ArmIn: Explore the Feasibility of Designing a Text-entry Application Using EMG Signals

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MobiQuitous
Mobile and Ubiquitous Systems

Outline

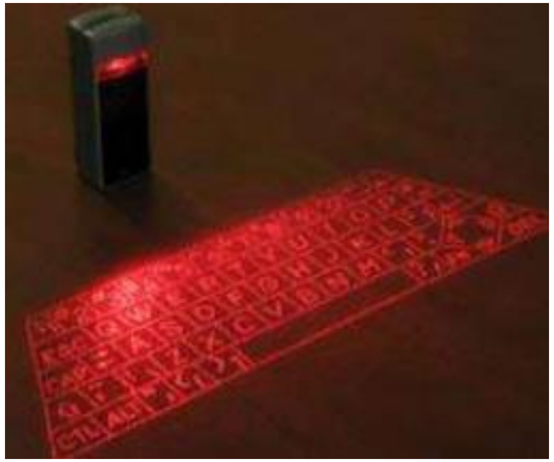
Motivation

Traditional keyboard or touch screen is **too small** on wearable devices

Extended keyboard

Bluetooth

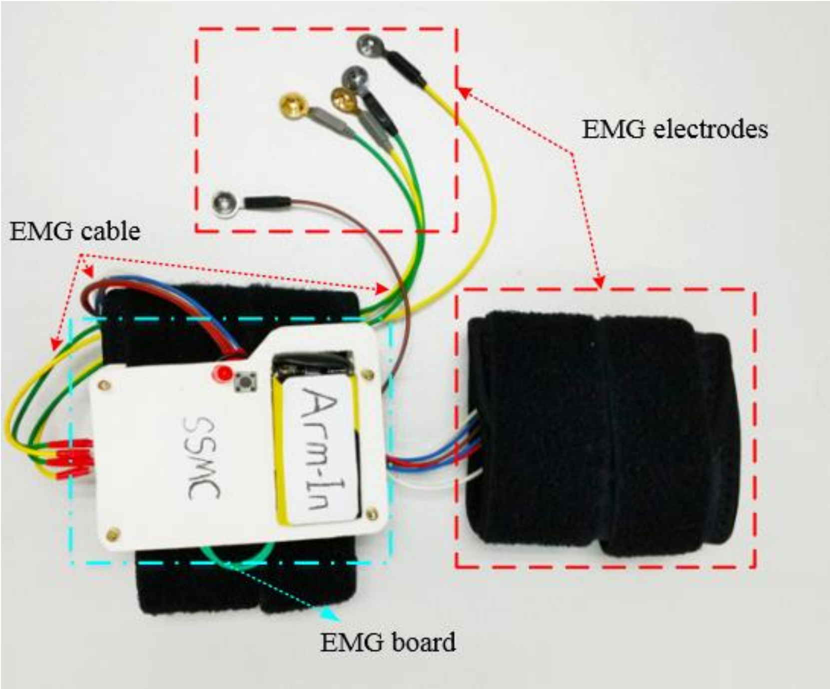
Flexible material



Infrared ray

Large / Expensive !

ArmIn: EMG-based virtual keyboard



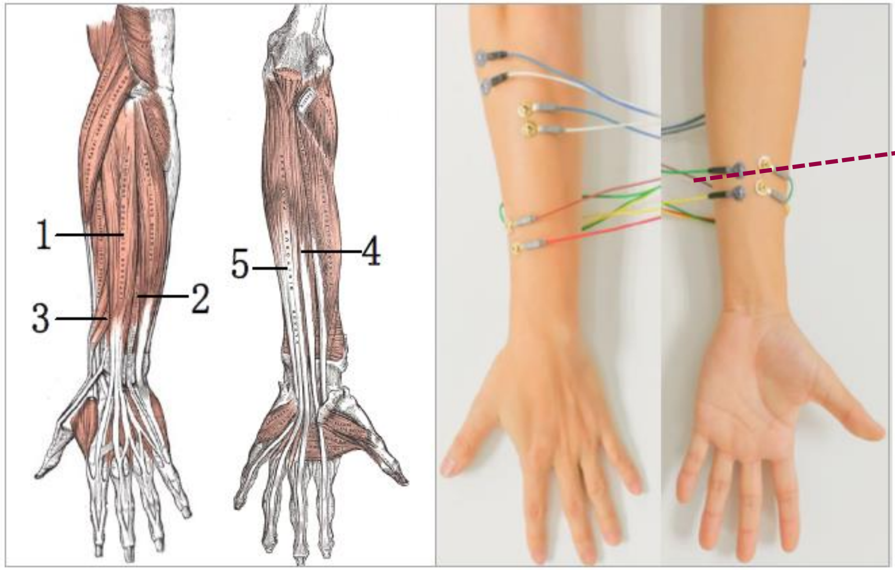
Low-cost

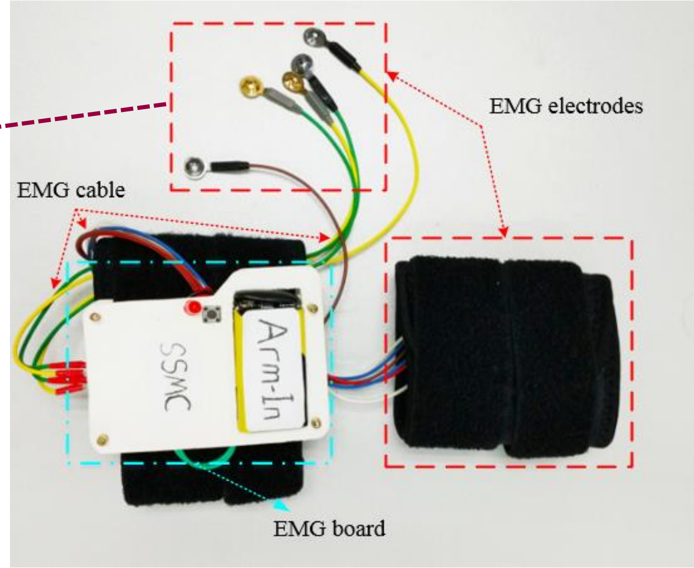
Small scale

Commercial hardware

Bind on your arm and input on the virtual keyboard!

