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Wireless IoT Motion-Recognition Rings and a Paper Keyboard

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ABSTRACT In this paper, we present a new scheme for implementing virtual keyboards, which uses only two to four motion-recognition rings per hand and a two-dimensional keyboard template (e.g., an A4 size paper with printed key positions). It has the benefit of portability, customizability, and low-cost when compared with existing approaches. Essentially, we have shown that wearing two wireless IoT rings on the middle phalanges of two fingers of each hand, users can input the alphabetic characters into a computing device by typing on a flat paper on a desk, and potentially in mid-air. We have demonstrated that two rings are sufficient in capturing the gestures and motions of all fingers in a typing hand for keystrokes recognition. A single wireless IoT ring, which weighs 7.8 grams, consists of a Bluetooth low energy (BLE) unit, a micro inertial measurement unit (mIMU), and a cell battery. The 3-axes attitude angles and the Z-axis acceleration of each ring are adopted as the features for keystroke recognition. The overall keystroke recognition accuracy rate can reach as high as 94.8% when two IoT rings are worn by a user on each hand; this accuracy rate increases to 98.6%, when four rings are worn on each typing hand.

INDEX TERMS Wearable sensors, wireless IoT ring, keystroke recognition, virtual keyboard, micro IMU.

I. INTRODUCTION

Nowadays human-computer interaction has become an essential living skill for the general public. In particular, the typing on QWERTY keyboards has been a dominant communication method between humans and machines for many years. Although technological advances have greatly accelerated the development of other devices and computer input methods, the keyboard is still the pervasive device today for the general users of computing systems. But the problems that consumers experience when using a keyboard, such as poor portability and typing noise, have yet to be solved. To address these problems, various methods and devices have been developed with the goal of replacing the physical keyboard for human-computer interactions. For example, speech input [1] is a popular alternative solution, which seems more natural and much more ''portable'', but it has problems such as low accuracy of dialectal accent recognition and voice interference to and from people nearby. Another increasingly popular input method is using a software-based screen keyboard [2], but this method limits the input speed and the accuracy becomes a concern when a screen becomes too small.

Many concepts and prototypes of virtual keyboard have been proposed and developed recently against the backdrop of booming human-computer interaction technologies in the past few years. Unlike QWERTY keyboards, virtual keyboards break the limitation of physical contact between fingers and keys, and an increasing number of commercial virtual keyboards have been developed based on different principles and platforms, but thus far, no virtual

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keyboard technology has gained wide consumer acceptance. Virtual keyboards can be roughly divided into three categories: *vision-based*, *wearable*, and other *non-contact* virtual keyboards.

A. VISION-BASED VIRTUAL KEYBOARDS

This type of virtual keyboard come in two popular types. The first type generally adopt a camera to recognize keystrokes by tracking finger movements or position through optical image data and gesture recognition algorithms [3]–[9]. The other type is the laser-based virtual keyboards [10]–[13] that mostly utilizing Infrared (IR) light and a camera to detect the movement and position of the fingers on a laser-projected virtual keyboard. A key problem with this type of technology is that, when a finger pauses on a key's virtual position, it is hard to determine whether to the motion should be interpreted as a key-typing input or just a resting finger. Also, this method still has the portability problem compared to wearable virtual keyboards.

B. WEARABLE VIRTUAL KEYBOARDS

Wearable virtual keyboards [14]–[18] are installed with various sensors on the hands or fingers to detect their gestures and motion, which can be matched with the motions of typing different keys. The "data glove" [18]–[22], integrating sensors, is a common example. Through detecting finger gestures, it can be applied as a keyboard, a mouse, or other interactive devices. However, this kind of gloves is often unwieldy, constraining, and uncomfortable to use. Another type of virtual input scheme is the hand-writing approach [23]–[28], which applies the motion sensors to acquire the motion trajectories or motion features for the recognition of hand-written characters. All these wearable virtual keyboards are aimed at more portability and comfort, and they indeed have been improved significantly recently, but more revolutionary works are required in order to improve the existing devices for consumer acceptance.

C. OTHER NON-TOUCHED VIRTUAL KEYBOARDS

There are also many other types of novel and fashionable wearable virtual keyboards. The WIKEY system [29] proposed by K. Ali is a good example, which is established using the change in Channel Status Information (CSI) values of WiFi signals when typing. Also, other schemes such as acoustics-based [30]–[32], electromagnetic emissions-based [33] and EOG (electrooculography) or EEG (electroencephalogram) based [34]–[36] principles have also been explored to create virtual keyboards.

