

Touchless muscle activity monitoring for Hand gesture recognition



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Existing hand gesture recognition systems



Camera-based?
Occlusion
Complex
Privacy
Latency



Motion-based?
Bulky on finger and hand
Only surface motion



sEMG-based?
Direct skin contact
Ambiguity
Numerous electrodes

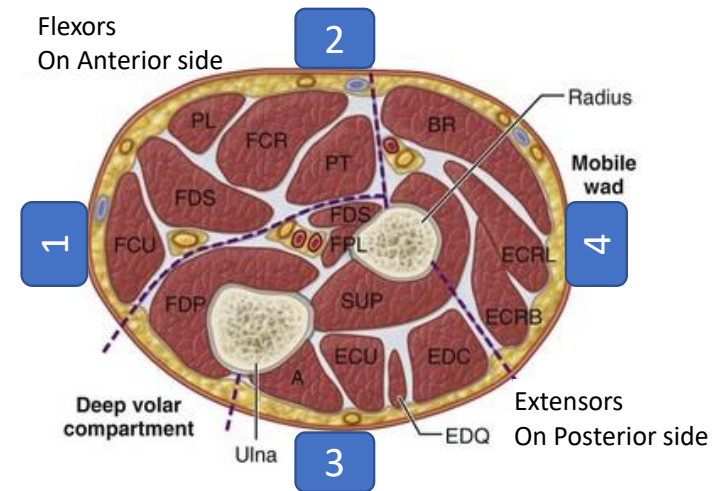
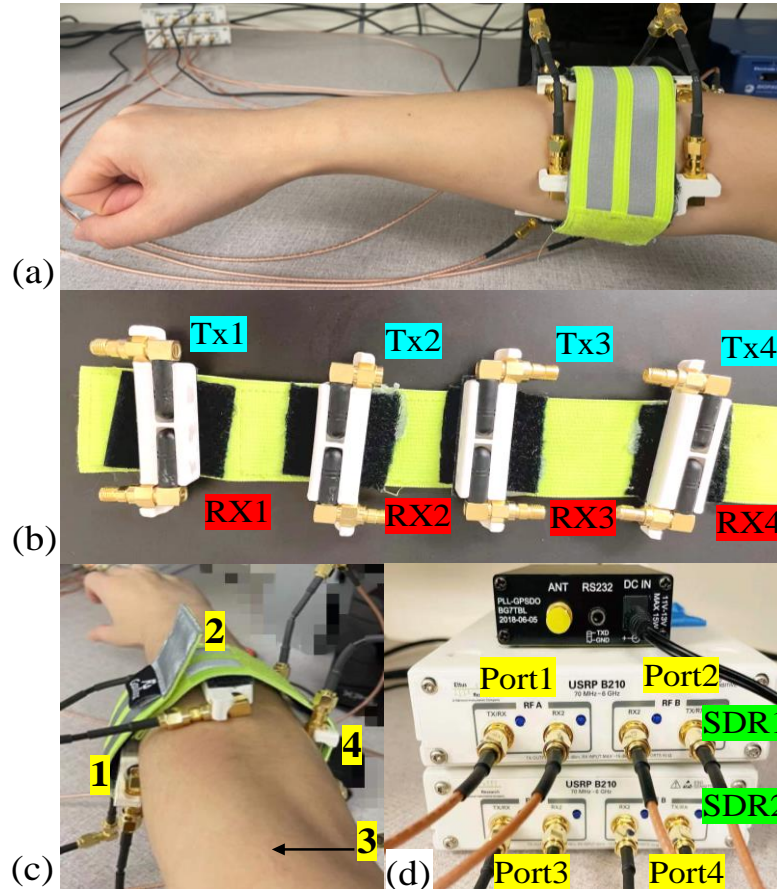


