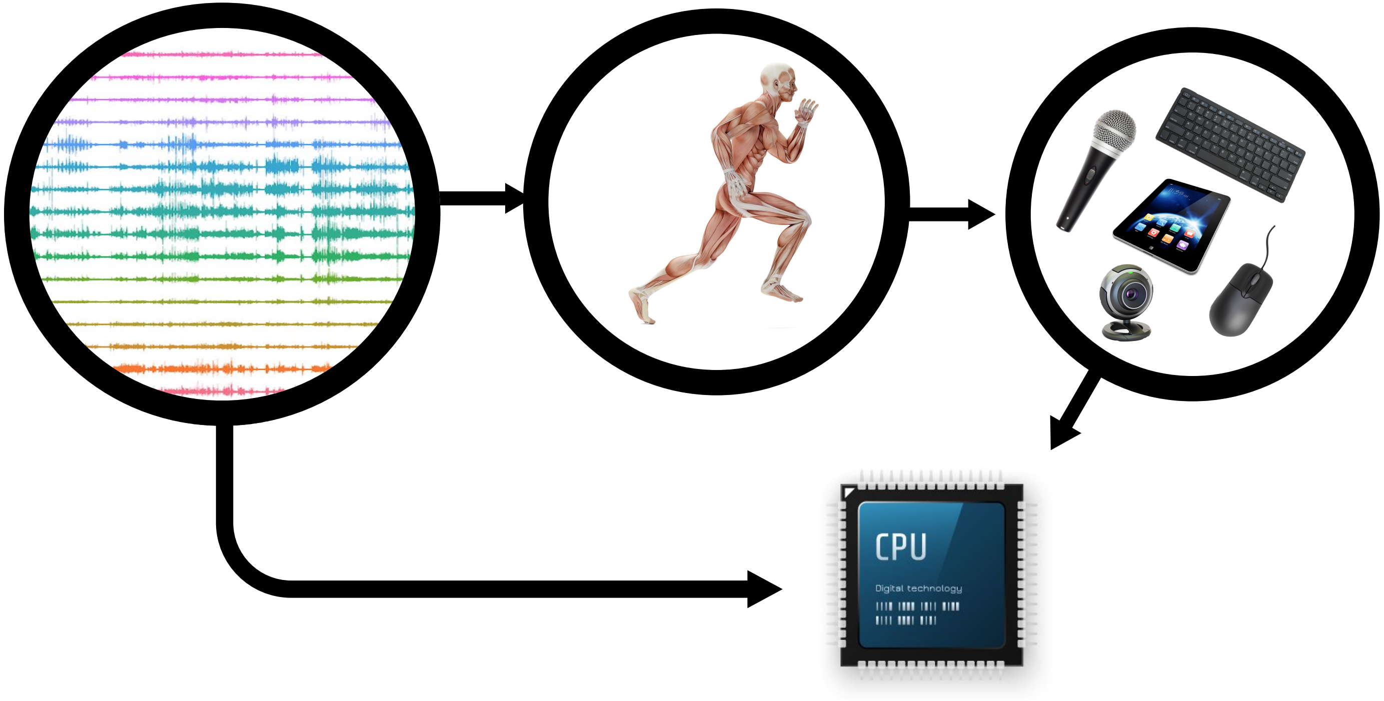

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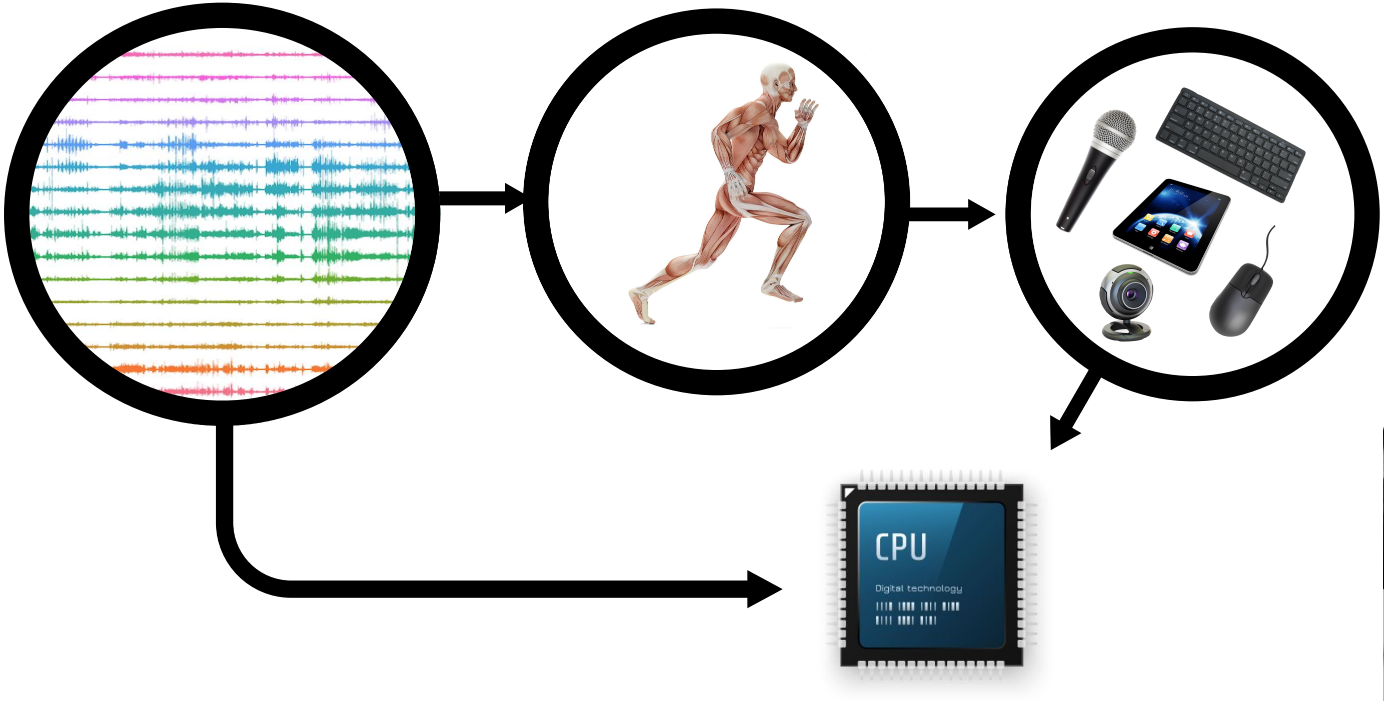
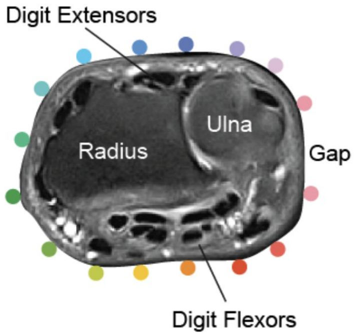


[Meta Orion Prototype]

Background on surface electromyography (sEMG)

- sEMG captures electrical signals from muscles via sensors on the skin, offering a non-invasive way to measure muscle activity.



Non-invasive electrode placement around the wrist circumference.

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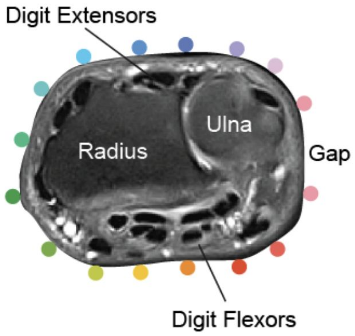
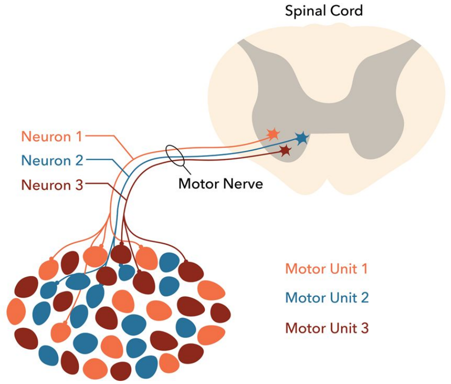


Non-invasive electrode placement around the wrist circumference.



