EchoWrite: An Acoustic-based Finger Input System Without Training

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Outline

Motivation

PC Era

Mobile Era

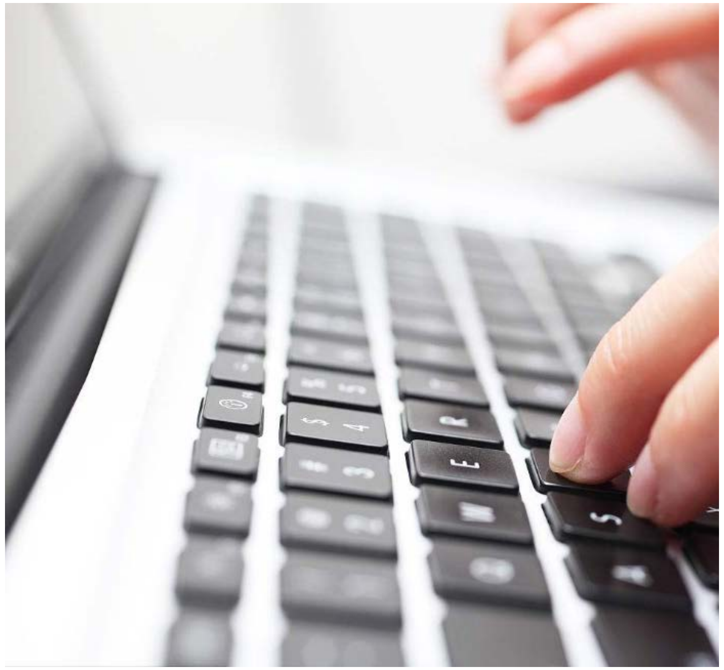
IoT Era

Motivation

Traditional interaction interface - Keyboard

Smartphone

Table computer



PC

Motivation

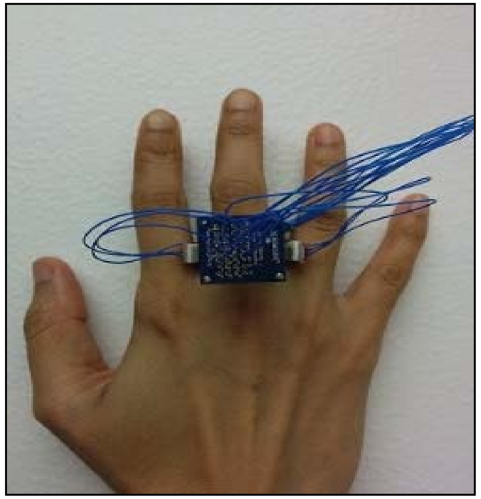
For new smart devices? **Small screen size / no screen!**

Smart watch

Smart glass

Smart home

Related work



RF

speech recognition

IMU

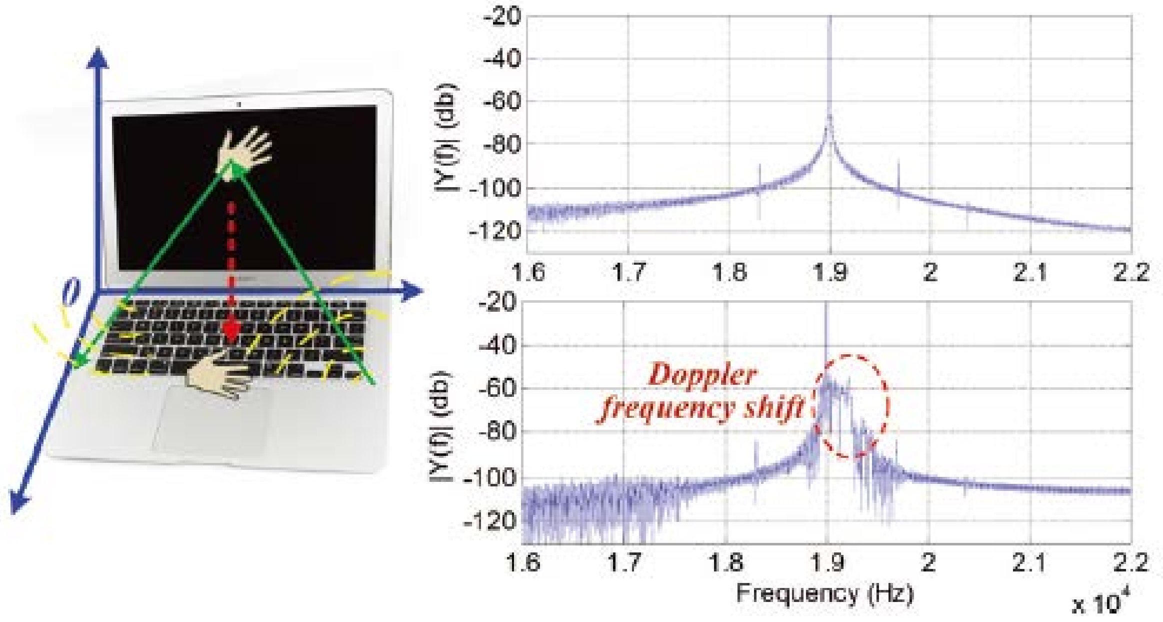
Unstable

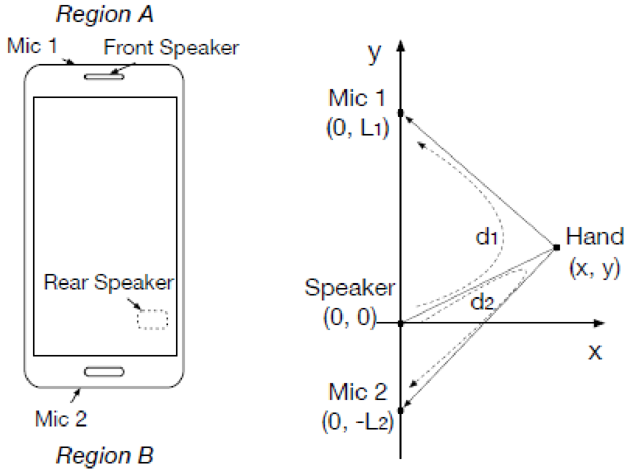
Privacy concern

Wearing device

1. L. Sun, S. Sen, D. Koutsonikolas, and K.-H. Kim, "Widraw: Enabling hands-free drawing in the air on commodity wifi devices," in Proceedings of ACM MobiSys, 2015.
2. J. Wang, D. Vasisht, and D. Katabi, "RF-IDraw: virtual touch screen in the air using rf signals," in Proceedings of ACM SIGCOMM, 2014.
3. S. Nirjon, J. Gummeson, D. Gelb, and K.-H. Kim, "Typingring: A wearable ring platform for text input," in Proceedings of ACM MobiSys, 2015.
4. C. Amma, M. Georgi, and T. Schultz, "Airwriting: Hands-free mobile text input by spotting and continuous recognition of 3d-space handwriting with inertial sensors," in Proceedings of IEEE ISWC, 2012.