Gloved-based?
Hinder hand motion
Inconvenient
Uncomfortable

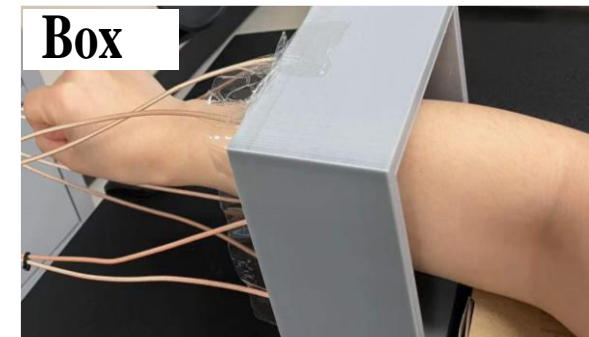
RMG (radio-myography) for muscle activity sensing

Multiple-input multiple-output (MIMO)
near-field coherent sensing (NCS) radio sensor










continuous muscle actuation sensing that can be wearable and touchless, capturing both superficial and deep muscle groups.



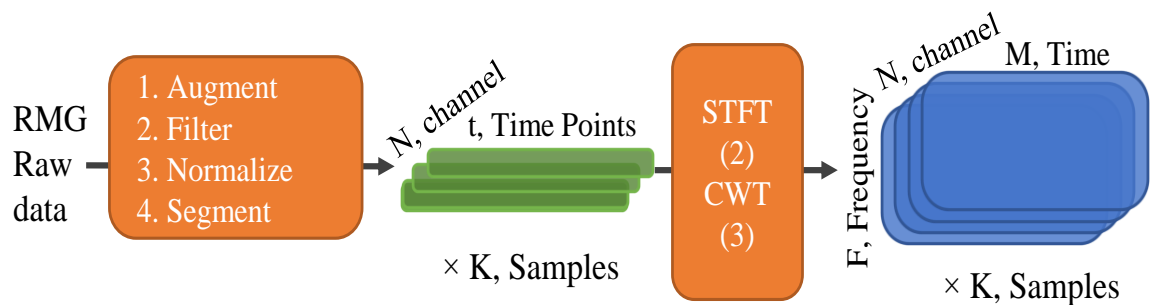
Touchless



Study protocol and data processing

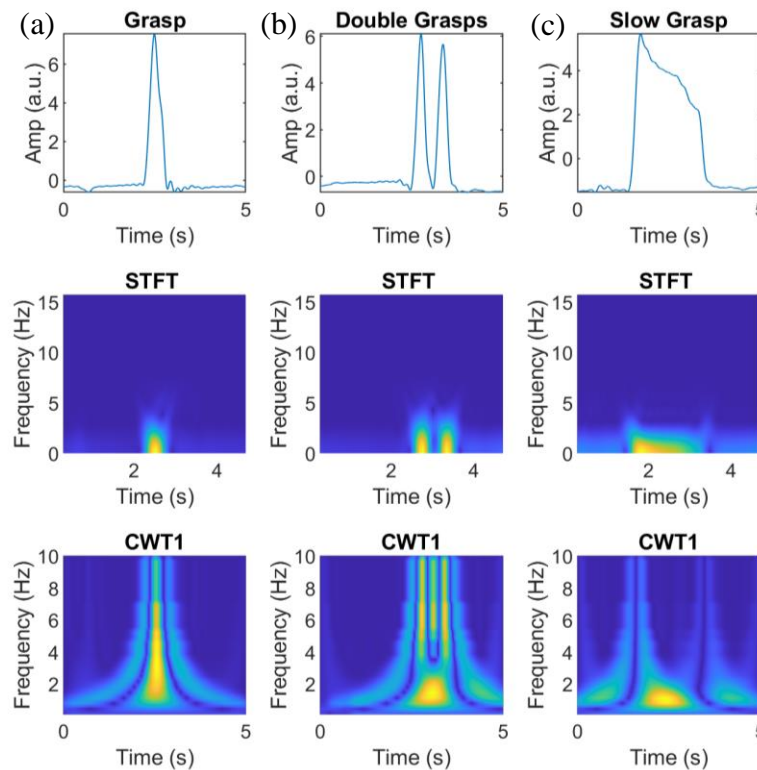
	Point Thumb	Point Index	Point Ind. +Mid.	Point 4 Finger	Grasp	Wrist Up	Wrist Down	Fist	Rest	
Basic Gesture										8 participants 5,847 samples 23 gestures
Quick	P1	P2	P23	P4	G	U	D			
Quick Double	P1×2	P2×2	P23×2	P4×2	G×2	U×2	D×2			
Slow	sP1	sP2	sP23	sP4	sG	sU	sD	sF	R	