The Motor Unit.
Image credit: Daniel Walsh and Alan Sved.
https://commons.wikimedia.org/wiki/File:Motor_unit.png

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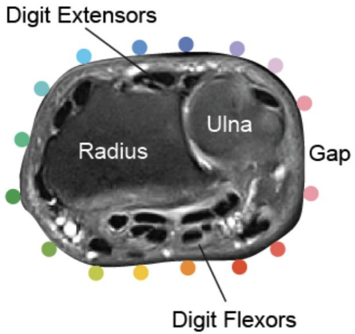
- It detects the electrical potentials generated by individual motor neurons enabling insights into neuromuscular activity with high temporal precision.
- Data is collected using a research-grade wristband with 16 gold-plated dry electrodes, providing high-quality sEMG signals at a sampling rate of 2 kHz.



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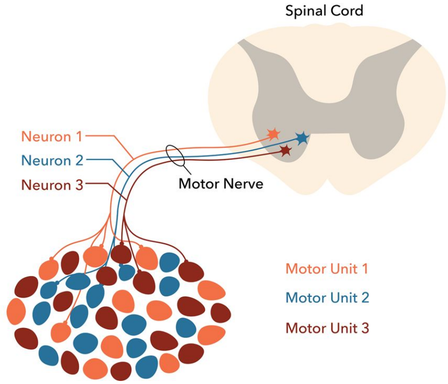

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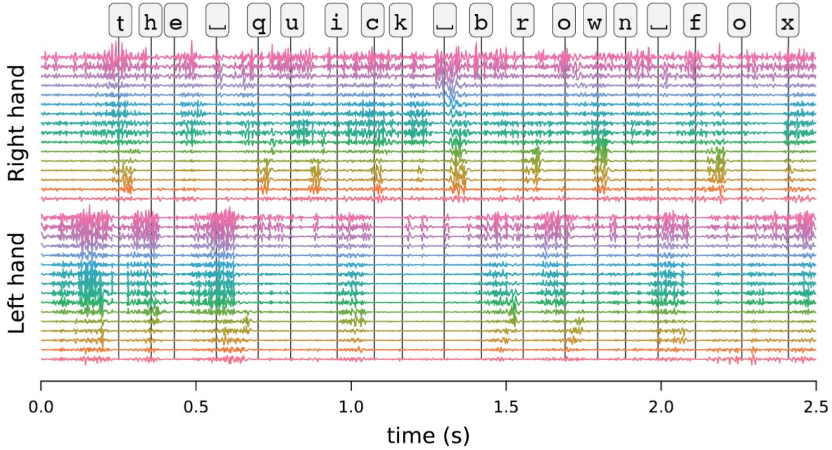
The sEMG research device as described in CTRL-labs at Reality Labs et al., 2024 used for data collection.

A dataset of sEMG collected while touch typing

16 electrode channels

16 electrode channels



sEMG recording for the prompt “the quick brown fox”. Vertical lines indicate keystroke onset. Signal is sampled at 2 kHz and is high-pass filtered.

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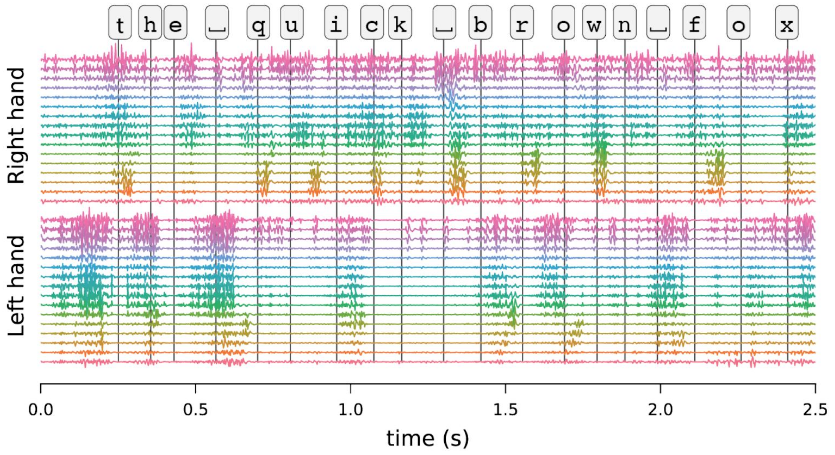

sEMG recording for the prompt “the quick brown fox”. Vertical lines indicate keystroke onset. Signal is sampled at 2 kHz and is high-pass filtered.