Related work





Hand gesture recognition

Coarse-grained HAND gesture

Acoustic finger tracking

Two microphones are required

5. *S. Gupta, D. Morris, S. Patel, and D. Tan, "Soundwave: using the Doppler effect to sense gestures," in Proceedings of ACM CHI, 2012.*
6. *W. Wang, A. X. Liu, and K. Sun, "Device-free gesture tracking using acoustic signals," in Proceedings of ACM Mobicom, 2016.*
7. *Y. Zou, Q. Yang, Y. Han, D. Wang, J. Cao, and K. Wu, "Acoudigits: Enabling users to input digits in the air," in IEEE PerCom, 2019*
8. *W. Ruan, Q. Z. Sheng, L. Yang, T. Gu, P. Xu, and L. Shangguan, "Audiogest: enabling fine-grained hand gesture detection by decoding echo signal," in ACM Ubicomp, 2016.*

Related work

<table>
<tr><th></th><th>Device</th><th colspan="3">Device-free</th></tr>
<tr><td>Training</td><td>[3] [4]</td><td colspan="3">[7]</td></tr>
<tr><td rowspan="3">Training-free</td><td rowspan="3">[1] [2]</td><td></td><td>Coarse-gained</td><td>Fine-grained</td></tr>
<tr><td>Two mics</td><td>-</td><td>[6]</td></tr>
<tr><td>One mics</td><td>[5] [8]</td><td>EchoWrite</td></tr>
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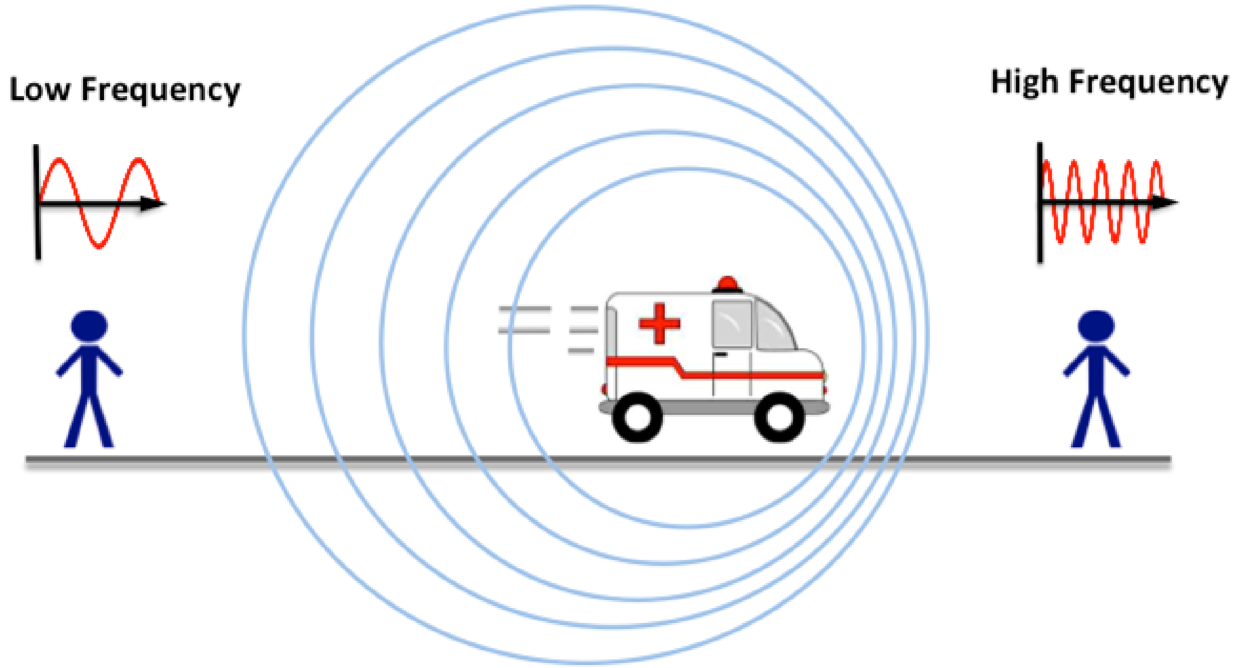
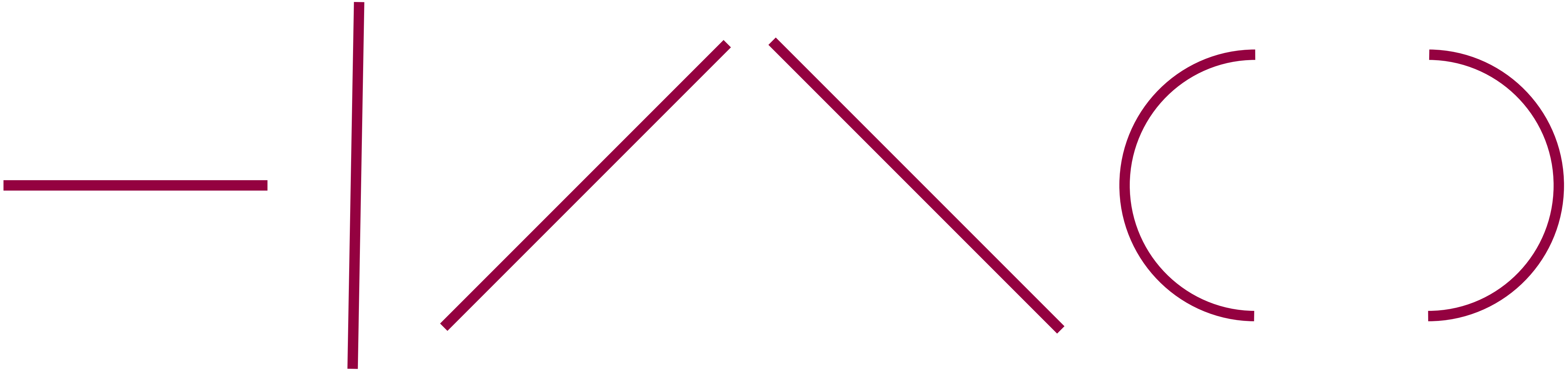
System Design - Basic idea