In this paper, we present a new wearable virtual human-computer interaction technique based on using as little as two wireless IoT rings on each hand and a paper with printed keyboard patterns. For this new technology, keystrokes are recognized based on the varying finger motions and gestures when typing different keys. Attitude angle and acceleration of the fingers on each hand are used as the main features for keystroke recognition. By analyzing the correlation between the touching finger and non-touching fingers during typing, we found that two wearable IoT sensors are enough to support the letter-typing work of each hand with reasonable accuracy. In our experiments, the best combination for two rings on each hand is: two rings worn on the *little* and *middle* fingers of the left hand, and two rings worn on the *ring* and *middle* fingers of the right hand. The result shows that this scheme currently delivers an average recognition rate of about 94.8% for all 26 English alphabet keys on a 'paper keyboard'. With more data collection and feature selection, or possibly wearing more rings per hand, we are optimistic that this technology could provide a higher keystroke-input accuracy in the future.

We note here that, most of the proposed wearable virtual keyboards, such as the data glove and "Tap" [15] often require users to learn a new typing method different from the traditional keyboard-typing motions. Our proposed wireless IoT rings based method allows users to input letters with less constraint and type keys using their own typing behavior. With further refinement of software, we envision that users can transfer their typing habit from the traditional keyboards to our virtual keyboard smoothly. Moreover, our proposed scheme has the advantages of less typing noise and extreme portability; we expect this new type of input method can be used in many situations, such as quiet offices, meeting rooms, and even public places where using a physical keyboard is inconvenient. With the further development of wearable sensor technology, the IoT rings will be much smaller and cheaper in the near future, and therefore, it could shift the paradigm of virtual computer-human interaction technology for consumer computing devices in the coming decade.

II. SYSTEM SETUP

A. HARDWARE SYSTEM

The IoT ring consists of a BLE (Bluetooth Low Energy) unit, a mIMU (micro Inertial Measurement Unit), and a cell battery. The IoT ring has a small size (19mm $\times$ 17mm $\times$ 25mm) and weight (7.8grams in total, including a 0.8grams coin cell battery, a 1.7grams sensor board, and a "ring" structure weighing 5.3grams). In the future, these IoT rings can be further reduced in size such that users could wear these devices as jewelry items when typing on a desk or even in air. In designing the IoT rings, we mainly considered: 1) low energy consumption and 2) small chip size. In Table 1, we summarize the corresponding parameters of the commonly used chipsets which have BLE and mIMU chips.

As shown in Table 1, DA14583 chipset (which includes a BLE chip, a 3-axes accelerometer and gyroscope chip, and a 3-axes magnetometer chip) meets the requirement of lower wireless transmission power and smaller overall footprint. Hence, we developed wireless sensor module based on the DA14583 chipset with specifications of: 1) Bluetooth Low Energy chip using 3.4mA for data transmission and 3.7mA for receiving signals; 2) a BMI160 chip with 3-axes accelerometer ($+/-2$g range with resolution

TABLE 1. Parameter comparison between different commonly used chipsets with BLE wireless data transmission.

No.	Device Name	Power Consumption TX (mA)	Power Consumption RX (mA)	Voltage (V)	Chip Size
1	Dialog Semi. DA14583	3.4	3.7	2.4~3.3	5 mm×5 mm
2	TI CC2650	6.1	5.9	1.8~3.8	5 mm×5 mm
3	Nordic Semi. nRF52832	5.3	5.4	1.7~3.6	6 mm×6 mm
4	Toshiba TC35680FSG	6.0	5.1	1.9~3.6	5 mm×5 mm

of 16384LSB/g) and 3-axes gyroscope (+/ − 2000deg/sec range with resolution of 16LSB/(deg/sec)); 3) a BMM150 chip with 3-axes magnetometer (+/ − 2300μT (x, y-axis), +/ − 2500μT (z-axis) range with resolution of 0.3μT/LSB).

The entire board could be operated with a 48mAh coin cell battery, which could function for about 8 hours continuously (with sample frequency of the IoT Ring set to 65HZ for data collection). The chipset is widely used in such applications such as augmented reality, indoor navigation, and motion capturing (e.g., see [37]). The overall electrical components are orderly arranged in a small space, which could be integrated within a wearable ring for our project, as shown in Fig. 1(a). For the experiments described in this paper, the rings are worn on the middle phalanges of the fingers, as shown in Fig. 1(b).