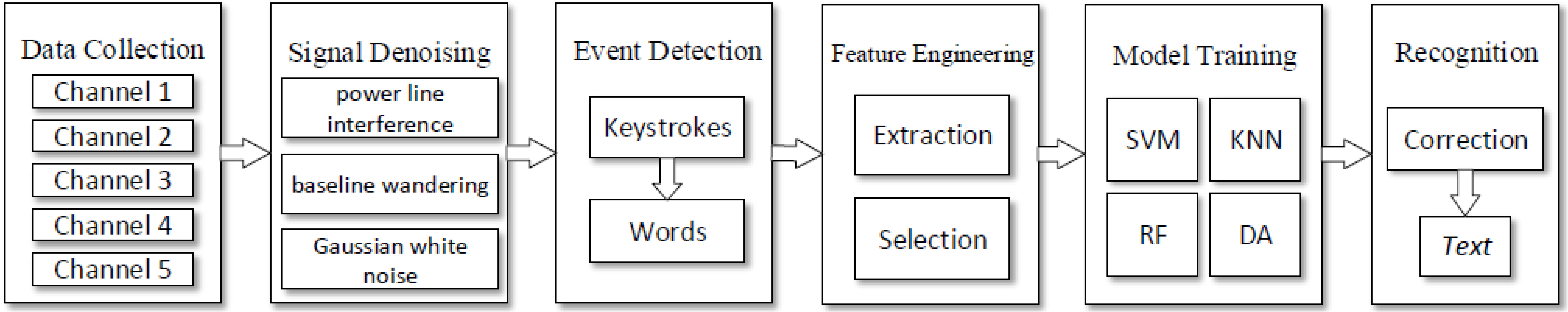
EMG Signal collection





Stick electrodes on your forearm

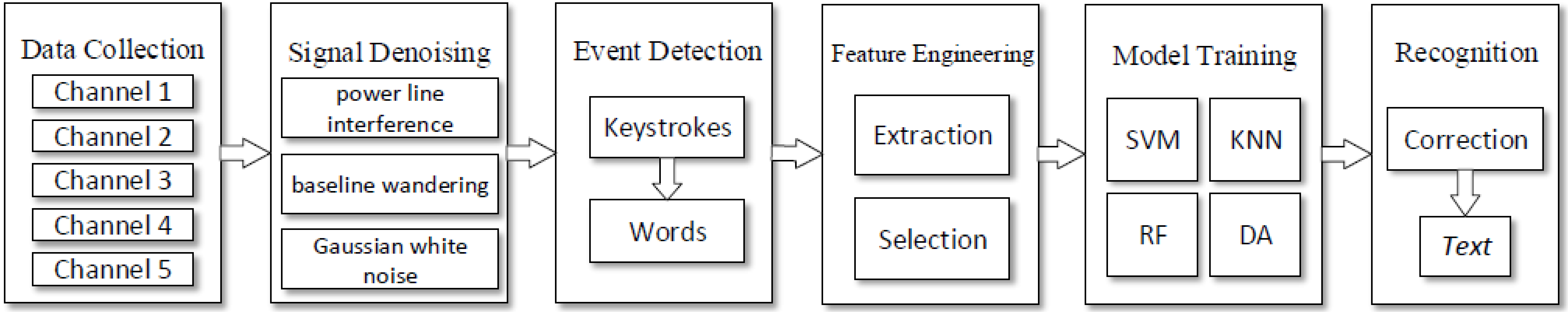
System workflow



System workflow

4. *How to enhance the text-entry performance?*

2. *How to remove the effect of channel asynchrony?*



1. *How to eliminate noise inference?*

3. *How to choose an effective model to recognize keystrokes?*

Challenges

1. *How to eliminate noise pollution?*

2. *How to remove the effect of channel asynchrony?*

3. *How to choose an effective recognition model?*

4. *How to enhance the text-entry performance?*

1. How to eliminate noise pollution?

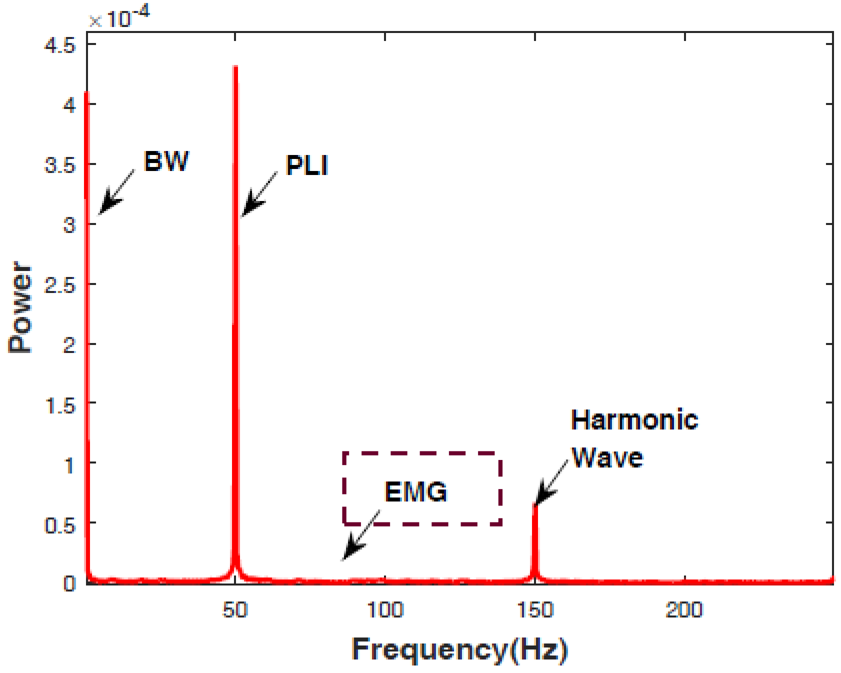


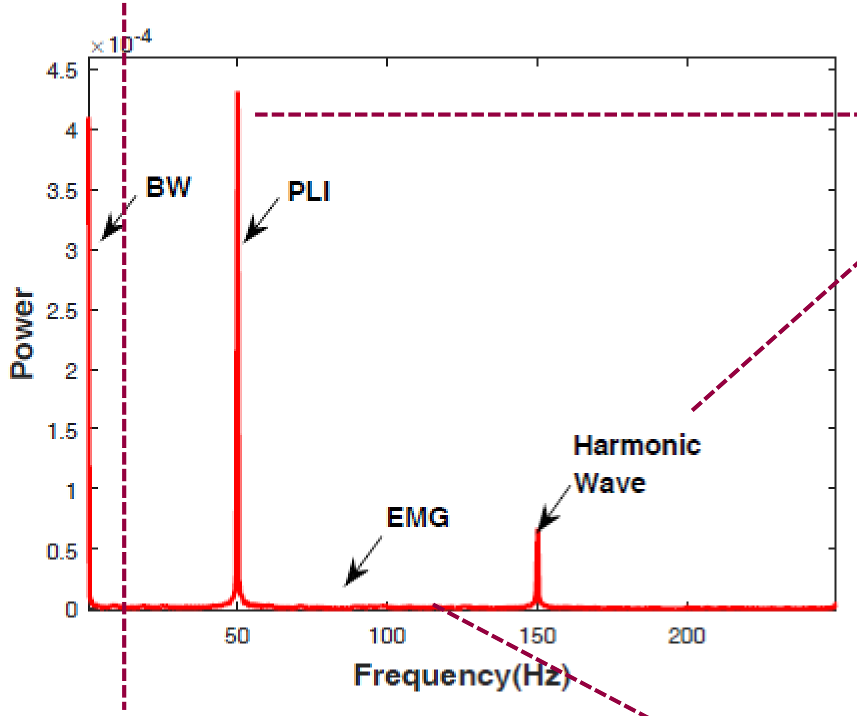
Figure 3: Spectrum of raw EMG signals.