Principle: Doppler Effect

Frequency of a sound wave changes as a listener moves toward or away from the source



System Design - Basic idea

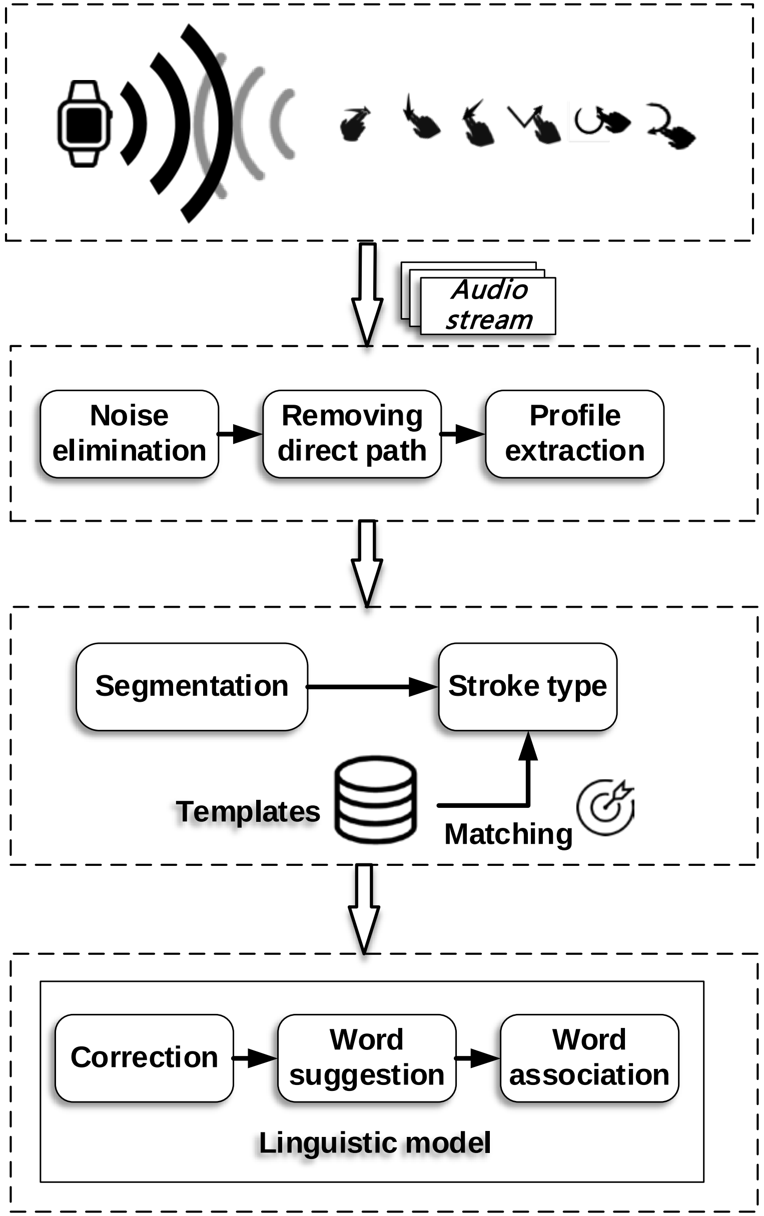


*Six basic strokes of English letters**

horizontal | vertical | left-falling | right-falling | Left-arc | Right-arc

*“*Using Mobile Phones to Write in Air*”, Sandip Agrawal , et.al, *ACM MobiSys*, 2011

System Design - framework



Data collection

Preprocessing

Stroke recognition

Text recognition

System Design - Challenges

1. *How to recognize finger gestures in a training-free way?*

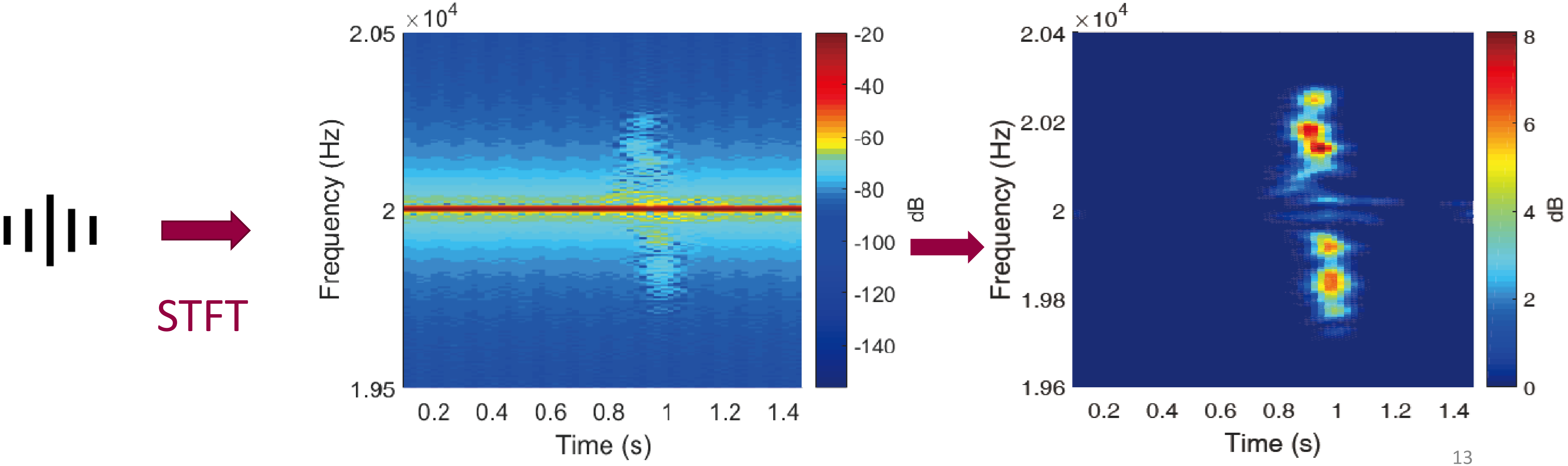
2. *How to input continuously under ambient interference ?*

3. *How to input text efficiently based on finger gestures?*

C1. How to recognize finger gestures in a training-free way?