23 hand gestures used in the study protocol

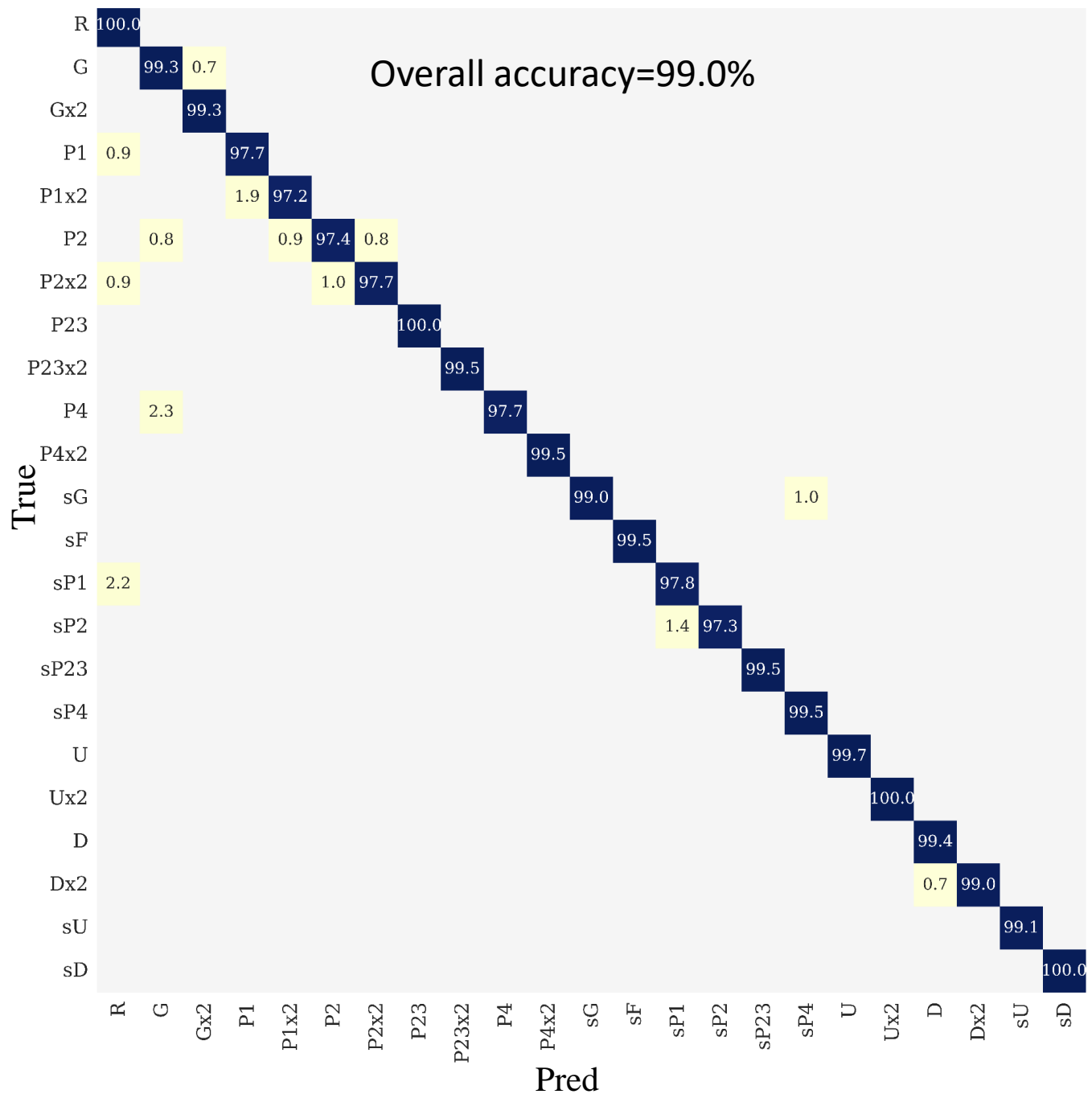


data pre-processing

Each gesture is segmented into 5s time window



1D time series
To
2D spectrogram
1. STFT
2. CWT

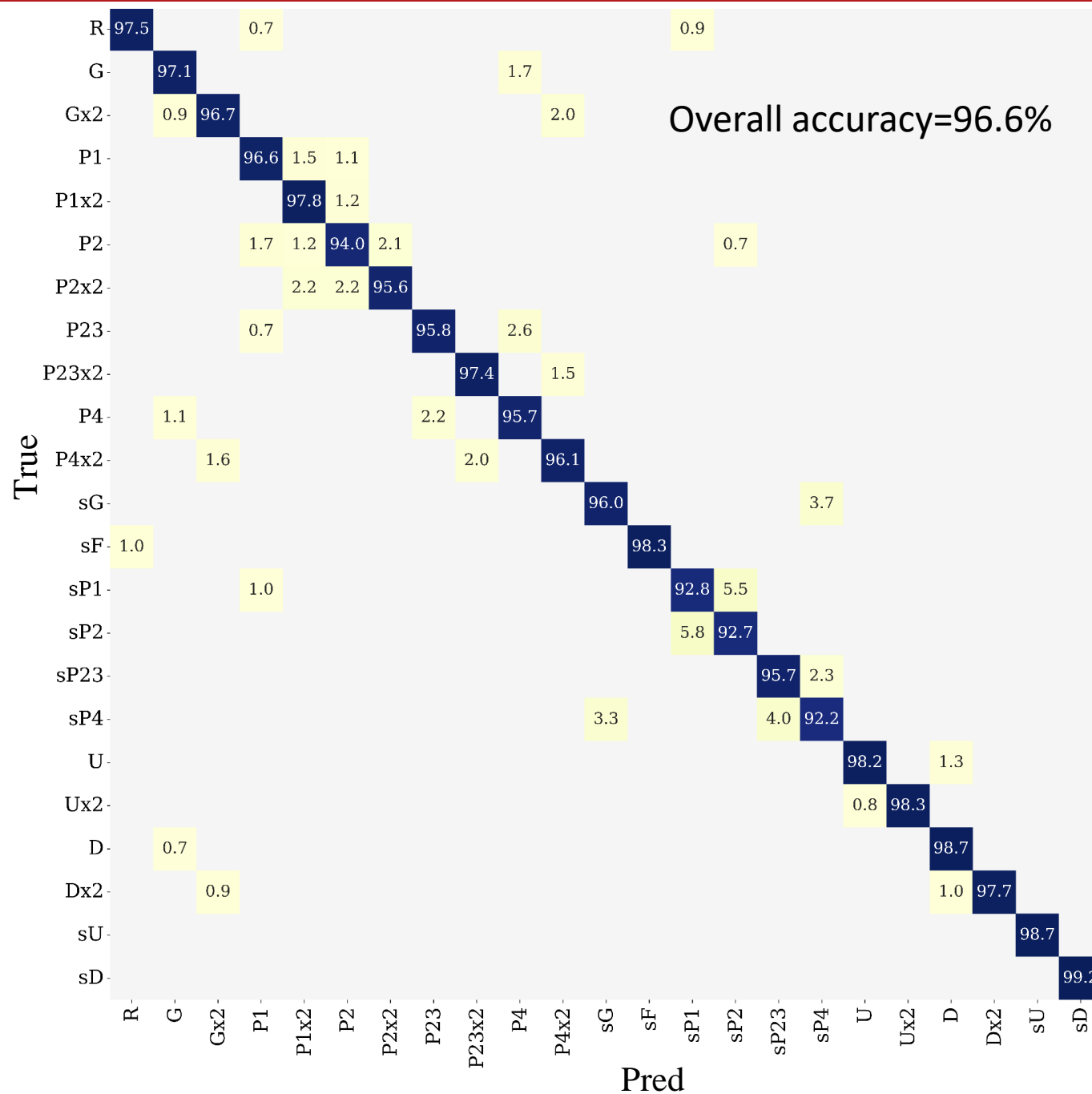