Baseline wandering (BW)

Power line interference (PLI)

Gaussian white noise (WGN)

1. How to eliminate noise pollution?



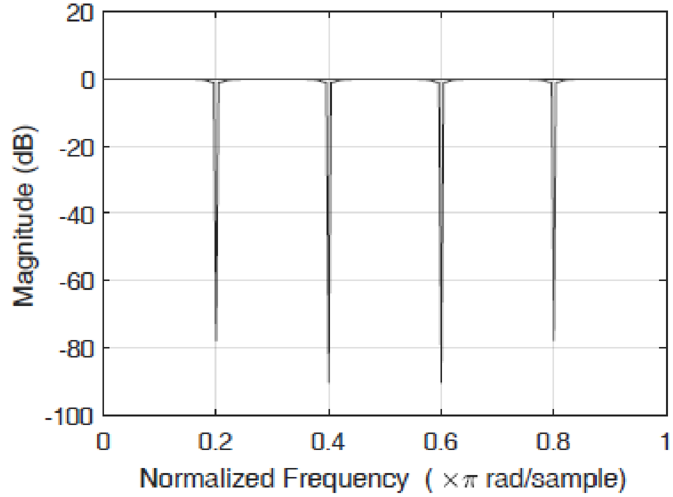
<15Hz

Baseline wandering (BW)

Bandpass Butterworth filter

Power line interference (PLI)

Produced by alternating current(AC) at 50Hz, 150Hz,···

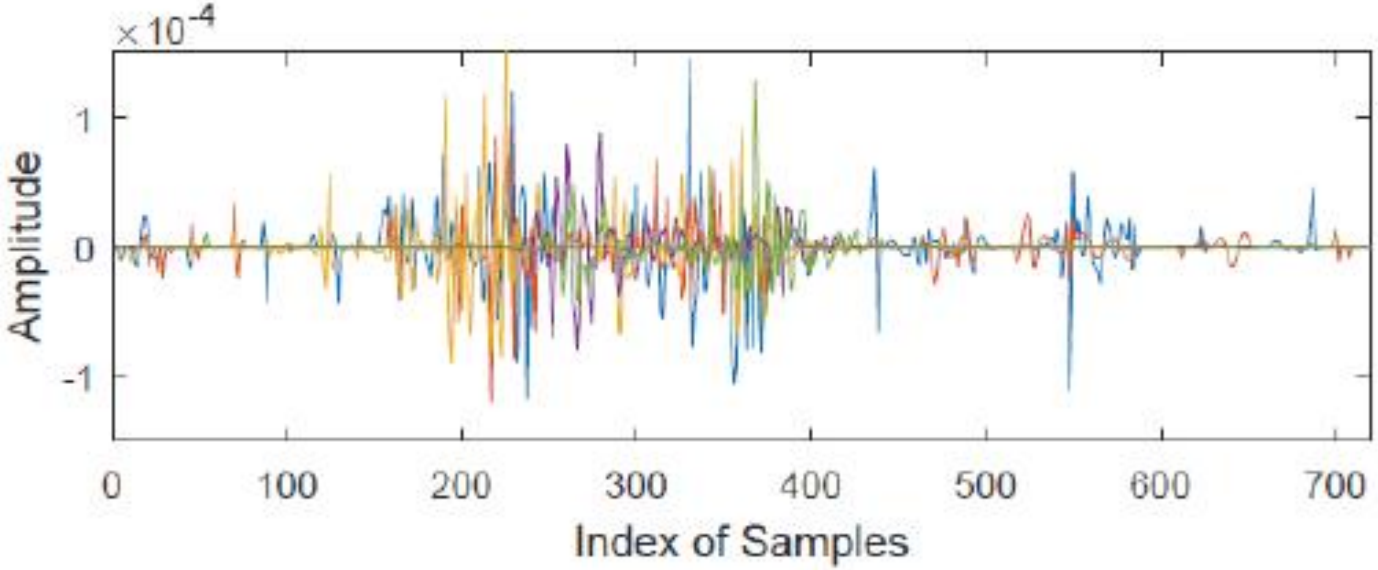


Elliptic filter-based 3-order notch filter

Gaussian white noise (WGN)

Soft threshold wavelet-based denoising

2. How to remove the effect of channel asynchrony?



Electrodes are attached at different positions of muscles, EMG signals cannot be captured simultaneously in multi channels.