Noise elimination

- Random noise: median filter
- Direct path: spectrum subtraction

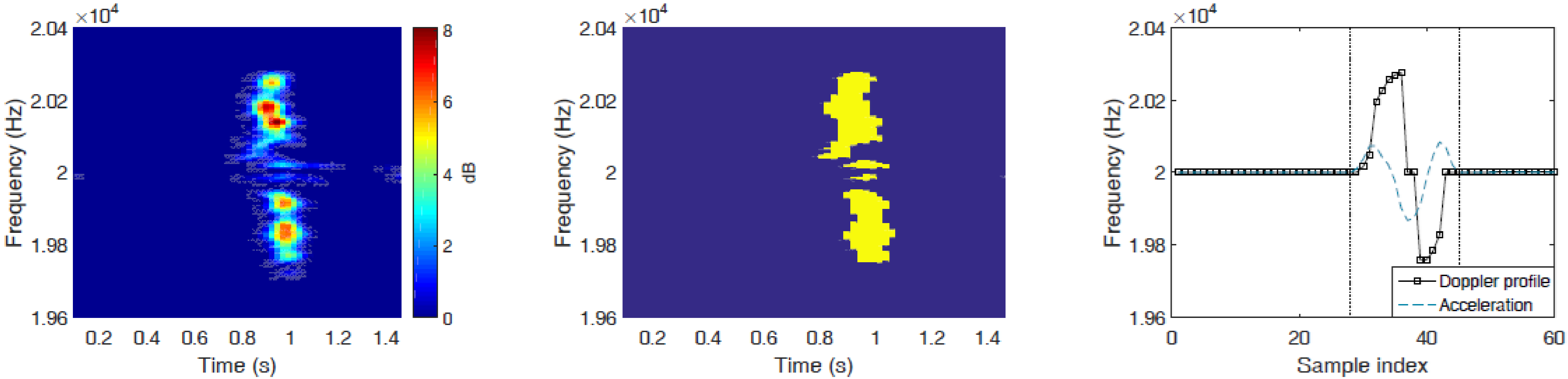


C1. How to recognize finger gestures in a training-free way?

Stroke profile extraction

- Normalization + Binarization
- Image processing: *Area open, flood fill*
- Profile extraction: Mean Value-based Contour Extraction (MVCE) algorithm

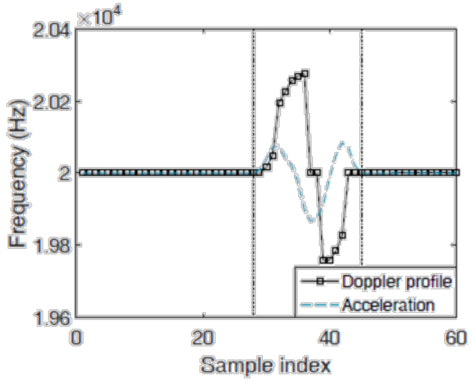
Stroke profile



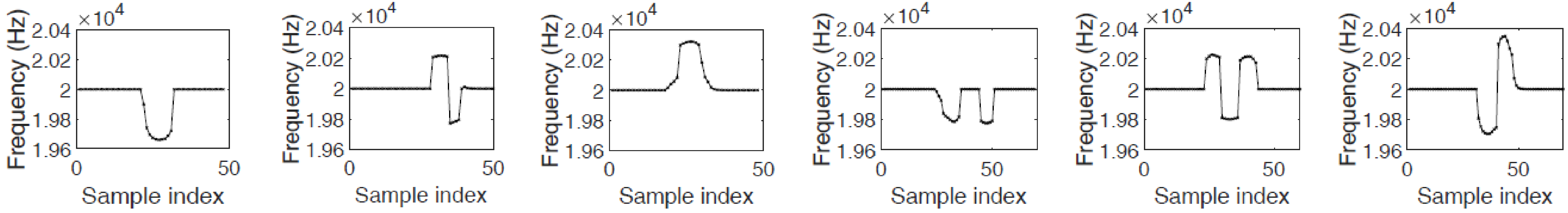
C1. How to recognize finger gestures in a training-free way?

Strokes Recognition

- Template matching
- Dynamic time wrapping (DTW)



DTW



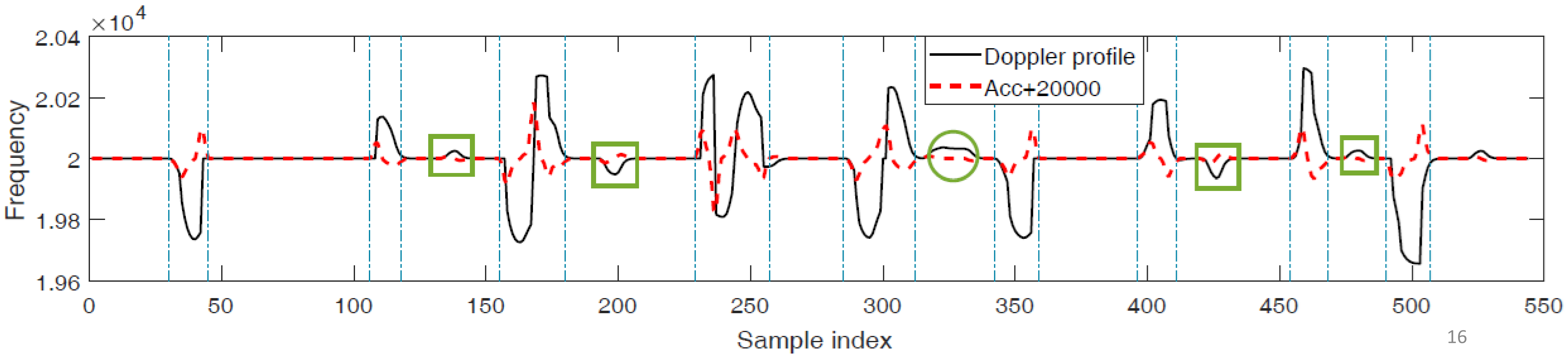
(a) S_1 (b) S_2 (c) S_3 (d) S_4 (e) S_5 (f) S_6

S_2

C2. How to input continuously under ambient interference ?