Classification results using deep learning

personal training model

Model:
Vision transformer

7-fold CV



Classification results using deep learning

Transfer learning on the unseen participant by 1/5 of new data.

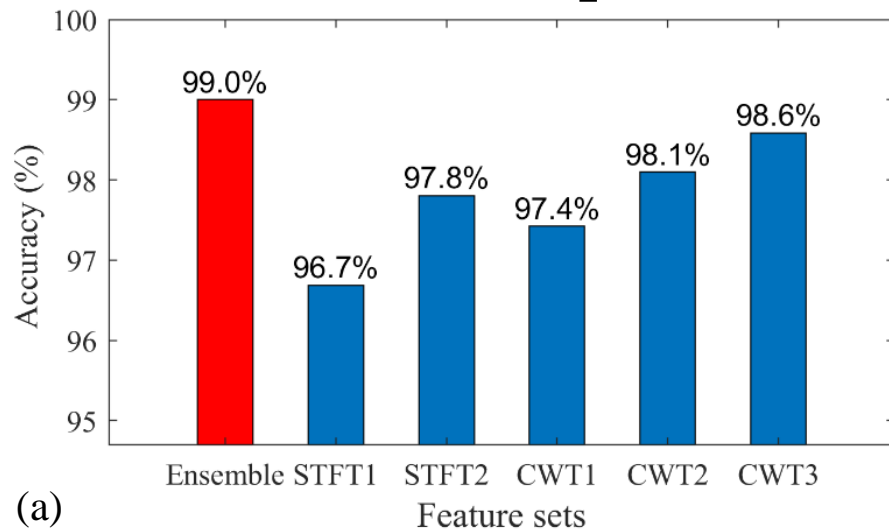
Pre-train on general model

Fine-tune by few cases of new participant

Model: Vision transformer

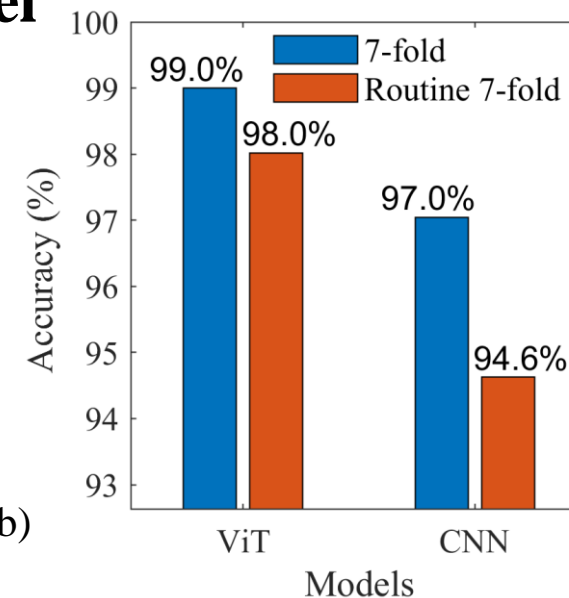
Analysis on classification results

personal training model



(a)