1 Motivation

2 System Overview

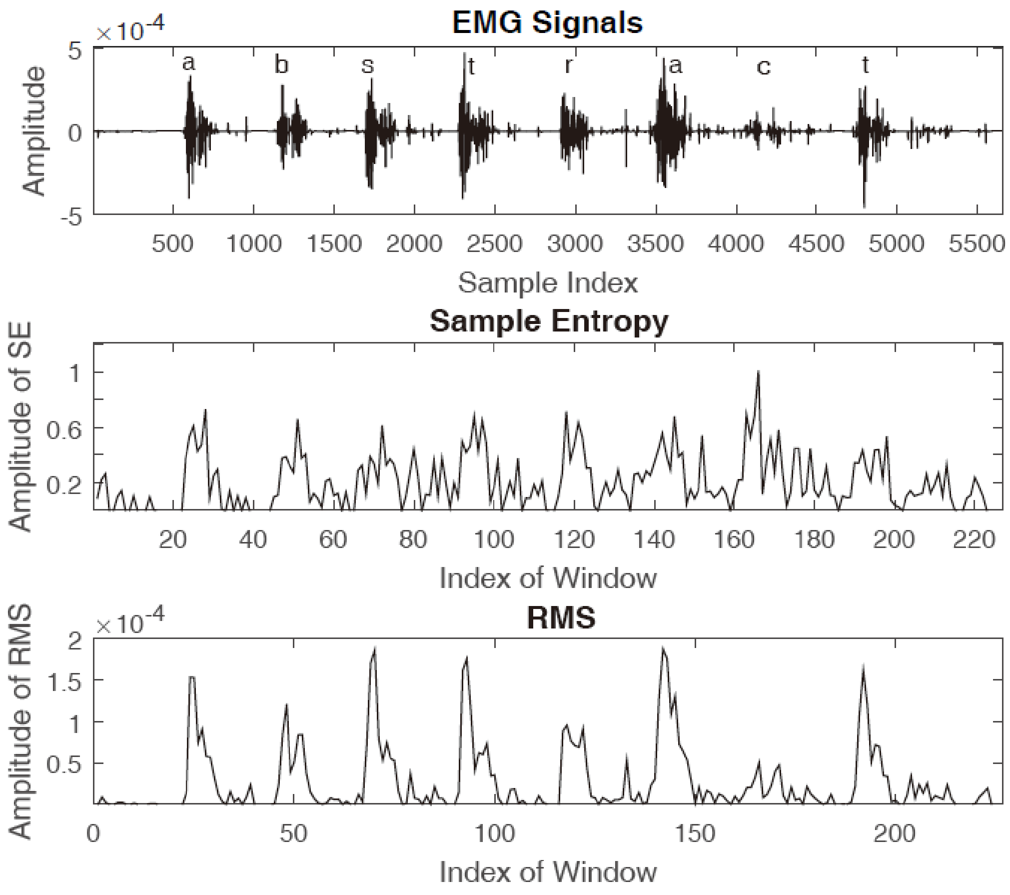
3 Challenges and Solutions

4 Evaluation

5 Conclusion

2. How to remove the effect of channel asynchrony?

Observation



SE can be used as a weight to balance EMG signal and noise.

Because of the randomness of noises, SE can be regarded as an indicator.

Real EMG signal owns more power so that can be described by RMS.

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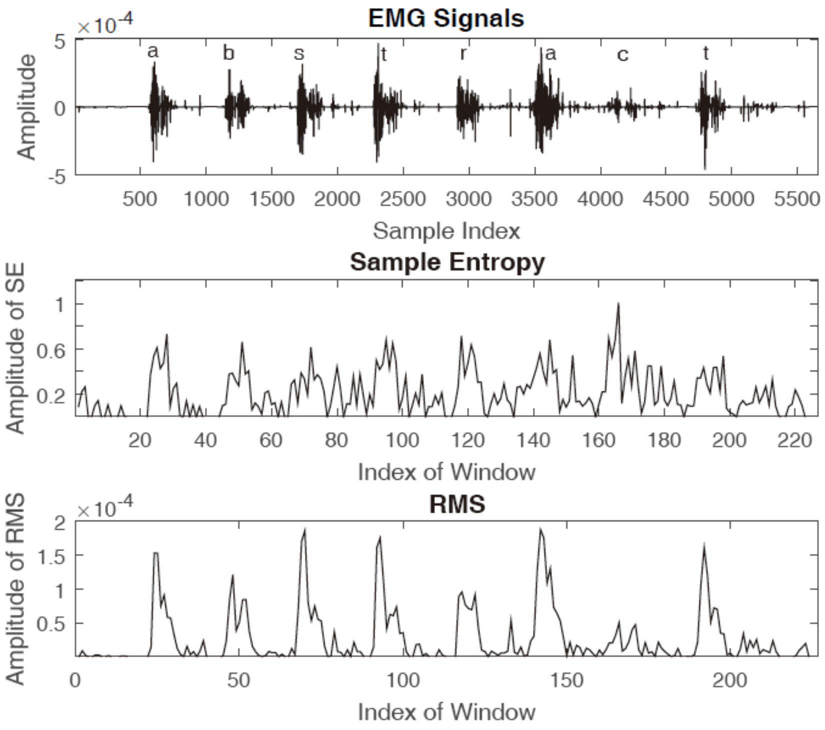
2. How to remove the effect of channels asynchrony?



Definition: $C(w)$

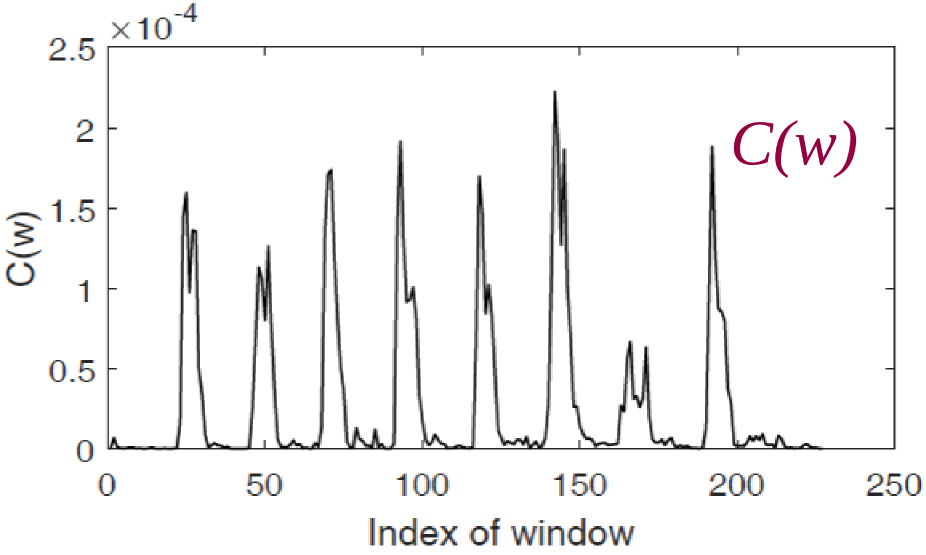
$$C(w_i) = SE_i \cdot RMS_i^T = \sum_{j=1}^{5} (SE_i^j \cdot RMS_i^j)$$