Successive Strokes Segmentation:

- Traditional methods: based on speed (i.e. Doppler frequency)
- **Key observation:** In the end of stroke writing, the speed remains but acceleration decreases notably.
- Acceleration can be utilized to discriminate strokes and other movement (arm, body, and other objects)

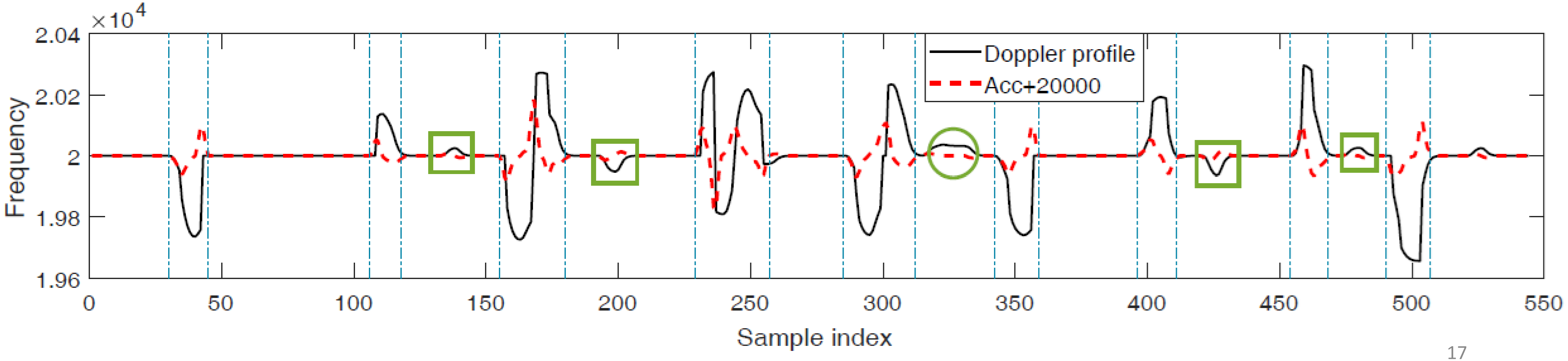


Successive Strokes Segmentation

- Acceleration: first-order difference
- Green box: moving objects
- Green circle: Uninterrupted writing

$$f_t = \frac{1 \pm \frac{v_f}{v_s}}{1 \mp \frac{v_f}{v_s}} f_0 = \pm \frac{2 f_0 v_f}{v_s \mp v_f} + f_0 \approx \pm \frac{2 f_0 v_f}{v_s} + f_0$$

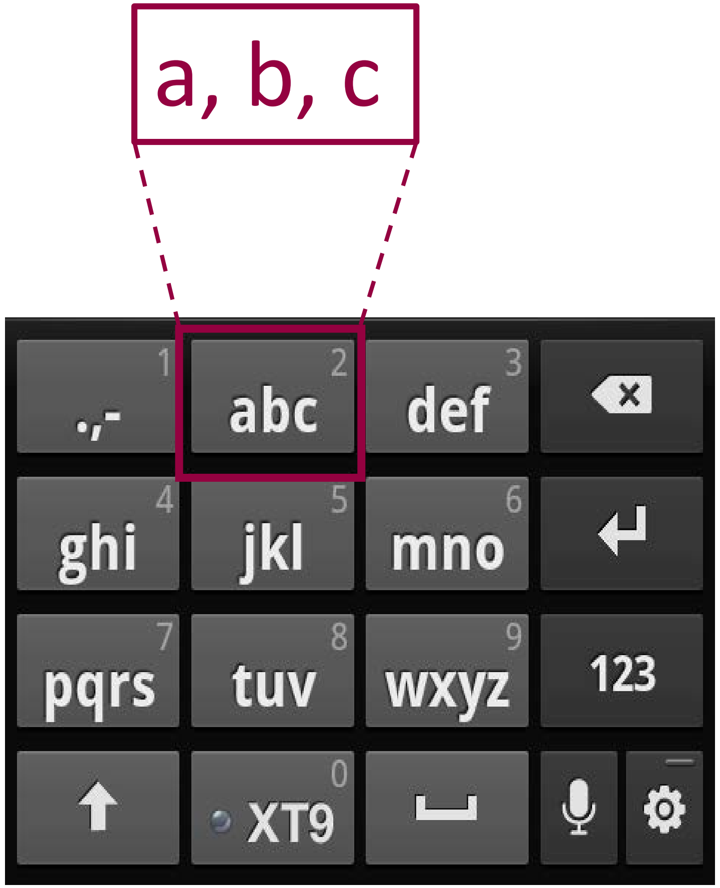
$$f_t' = \frac{2 f_0}{v_s} v_f' = \frac{2 f_0}{v_s} a$$