Total subjects	108
Total sessions	1,135
Avg sessions per subject	10
Max sessions per subject	18
Min sessions per subject	1
Total duration	346.4 hours
Avg duration per subject	3.2 hours
Max duration per subject	6.5 hours
Min duration per subject	15.3 minutes
Avg duration per session	18.0 minutes
Max duration per session	47.5 minutes
Min duration per session	9.5 minutes
Avg typing rate per subject	265 keys/min
Max typing rate per subject	439 keys/min
Min typing rate per subject	130 keys/min
Total keystrokes	5,262,671

emg2qwerty dataset statistics

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Uniqueness of *emg2qwerty*

Unique in terms of

1. **Scale:** Order of magnitude larger with 108 subjects and an average of 10 sessions per subject.

Dataset	Hardware grade	Application	Recording location	Subject count	Multiple sessions/-subject
Amma et al. 2015	Clinical	HCI	Forearm	5	Yes
Du et al. 2017	Clinical	HCI	Forearm	23	Yes
Malesevic et al. 2021	Clinical	Neuroprosthetics	Forearm	20	No
Jiang et al. 2021	Clinical	HCI, Neuroprosthetics	Wrist	20	Yes
Ozdemir et al. 2022	Clinical	Neuroprosthetics	Forearm	40	No
Kueper et al. 2024	Clinical	Neuroprosthetics	Forearm	8	Yes
Palermo et al. 2017	Clinical	Neuroprosthetics	Forearm	10	Yes
Atzori et al. 2012	Consumer	Neuroprosthetics	Forearm, Wrist	27	No
Pizolato et al. 2017	Consumer	Neuropresthetics	Forearm, Wrist	78	No
Lobov et al. 2018	Consumer	Neuropresthetics	Forearm	37	No
emg2qwerty	Consumer	HCI	Wrist	108	Yes

Comparison with prior EMG datasets

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2. **Hardware Properties:** Consumer-grade practicality with clinical-grade signal quality.
3. **Task Activity:** Naturalistic behavior of typing, rapidly time-varying task.

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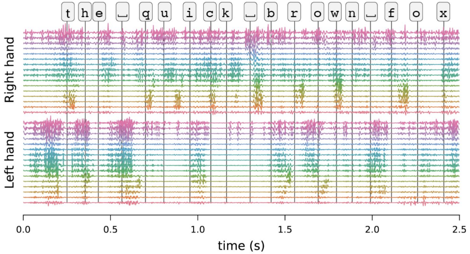
Baseline via Automatic Speech Recognition (ASR) Methodologies



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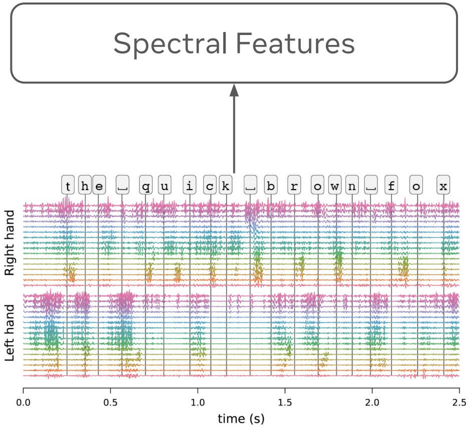

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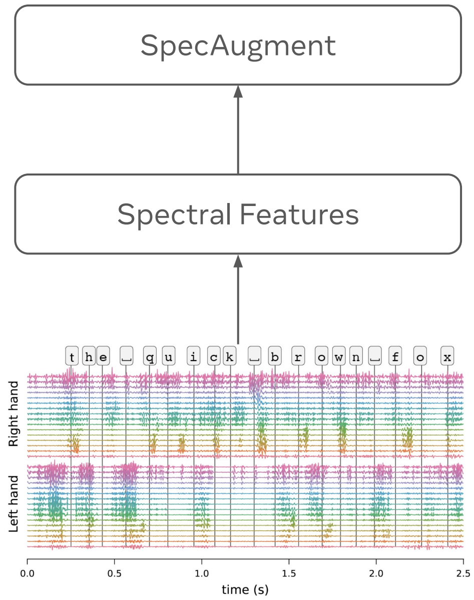