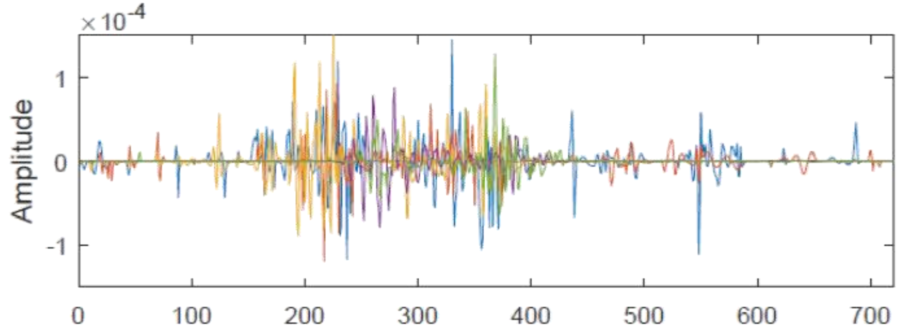
$$SE_i = (SE_i^1, SE_i^2, SE_i^3, SE_i^4, SE_i^5)$$

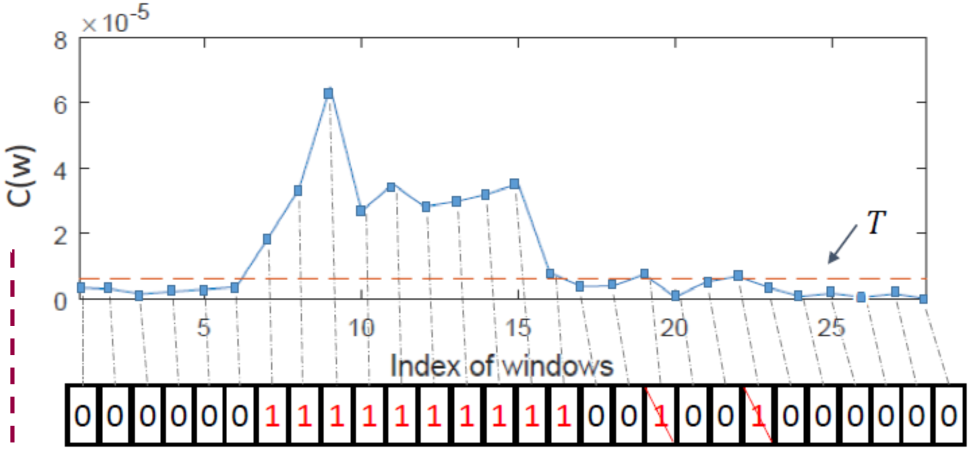
$$RMS_i = (RMS_i^1, RMS_i^2, RMS_i^3, RMS_i^4, RMS_i^5)$$

Where $\boldsymbol{w_i}$ denotes the i th window,
$\boldsymbol{SE^j_i}$ means the SE of i th window in j th channel,
$\boldsymbol{RMS_j}$ is defined as the RMS of i th window in j th channel.

2. How to remove the effect of channels asynchrony?







Revision:

1. Short pause or shift (1-0-1) → (1-1-1)
2. Short time < 5 windows (0.3s) → 0

Use threshold T to encode *C(w)*, then endpoints can be detected.

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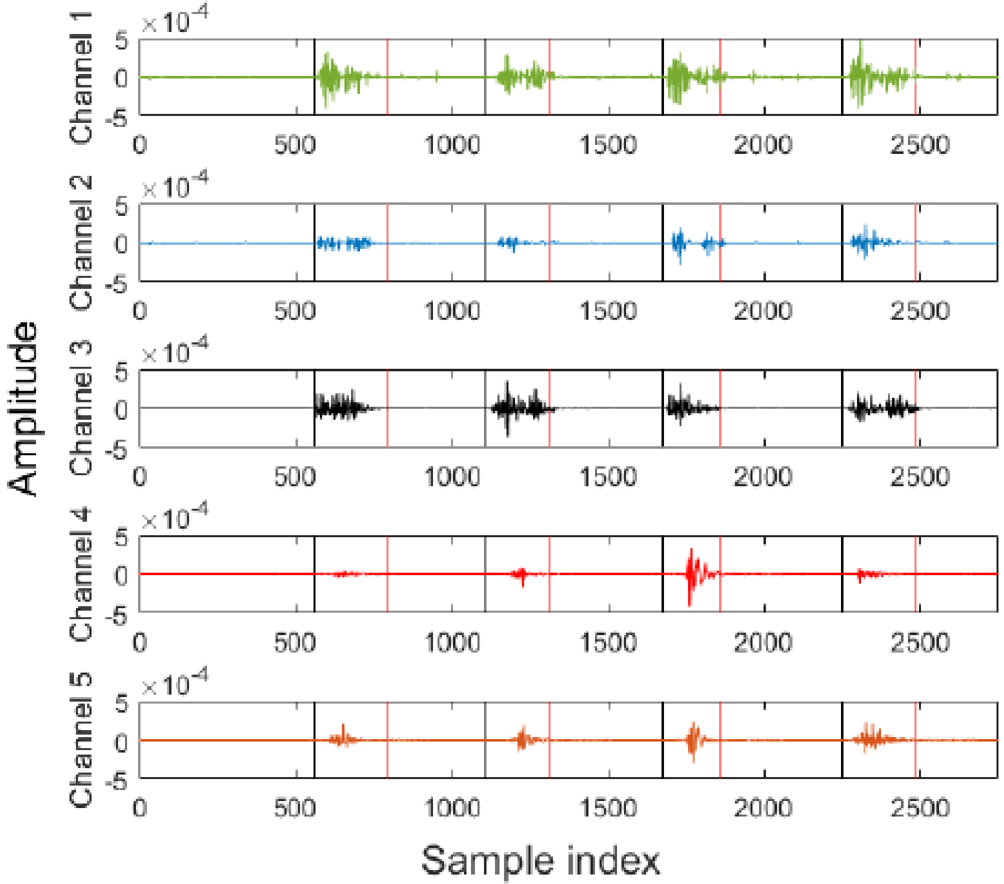


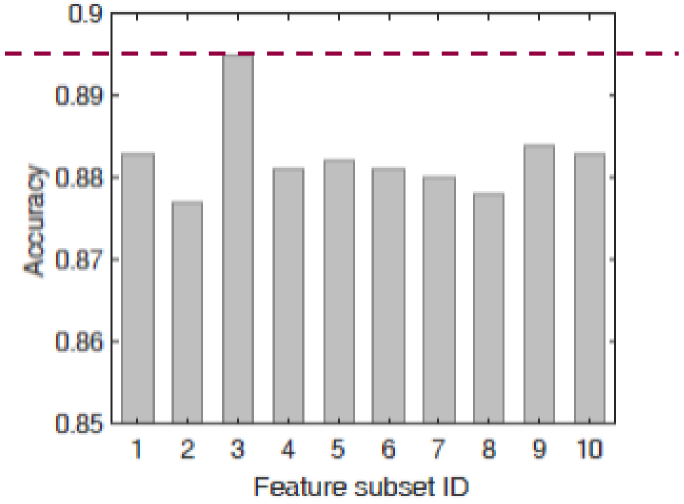
Endpoints can be detected even though that EMG signals of each channel are asynchronous.