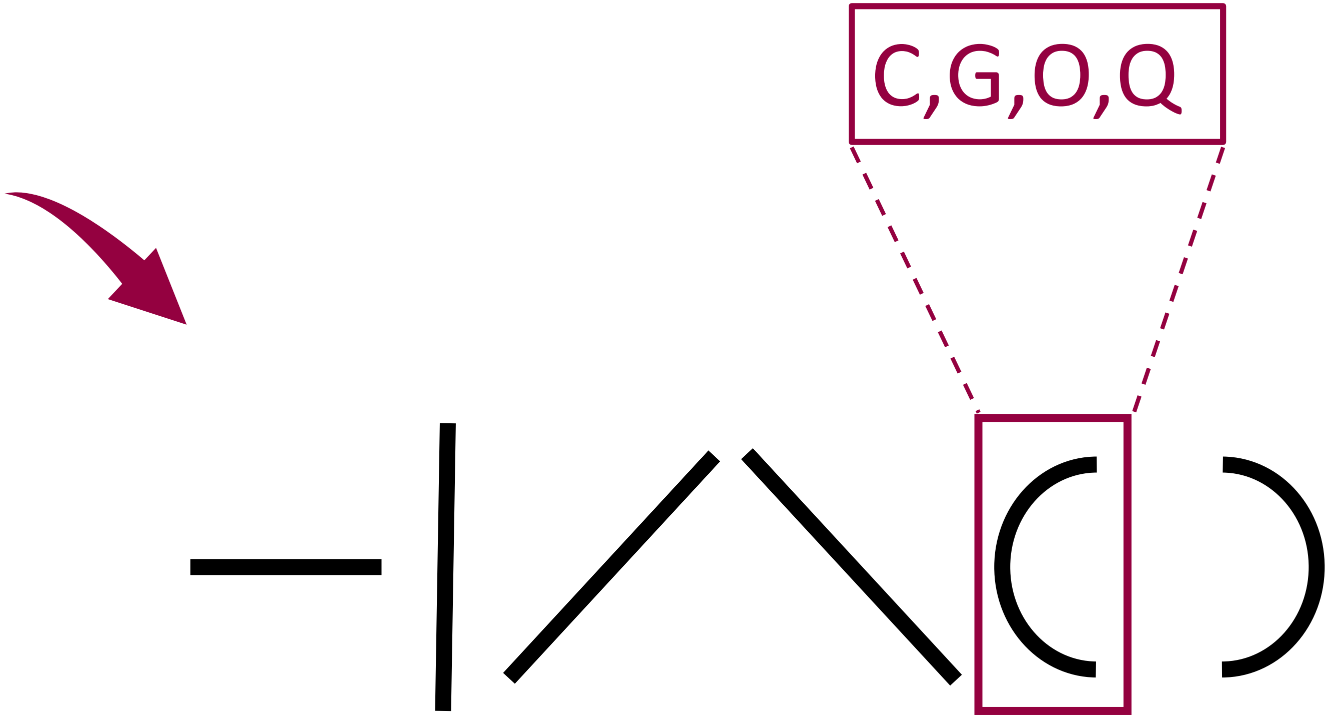


C3. How to input text efficiently based on finger gestures?

Referring to T9 Keyboard

- Each stroke represents several letters (started by this stroke when writing).
- Users can customize their own writing habits.





Example: Input 'TO'

I, T, Z, J

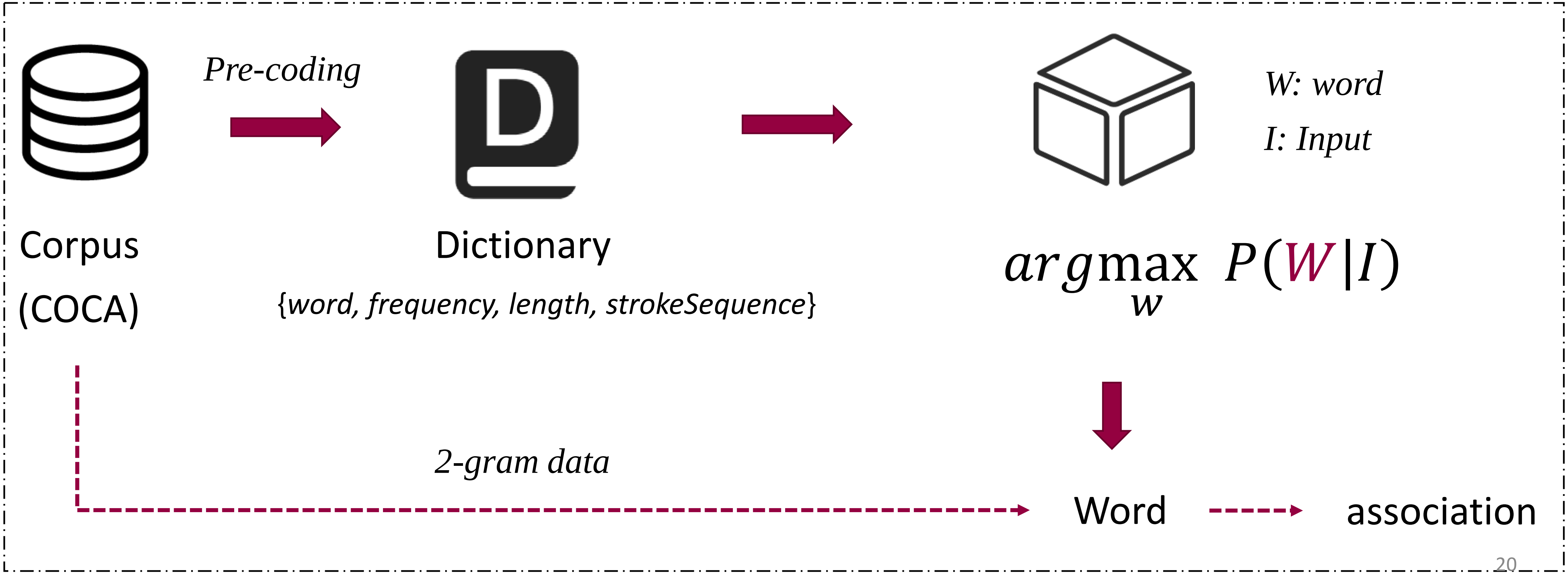
C, G, O, Q

IC
IG
IO
IQ
TC
TO ☑
TQ
…

Bayesian-based Linguistic Model

- Tolerating possible errors (recognition or writing)
- Auto-associating the next possible word.