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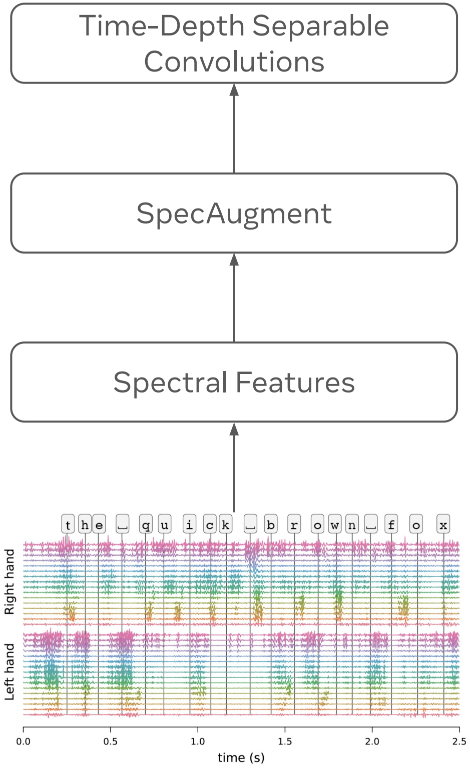

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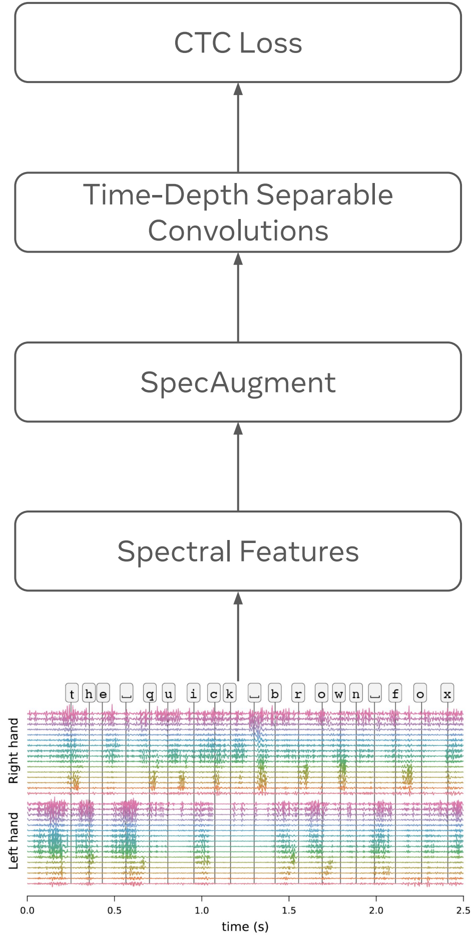