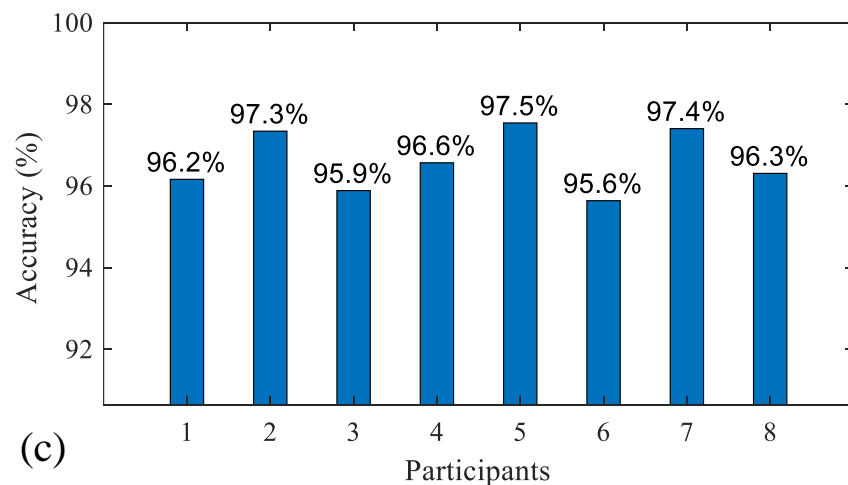
Ensemble
boosts
accuracy



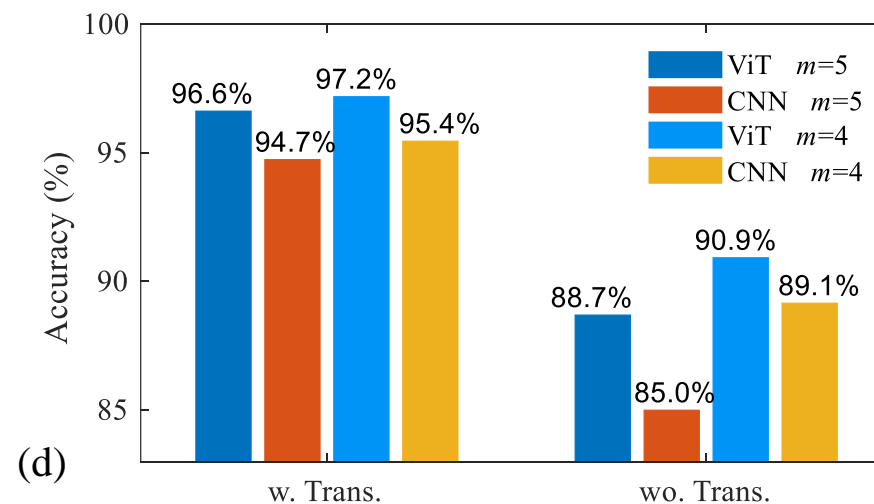
(b)

Vision
Transformer
outperformed
CNN

Transfer learning for unseen users

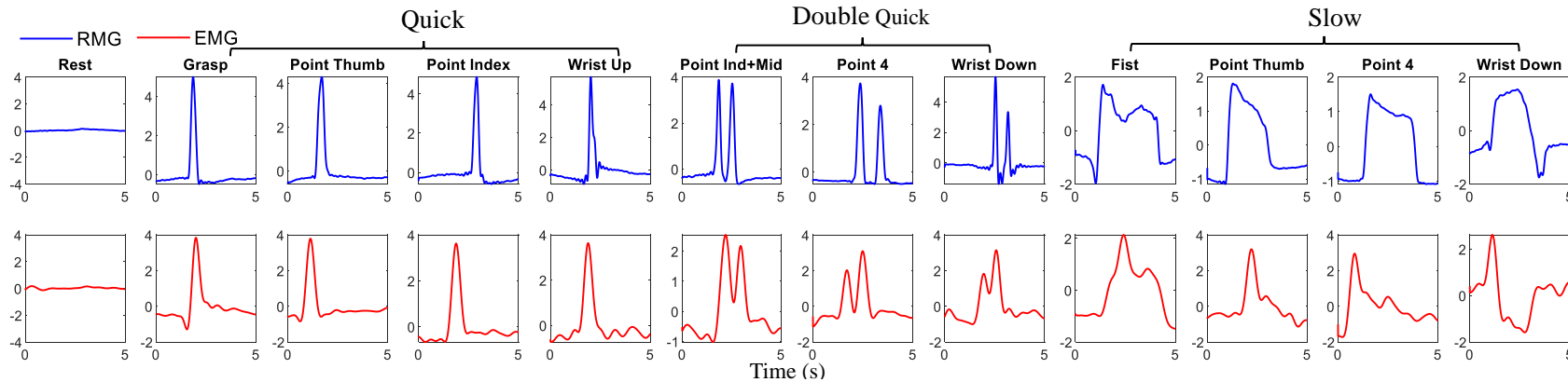


(c)