4. How to choose an effective recognition model?

Table 1: Feature Subsets

SubsetID	Time domain	Frequency domain
1	MAV2,SamEn,MAV	MDF,VCF,MNP SM3,PSR
2	SamEn,WL	MDF,SM2,VCF,MNP
3	MAV2,SamEn,MAV	MDF,SM3,TTP
4	MAV,RMS,SamEn VAR,WL	MDF,MNF,SM1,VCF
5	ACC,MAV1,MAV SamEn,VAR	MDF,SM1,SM3,VCF
6	MAV2,SamEn,WL	MNF,MDF,SM1,VCF
7	MAV2,SamEn,MAV	SM3,TTP,PSR
8	IEMG,MAV,MAV1 SamEn,WL	MNF,MDF,SM1 SM3,VCF
9	ACC,MAV1,MAV SamEn,VAR,WL	SM3,VCF
10	ACC,MAV,MAV WL,SampEn,SSI	MNF,VCF,SM1

Feature domain	Feature	Description
Time domain	MAV2	Modified mean absolute value type 2
	MAV	Mean absolute value
	SampEn	The sample entropy of signals
Frequency domain	MDF	The Median frequency
	SM3	The 3rd Spectral moments
	TTP	The total power

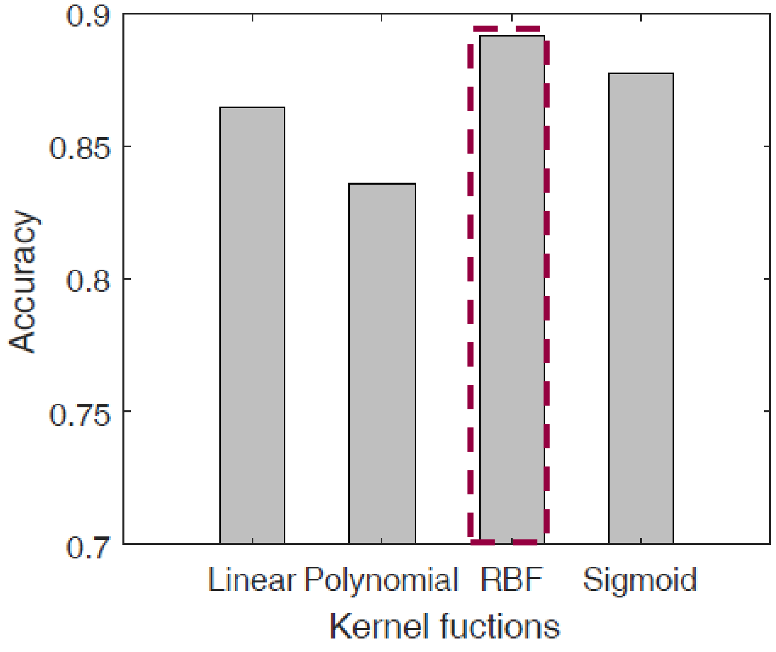


Feature selection (Wrapper method)

10-fold cross validation

4. How to choose an effective recognition model?

SVM / KNN / random forests (RF) / Discriminant Analysis (DA)?



C	1	1	2	2	2	4	4	4	8	8
γ	0.05	0.125	0.05	0.025	0.125	0.025	0.125	0.25	0.05	0.125
P	87%	85.7%	89.2%	87.5%	87%	87.5%	88.6%	85.7%	86.4%	87.6%

Penalty coefficient C
Kernel function coefficient γ

SVM

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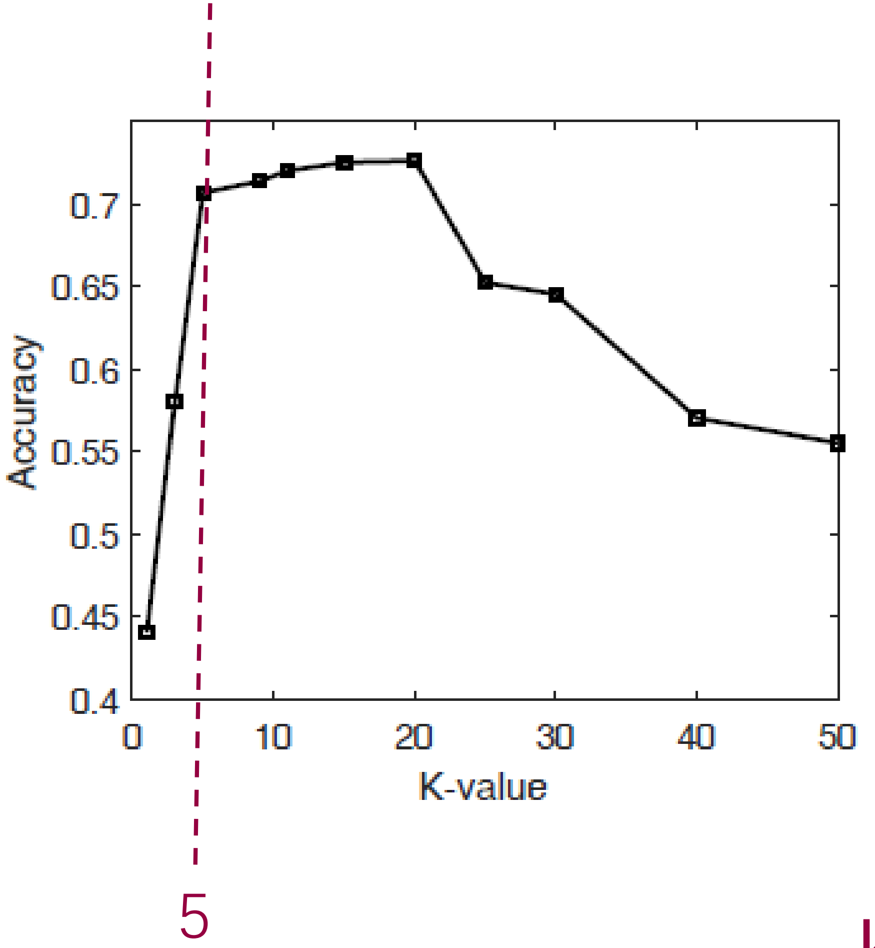


Achieve a balance between training time and performance

KNN

4. How to choose an effective recognition model?

SVM / KNN / random forests (RF) / Discriminant Analysis (DA)?