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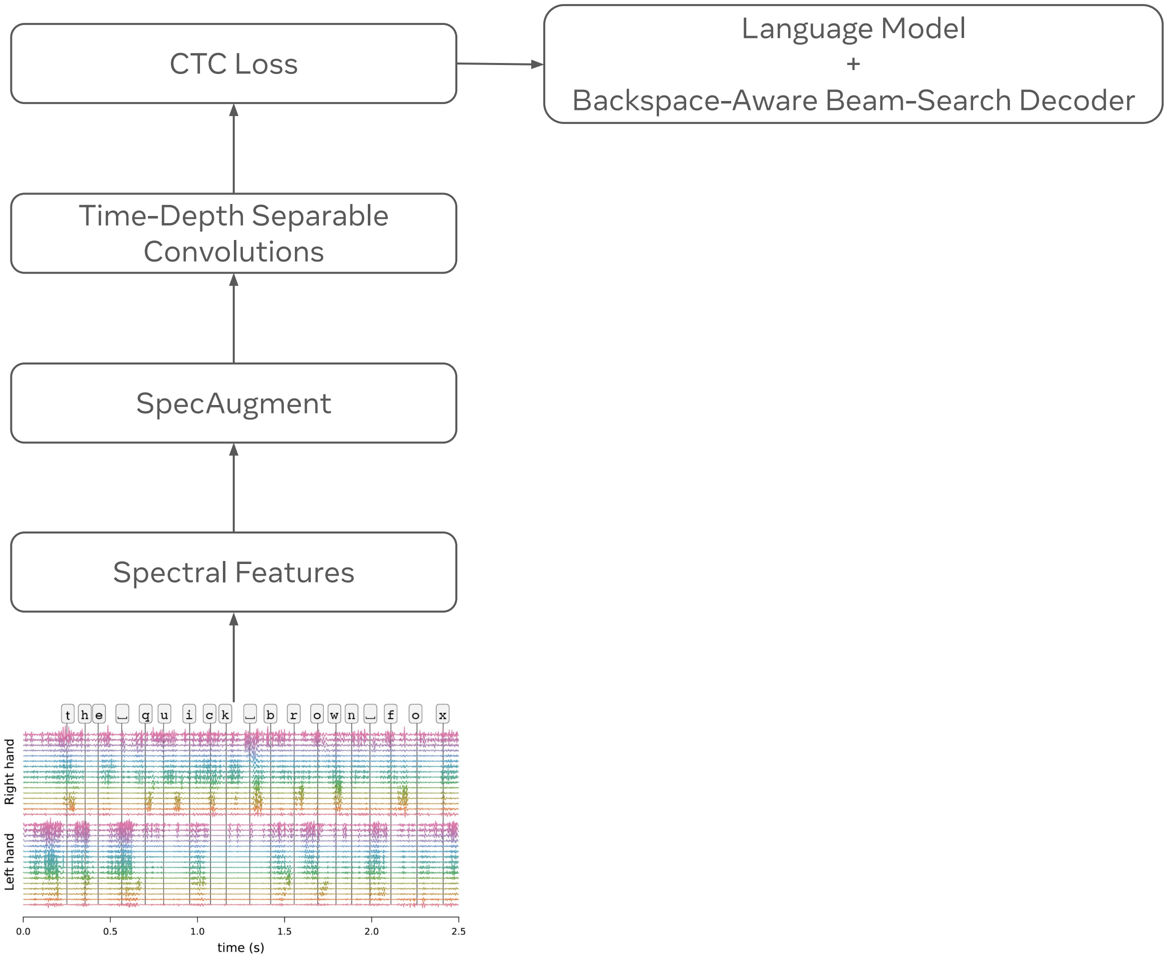
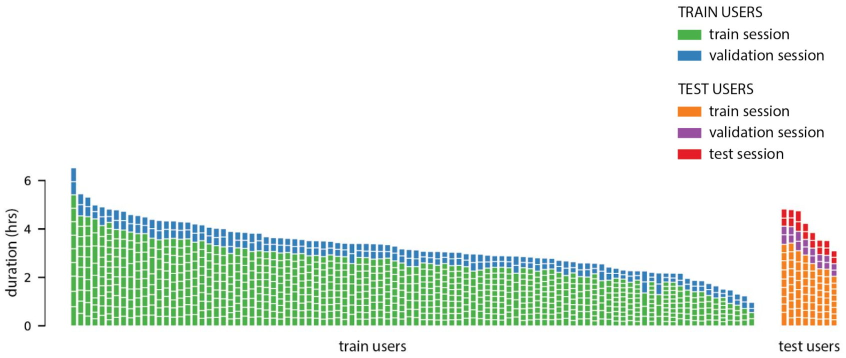


Benchmarks

Model Benchmark	Test Character Error Rate (CER)	
	No Language Model	6-gram Character-Level Language Model
Generic (no personalization)	55.38 ± 4.10	51.78 ± 4.61
Personalized (random-init)	15.38 ± 5.88	9.55 ± 5.16
Personalized (finetuned)	11.28 ± 4.45	**6.95 ± 3.61**

Character Error Rate (CER): Lower is better.

Models tend to become usable at a CER of 10% or less.



