Demo: Virtual Keyboard for Wearable Wristbands

Wenqiang Chen
Shenzhen University
Shenzhen, Guangdong, China
winston110110@gmail.com

Yanming Lian
Shenzhen University
Shenzhen, Guangdong, China

Lu Wang
Shenzhen University
Shenzhen, Guangdong, China
wanglu@szu.edu.cn

Rukhsana Ruby
Shenzhen University
Shenzhen, Guangdong, China

Wen Hu
University of New South Wales
Australia

Kaishun Wu
Shenzhen University
Shenzhen, Guangdong, China
wu@szu.edu.cn

ABSTRACT

The wearable devices are small and easy to carry but typically with poor interaction experience. For example, Apple iWatch does not support instant text message input feature because of the lack of keyboard availability on the tiny touch screen. To address this problem, we develop a novel system, termed iKey, which enables users to use the back of one of their hands as virtual keyboard for wearable wristbands. iKey recognizes keystrokes based on a location-based training model via body vibration. We will demonstrate a real time functional prototype of iKey in this demo.

CCS CONCEPTS

• **User Interfaces** → Input devices and strategies;

KEYWORDS

Smart watch text input, keystroke recognization, vibration localization

ACM Reference Format:
Wenqiang Chen, Yanming Lian, Lu Wang, Rukhsana Ruby, Wen Hu, and Kaishun Wu. 2017. Demo: Virtual Keyboard for Wearable Wristbands. In *Proceedings of 15th ACM Conference on Embedded Networked Sensor Systems (SenSys'17).* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3131672.3136984

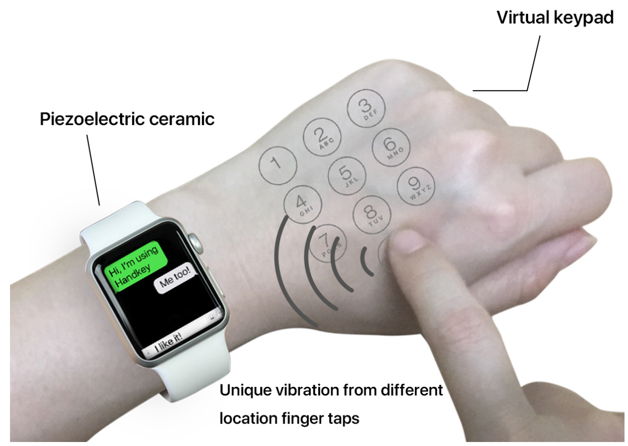

Figure 1: A sample example of iKey.

1 INTRODUCTION

In the past few years, we have seen the take-off of wearable wristbands such as Fitbit and Apple iWatch for fitness applications. The size of smart wristbands becomes smaller and lighter to provide better user experience. As a result, the touch screens on the wristbands also becomes smaller, which make user device interaction difficult. For example, Apple iWatches don't support instant text message input feature because the lack of keyboards in the tiny touchscreens.

Currently, to overcome the limitations of a small screen, speech recognition is one of the methods but sensitive to noise levels in the environments. Moreover, it is insecure for sensitive information such as password input because speech input is easy to be eavesdropped. For the same reason, it is also intrusive to the people surrounding the user. Recent work, FingerIO [3] and LLAP [5] achieve the mm level accuracy for fingertip tracing, which enables users to write letters on ubiquitous surface instead of tiny touchscreens. However, writing letters is significantly slower than typing them, which results in poor user experience.

In this demo, we present a novel system, termed iKey (in Figure 1), which enables a user to type on the back of one of her hands (her opisthenar) instead of a tiny touchscreen of a smart wristband. The idea is to utilize vibration mechanism as tapping in different locations on the opisthenar carries energy at different frequencies and over different distances to a vibration sensor on a fixed location of a wrist. The advantage of iKey is that vibration is resistant to sound noise. And the size of the opisthenar of a user is larger than tiny touchscreens which enables the user to type more quickly and conveniently. Specifically, we design a keystroke identification scheme that leverages location-based vibration information derived from a small piezoelectric ceramic vibration sensor which can be embedded to a smart wristband. Although keystroke identification via body vibration has been studied in Skinput [1], in which signal is collected from 10 sensors of an armband with a very high sampling rate (e.g., 55 kHz), iKey uses a small form factor sensor (see Fig. 2) only that makes it easier and more cost effective to be embedded on smart wristbands, and samples at an order-of-magnitude lower rates (e.g., 600 Hz) that makes it more efficient to run on resource limited smart wristbands. On the other hand, sampling at lower

SenSys'17, November 6–8, 2017, Delft, The Netherlands

ACM ISBN 978-1-4503-5459-2/17/11...$15.00
https://doi.org/10.1145/3131672.3136984

rate produces significantly less vibration information, we need to investigate novel methods and signal features for keystroke identification via body vibration.

To cope with these challenges, we first consider Mel-frequency cepstral coefficients (MFCC) as the features to describe the fine-grained location-based vibration information. Second, we use random subspace [2] concept to increase the diversity of limited training samples. Third, we use class-center classification and ensemble learning concept with majority voting to classify keystrokes. As a result, iKey achieve high keystroke recognition accuracy with one vibration sensor and significantly lower sampling rate.