Set	1	2	3	4	5	6	7	8	9	10
trees	180	140	200	160	120	120	100	100	140	140
Dim	4	4	8	12	4	4	8	4	8	4
P	85.7%	84.6%	84.7%	84.5%	84.2%	84%	83.9%	83.8%	83.6%	83.6%

RF

Trees: Number of trees
Dim: number of branches in each node

Discriminant Analysis(DA)	Performance
Liner Discriminant Analysis(LDA)	☆84.43%
Diaglinear Discriminant Analysis(DDA)	82.57%
Quadratic Discriminant Analysis(QDA)	83.25%

DA

4. How to enhance the text-entry performance?

Intended word: $W = w_1 w_2 \dots w_n \dots$

Recognized letters: $\mathrm{T} = t_1 t_2 \dots t_n \dots$

$$\max_V P(W|I) \approx \max_V P(I|W) \times P(W)$$

$$P(I|W) = \prod_i^n P(l_i|w_i) = \prod_i^n CM(w_i, l_i)$$

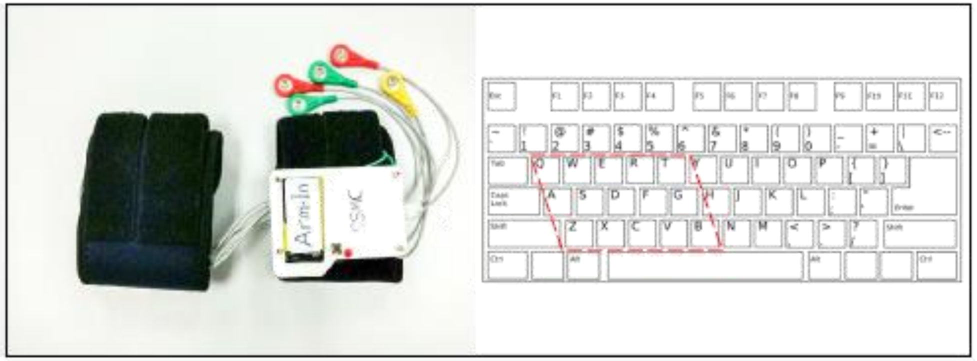
$$\begin{aligned} max_V P(W|I) &\approx max_V P(I|W) \times P(W) \\ &\approx max_V \prod_i^n P(l_i|w_i) \times P(W) \\ &\approx max_V \prod_i^n CM(w_i, l_i) \times P(W) \end{aligned}$$

$P(W)$ can be obtained from corpus

$CM(w_i, l_i)$ is the confusion matrix of letters recognition.

Bayesian-based correction method

Experiment setup



(a) Hardware components of ArmIn (b) Keyboard layout and testing keystrokes

ArmIn prototype

(a) Experiments on printed keyboard (b) Experiments on physical keyboard

Experiments on printed and physical keyboard

For left hand key area,

8 participants X **16** letters X **130** repetitions X **2** keyboards
8 participants X **15** words X **30** times

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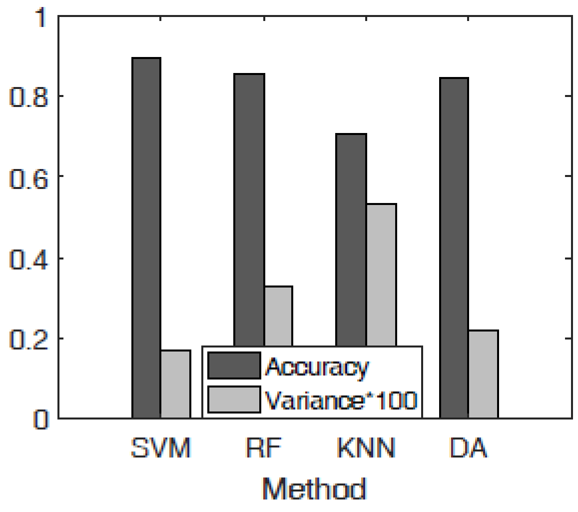
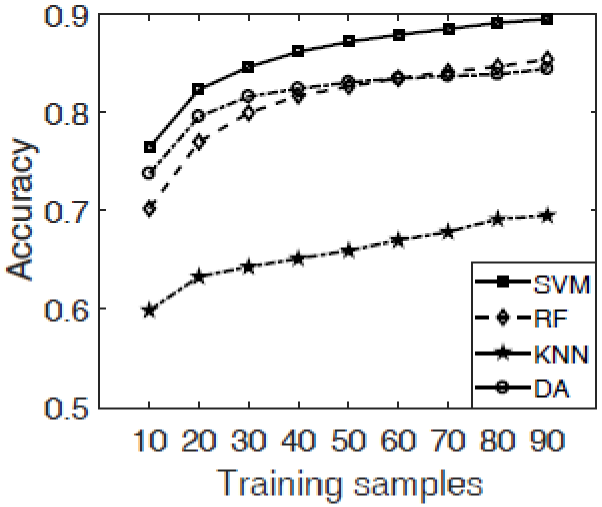
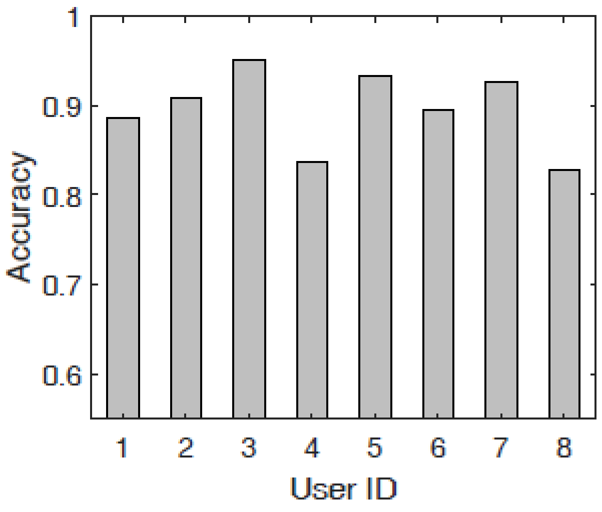
Evaluation