Stroke sequence *(I)*



Evaluation - setup

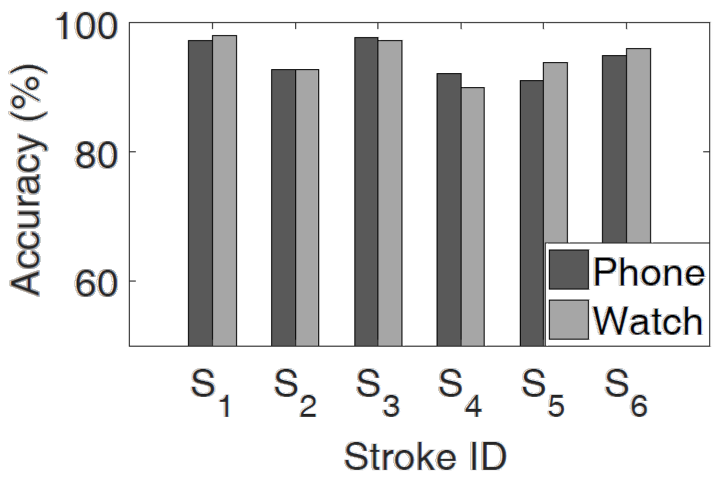
Meeting room	Lab area	Entertainment zone

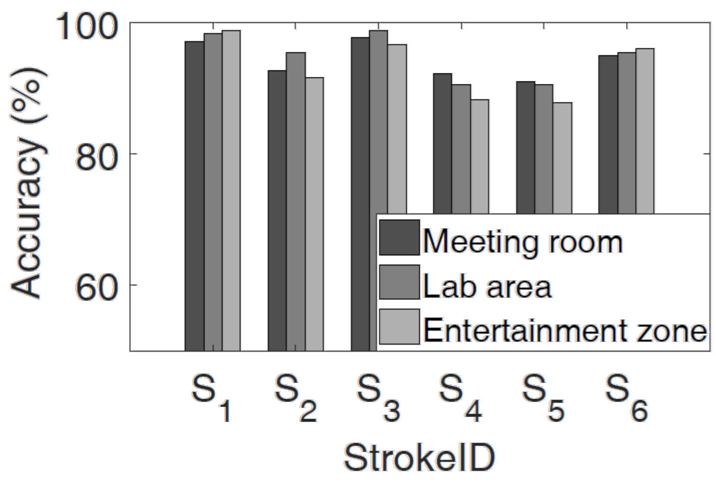
3(settings) X 6(participants)X 6(strokes)X 30(repetitions) = 3240 *strokes*

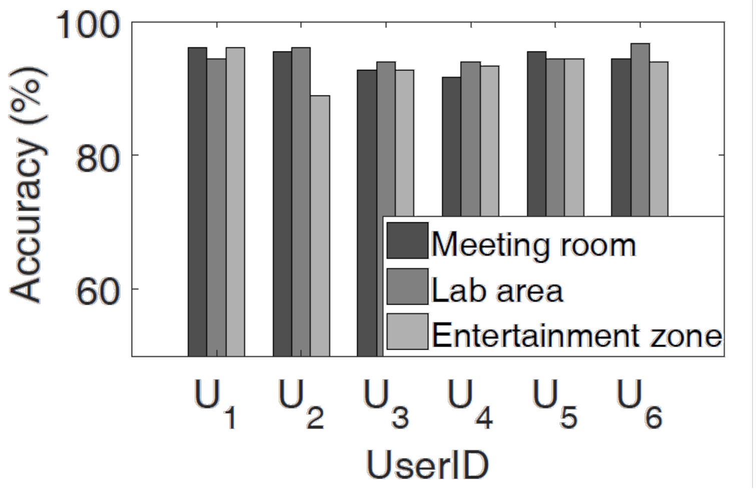
6(participants) X 10(words) X 20(repetitions) = 1200 *words*

Huawei watch 2 vs Huawei mate 9

Evaluation – stroke recognition







Different devices

- Smartwatch: 94.4%, Smartphone: 94.7%

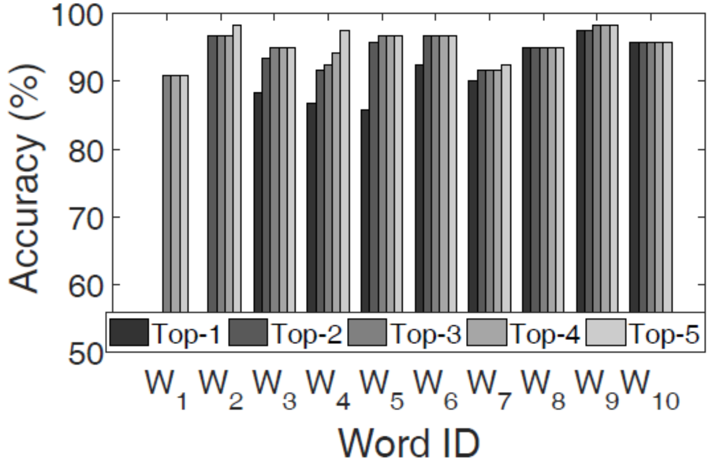
Different environment

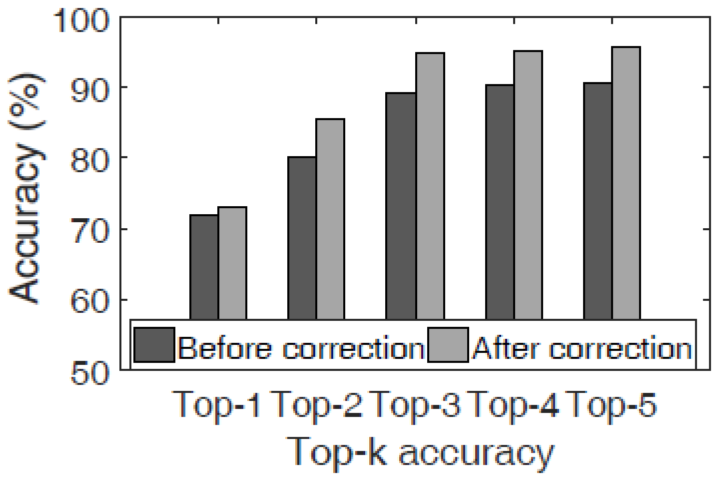
- 94.4%, 94.9% and 93.2% in meeting room, lab area and entertainment zone.

Different participants

- 95.6%, 93.5%, 93.1%, 93.0%, 94.8% and 95%, respectively.
- The standard deviation is about 1.1%.