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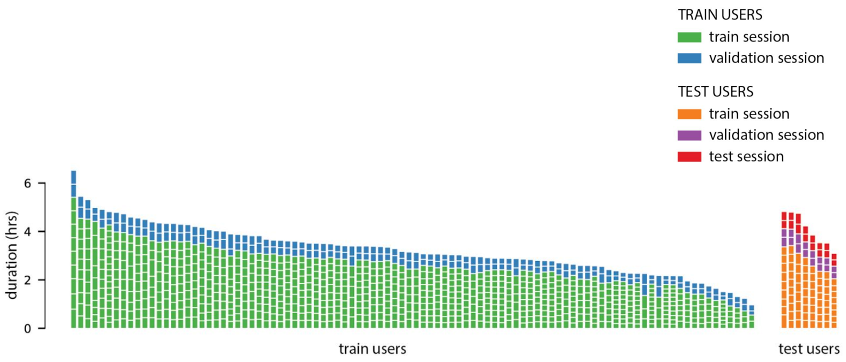

Dataset Splits

- Personalized models finetuned from a generic model perform best.
- sEMG representations can generalize across users despite variations in sensor placement, anatomy, physiology, and behavior.
- Generic model at current scale remains unusable, although CTRL-labs at Reality Labs et al., 2024 demonstrates out-of-the-box generalization with an order of magnitude more training users on different tasks.
- Motivates research into data-efficient strategies to improve generalization.

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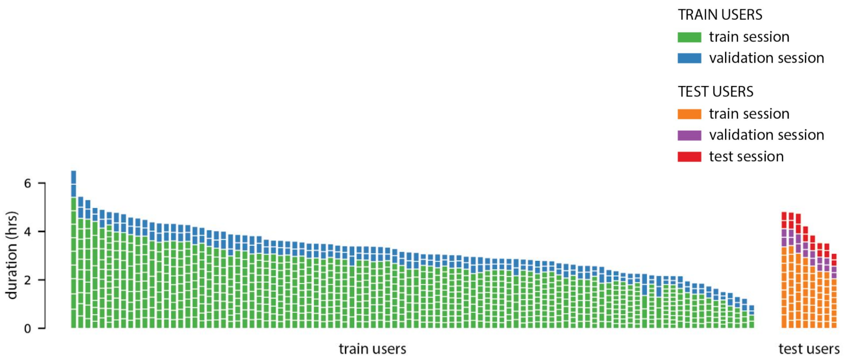