2 IKEY ARCHITECTURE

2.1 Sensing

Piezoelectric ceramic sensor uses the piezoelectric effect, to measure the vibration intensity, by converting it to an electrical charge. In a piezoelectric ceramic device, mechanical stress, instead of externally applied voltage, causes the charge separation in the individual atoms of a material. Thus, the vibration caused by finger taps is able to be converted to an electrical charge. Figure 2 shows a sample piezoelectric ceramic sensor whose external diameter is 20 mm and thickness is only 0.35 mm. The small form factor of the sensor makes it easy to be embedded to a smart wristband as a chassis.

2.2 Data processing

We use dual-threshold endpoint detection algorithm [4] to segment keystrokes signal. Then, we use a 20 Hz Butterworth high pass filter to remove the DC component and low frequency noise. Also, it can remove the noise caused by human mobility at low frequency (less than 5 Hz). The vibration signal tapped on the opisthenar is realized in low frequencies (less than 200 Hz) domain. Thus, we set the cutoff frequency to 300 Hz of a Butterworth low pass filter. Furthermore, we use the MFCC as the features and set the number of channels in the Mel-Scale Filter Bank to 25 and use the first 40 MFCCs computed in a 35 ms windows with 5 ms window overlap.

2.3 Classification

We first adopt class-center classification concept, which is as follows. We calculate the center of each class in the training set. For each test sample, its distance is calculated from the center of each class. The nearest class will be the identification result. Due to the limited vibration information collected from a single sensor with low sampling rate, the accuracy is low with the class-center classification method. Then, we adopt random subspace method to increase the diversity of training samples. We sample randomly from the training set then get several sub-training-set in subspaces. For each subspace, with the class-center classification method, we obtain each sub-result. Finally, we use majority voting mechanism to process these sub-results and get the final identification result.

3 EVALUATION

We have implemented our system using a vibration sensor connected to a Raspberry Pi via an Analog to Digital Converter (ADC). We recruited 30 participants to tap on a marked TenKey layout mounted on one of their opisthenar 30 times for each key. Thus, we have 9000 ($10 \times 30 \times 30$) samples. We validate the resultant classification outcome via 10-fold cross validation technique. Figure 3 shows the average classification accuracy of each participant.

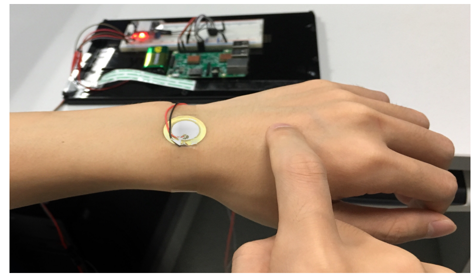

Figure 2: A sample prototype of iKey.

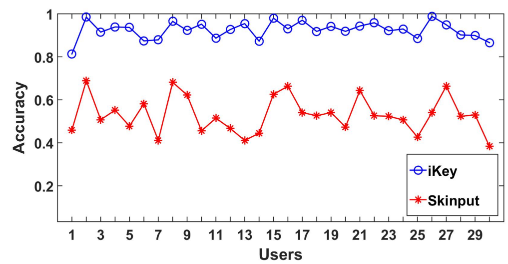

Figure 3: Classification accuracy comparison between iKey and Skinput.

The average accuracy of Skinput is 53% while that of iKey is 92.4%, which represents 1.74 times improvement.

4 DEMONSTRATION

We will encourage SenSys17 attendees to use our system. Participants will be asked to wear iKey to train the system. Then, participants will be guided to tap on the opisthenar to input numbers which simulates making a call on a smart wristband. At the time of demonstration, the input from users via iKey will be displayed on a 10.1-inch touchscreen connected to Raspberry Pi in realtime. We require one power point to power the 10.1-inch touchscreen. The normal Internet connection is satisfied for the system. We will require approximately half hour for our system setup.

ACKNOWLEDGMENTS

This research was supported in part by the China NSFC Grant 61472259, 61502313, Guangdong Natural Science Foundation 2017A030312008, Shenzhen Science and Technology Foundation (No. JCYJ20170302140946299, JCYJ20170412110753954, JCYJ20150324141711621), Guangdong Talent Project 2014TQ01X238, 2015TX01X111 and GDUPS (2015).

REFERENCES

[1] Chris Harrison, Desney Tan, and Dan Morris. 2010. Skinput: appropriating the body as an input surface. in Proc. ACM CHI, 453–462.
[2] Tin Kam Ho. 1998. The Random Subspace Method for Constructing Decision Forests. *in IEEE Transactions on Pattern Analysis and Machine Intelligence* (1998), 832–844.
[3] Rajalakshmi Nandakumar, Vikram Iyer, Desney Tan, and Shyamnath Gollakota. 2016. Fingerio: Using active sonar for fine-grained finger tracking. in Proc. ACM CHI, 1515–1525.
[4] L R Rabiner and R W Schafer. 2007. Introduction to Digital Speech Processing. *in Foundations and Trends in Signal Processing* (2007), 1(1):1–194.
[5] Wei Wang, Alex X Liu, and Ke Sun. 2016. Device-free gesture tracking using acoustic signals. in Proc. ACM Mobicom, 82–94.