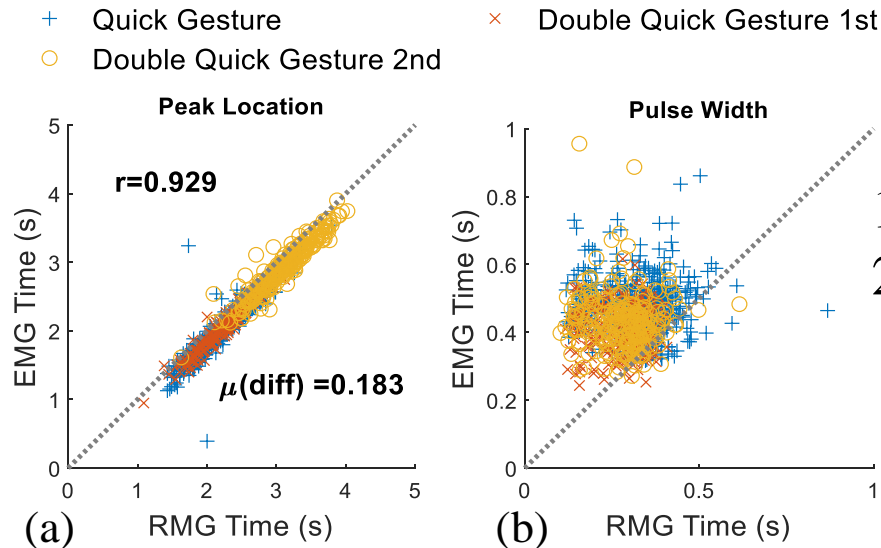


(d)