Evaluation – word recognition





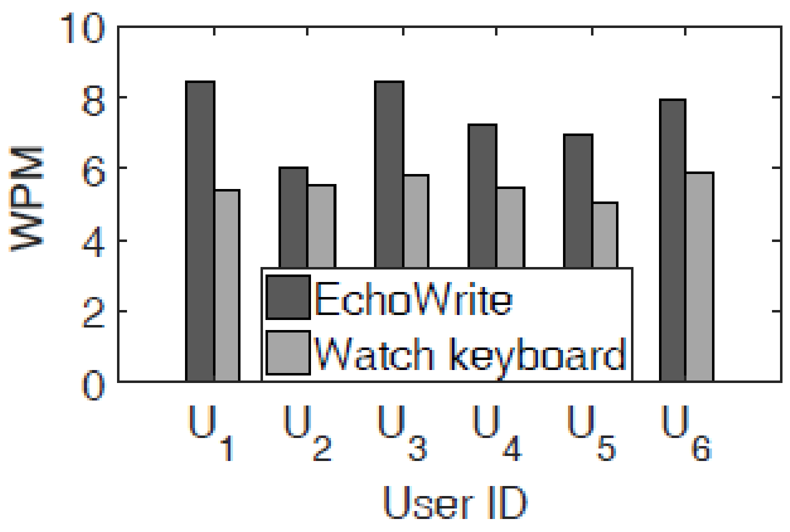
Different words

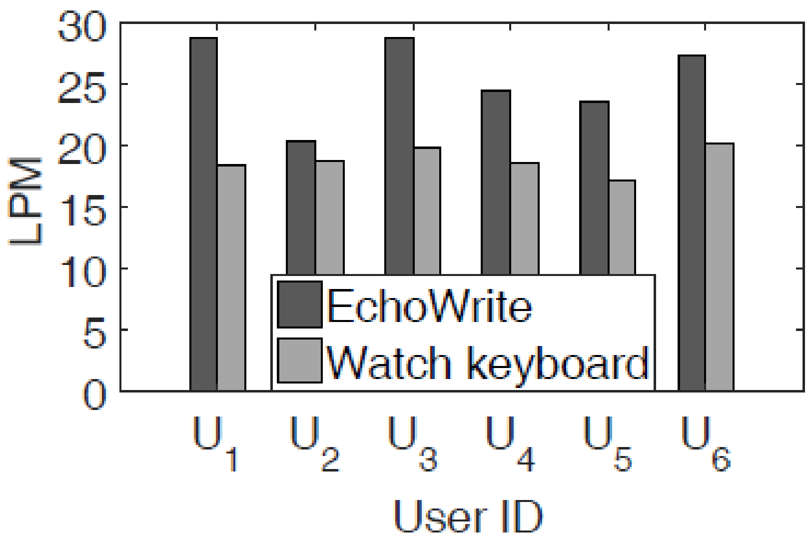
- Average top k accuracies over different words are 73.2%, 85.4%, 94.9%, 95.1% and 95.7%.
- Providing three candidates, the inferring accuracy is up to 94.9%.

Linguistic model

- The average accuracies are 84.5% and 88.9%, for cases with and without Linguistic model.

Evaluation – input speed



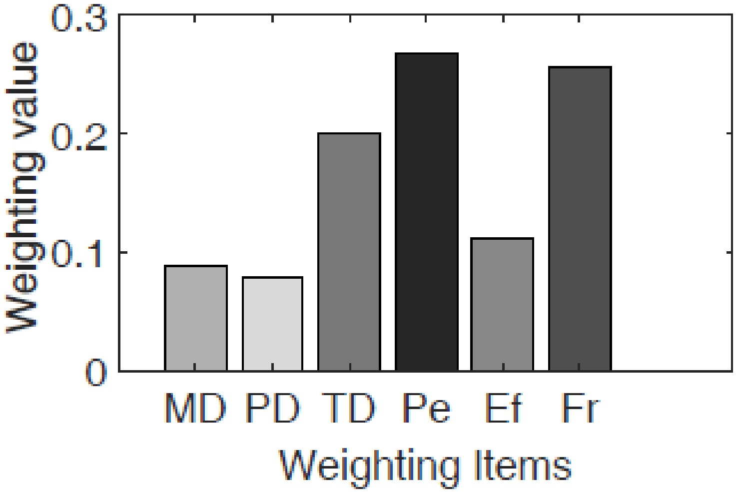


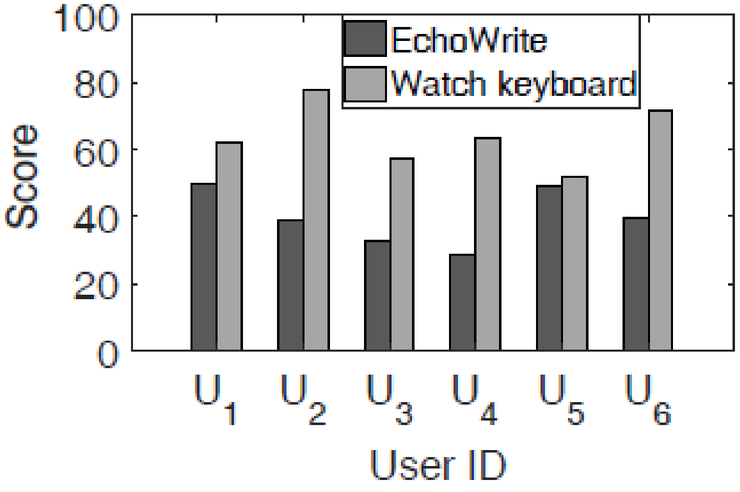
***WPM**: Words Per Min* ***LPM**: Letters Per Min*

Speed of text-entry

- The average texts-entry speeds over all participant with *EchoWrite* and smartwatch keyboard are 7.5 WPM and 5.5 WPM, respectively.

Evaluation - User experience





NASA-TLX workload factors:

- *mental demand (MD)*
- *physical demand (PD)*
- *temporal demand (TD)*
- *performance(Pe)*
- *effort (Ef)*
- *frustration (Fr)*

User experience assessment

- Performance, Frustration and temporal demand are the top 3 factors that affect users' assessment on a text-input system.
- the overall score of participants shows, smartwatch soft keyboard has higher workload than EchoWrite.

EchoWrite – conclusion

We design and implement EchoWrite which can recognize fine-grained finger-writing strokes without training.

With high-frequency signals and careful-designed processing pipeline, EchoWrite is robust to ambient noise and moving interference.

EchoWrite enables users to perform text-entry in the air with the speed of 7.5 WPM with the commodity microphone and speaker.

THANKS

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https://sites.google.com/view/yang-qiang/

Shenzhen University