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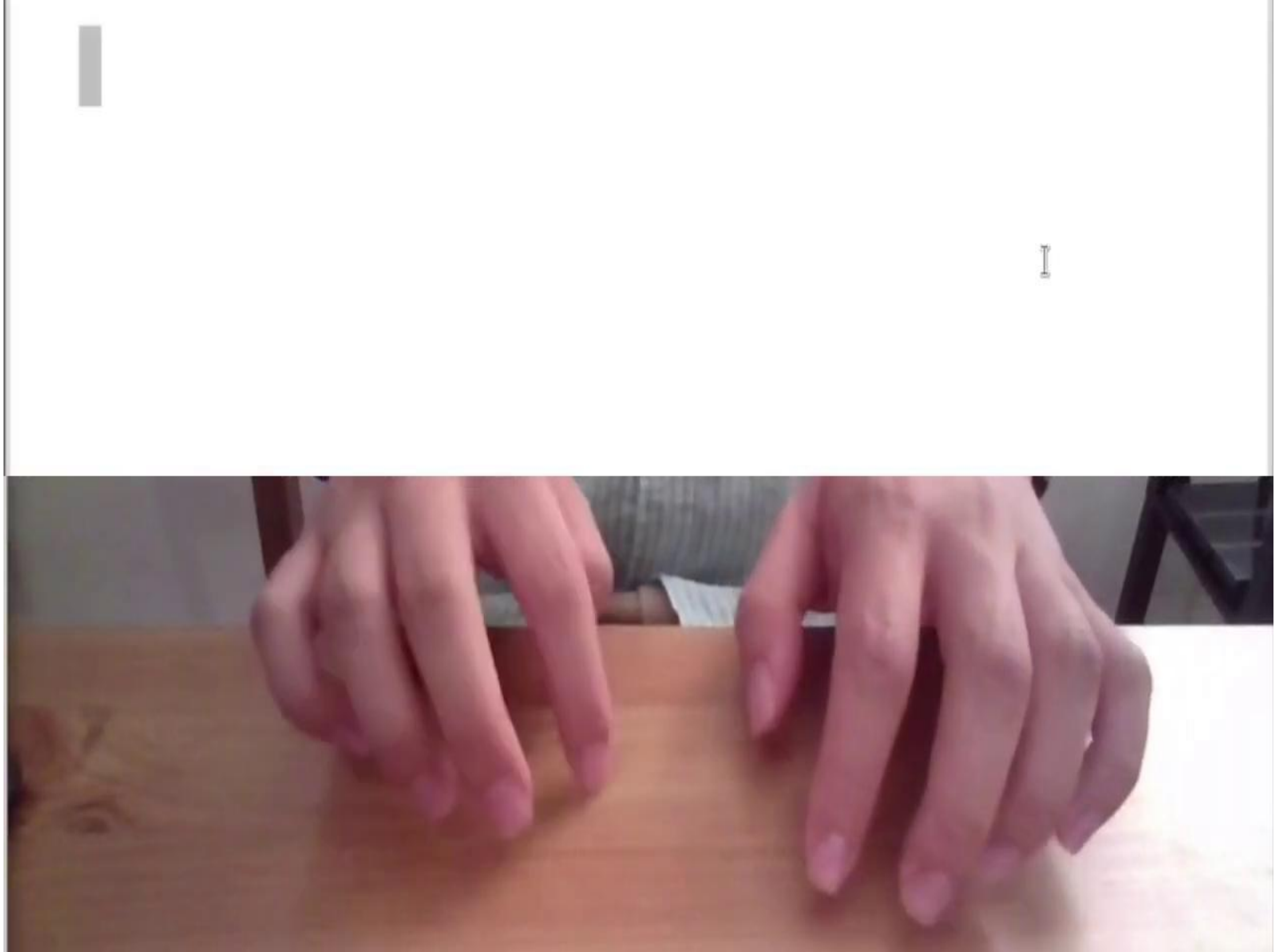
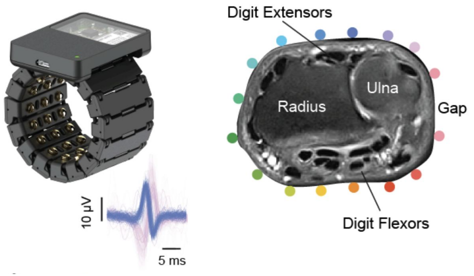
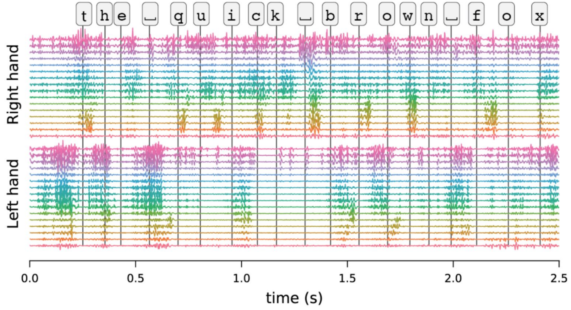


Summary

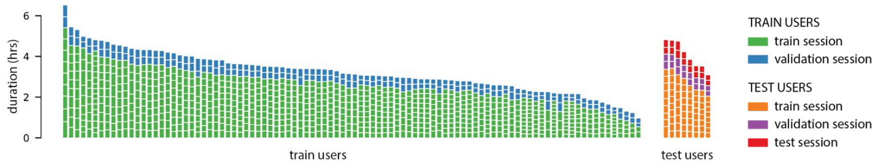
- Wrist-based surface electromyography (sEMG) enables building practical and scalable neuromotor interfaces.
- We release a large open sEMG dataset focused on the task of keyboard typing with accurate ground-truth.
- We establish benchmarks focused on generalization across unseen population and data-efficiency of personalization.
- We demonstrate competitive baselines using off-the-shelf ASR methodologies against those benchmarks.





Dataset and Code available now!

github.com/facebookresearch/emg2qwerty



Questions?

viswanath@meta.com

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