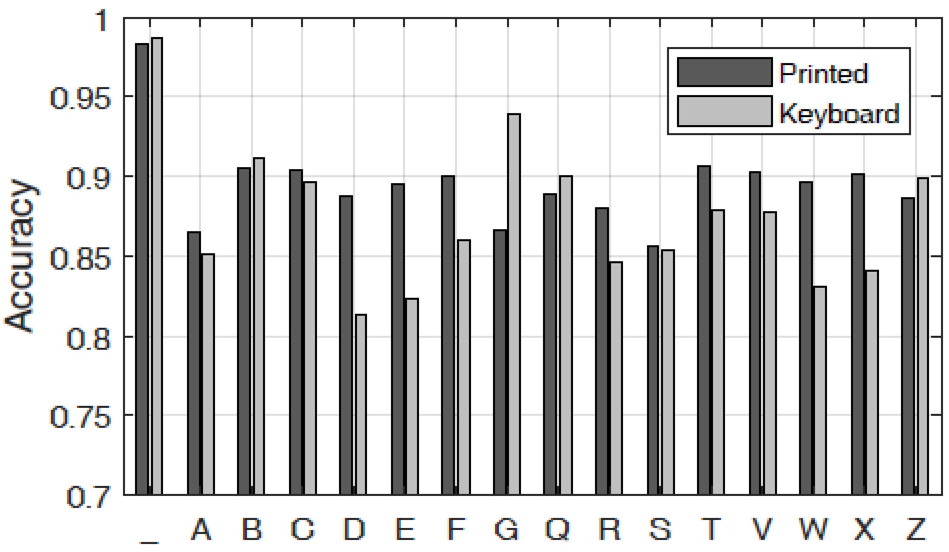


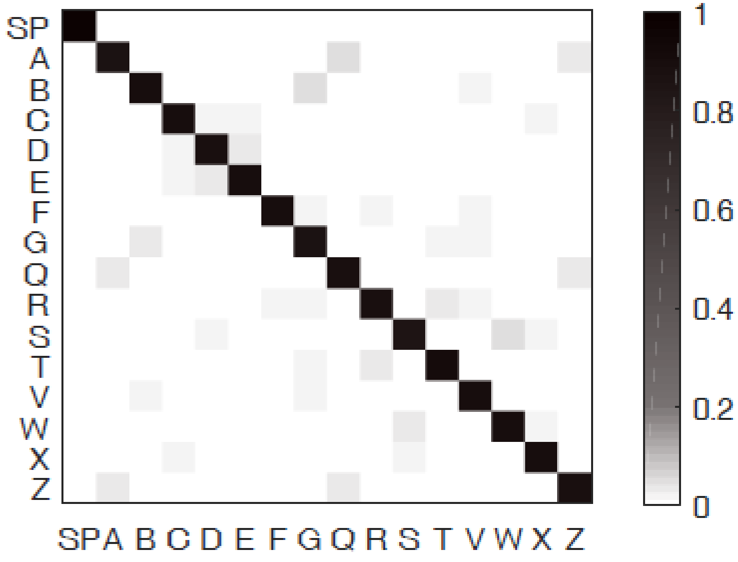
SVM achieves the best average accuracy (89.5%) over all participants with the lowest variance (0.17%).

Although SVM has a higher training overhead threshold, it still achieves the highest accuracy when the training sample number reaches 40. We use it as optimal model.

Among 8 participants, the best performance of them is 95.1% and the worst is 82.9%

Evaluation

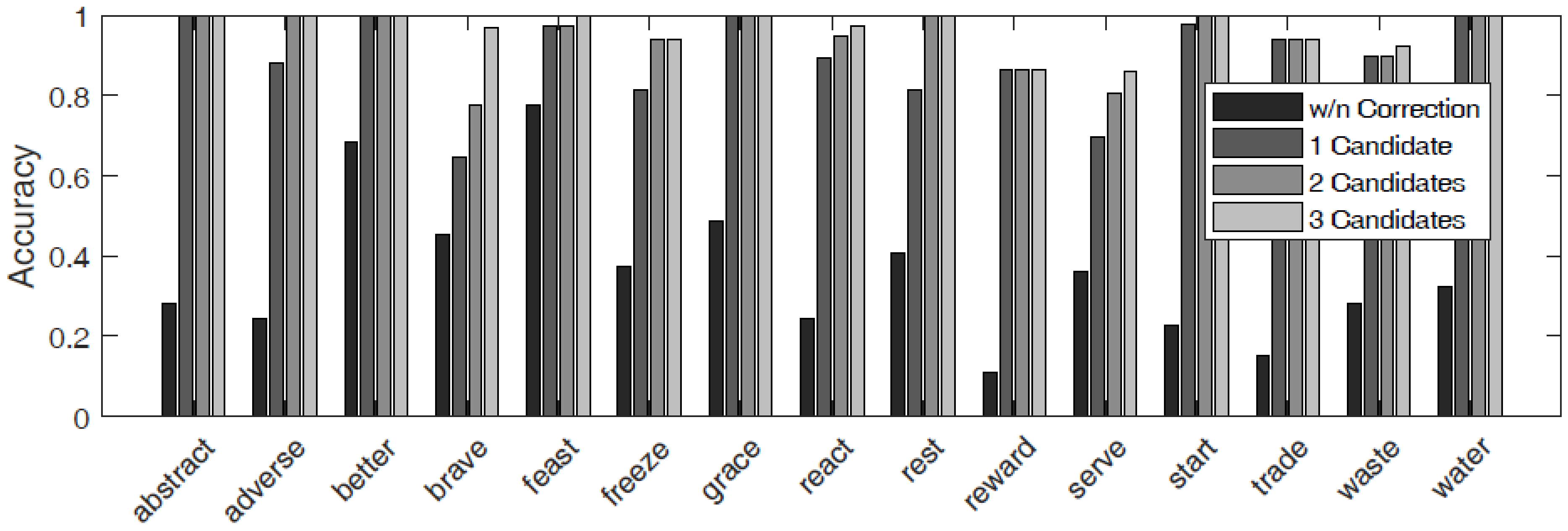




For printed and physical keyboards, the average recognition accuracy can achieve about 89.5% and 87.5%, respectively

The lowest accuracy among all letters is 85.6%, which means that ArmIn holds a stable recognition accuracy among different letters.

Evaluation



With one candidate word, the accuracy rises to 43.6%. When two candidate words are displayed, the system can achieve 92.5% accuracy.

The performance can be enhanced further by considering more candidate words, e.g., 93% accuracy for three candidate words.

Conclusion

We design and implement ArmIn with commercial EMG electrodes which can recognize fine-grained keystrokes.

We conduct experiment to evaluate its performance, and results show ArmIn can recognize keystrokes and word with accuracy of 89.5% and 92.5% (providing two candidates), respectively.

We prove the feasibility of designing a text-entry application using EMG signals, which opens up a new vision of HCI applications using EMG techniques.

THANK YOU

Questions?

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深圳大学