Benchmark with sEMG



RMG and sEMG waveforms for various gestures by DTW averaging on all samples

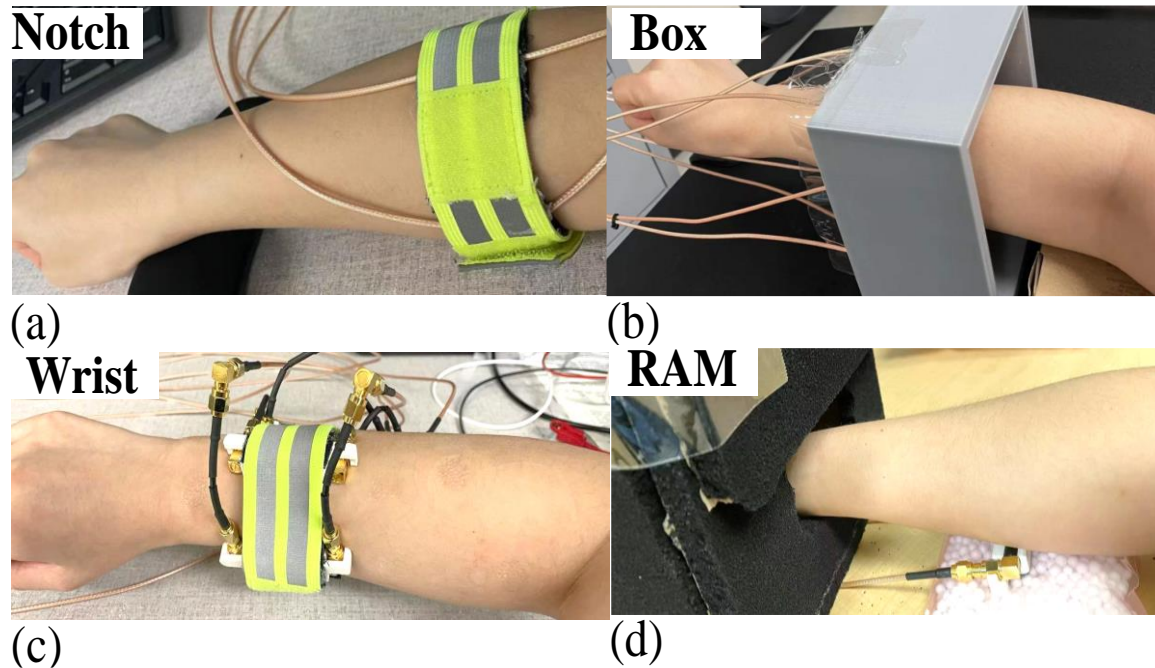


1. High temporal correlation
2. Consistent time lag

Accuracy comparison of RMG vs. sEMG

Exp:	1	2	3	μ
RMG	99.0 %	98.5 %	98.7 %	98.7 %
sEMG	68.2 %	70.8 %	66.7 %	68.6 %

Variation in experimental design

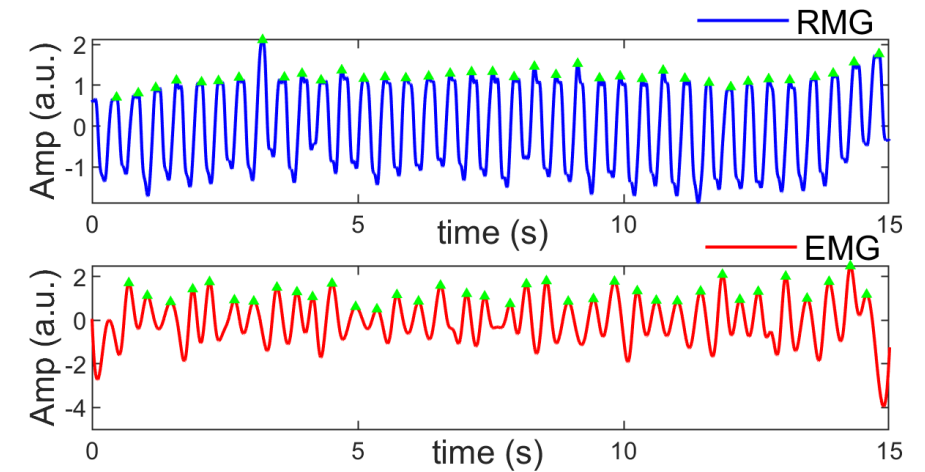


	Notch (a)	Box (b)	Wrist (c)
Accuracy (%)	99.0	97.4	95.8

Timing and latency

Sampling rate:

Camera: 60 fps RMG: 1M sps



	Timing Test	
	150 beats/minute	
	μ	σ
RMG	0.40 s	38 ms
sEMG	0.40 s	55 ms

Comparison of RMG to previous HGR works.

	Li 2019 ^[11]	Liao 2021 ^[19]	Ma 2019 ^[20]	Zhang 2016 ^[17]	Savur 2016 ^[4]	Qi 2020 ^[25]	Côté- Allard 2019 ^[40]	Moin 2021 ^[23]	This work
Class	8	9	6	8	27	9	7/18	13/21	23
Subject	5	8	-	4	1	-	17/10	2	8
Sensor setup	Camera	Visible light	Solar light	FMCW Radar	sEMG	sEMG	sEMG	sEMG	RMG
Algorithm	CNN	kNN	kNN	CNN	Ensemble	GRNN	ConvNet	Neural	ViT
Accuracy	98.5%	96.1%	96.0%	96.0%	79.4%	95.3%	98.3% (7) 69.0% (18)	97.1% (13) 92.9% (21)	99.0%

Applications in Human Machine Interface

Hand gesture recognition system

virtual reality gesture control



Smart device control



Virtual object manipulation