B. PROPOSED RING AND PAPER KEYBOARD CONCEPT

Our proposed paper-keyboard scheme is built based using wearable IoT rings. The individual rings are small, comfortable to wear, and easy to use compared with existing methods, such as vision-based, WiFi-based, and electromagnetic emissions-based input devices. The key concept is to use MEMS (microelectromechanical systems) motion sensors to collect the motions of fingers while they undergo typing motions for different keystrokes. Our basic hypothesis is that, during the typing motion of a particular key, a user will move some fingers towards to the key in a unique formation and direction, and hence, a special angular pattern in the time-series for typing each key can be detected by the IoT rings worn on specific fingers. We have shown that it is possible to utilize the attitude angle to quantify the unique patterns of the finger motions, and the relationship between finger motions and keystrokes could be mapped.

The keystroke recognition process, which is shown schematically in Fig. 2, entails data collection, data processing, feature extraction, and data classification. When the ''keys'' on a paper are pressed, the motion sensing rings will collect and send the motion data to a mobile device or a computer through BLE, and subsequently, the typing motion data is sent to a remote server via Cloud technology. All the feature extraction and classification work could be completed on 'Cloud' computing platforms if mobile phones or iPads could not perform the computing work fast enough.

Correspondingly, the implementation method of the experiments is shown in detail in Figure 1. Each alphabetic key is typed by a particular finger according to the standard typing method, which is shown in Fig. 1(c). Each subject can type in their habitual speed and gesture. Before typing, fingers of both hands are put on the Home Row Keys correspondingly. The Home Row Keys are defined as: ''ASDF'' for the left hand and ''JKL;'' for the right hand. Also, to eliminate the

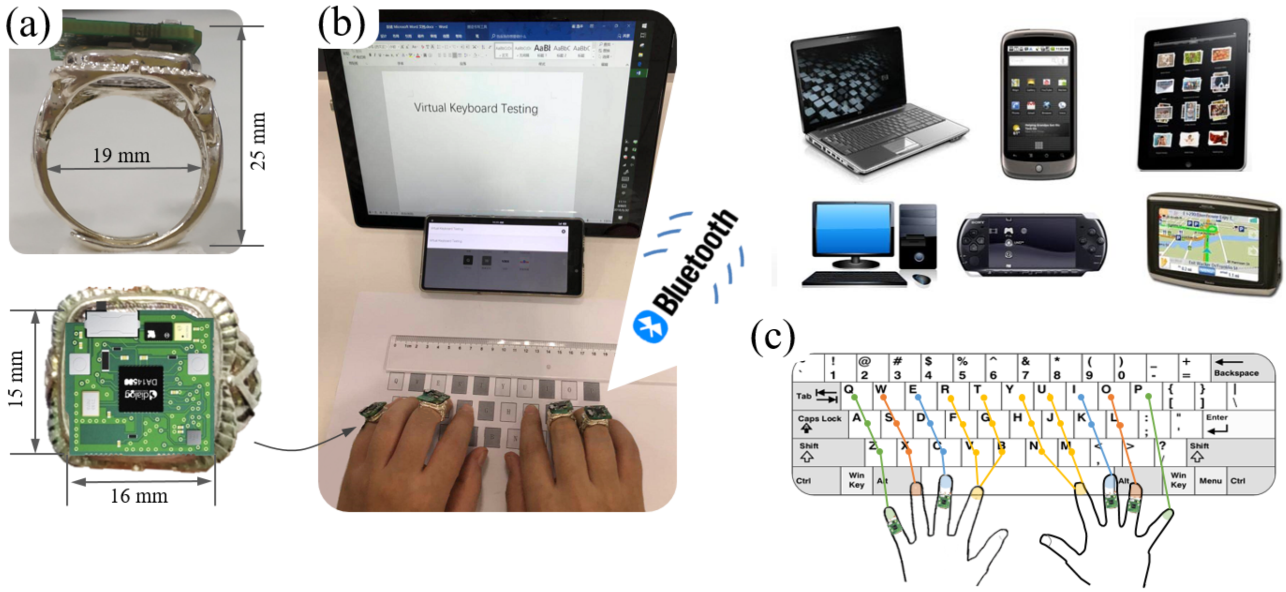

FIGURE 1. The experimental setup, which includes the wearable IoT rings and the paper keyboard. (a) Dimensions of the motion sensing board (including the coin cell battery) which is embedded in a ring. (b) Photograph of a student performing experiments using the IoT rings and a printed keyboard (18.5 × 5.5 cm) on a paper; the individual key dimensions and locations are the same as those of the keys of a standard physical keyboard. Bluetooth is adopted to transmit the IMU sensor data to the mobile devices. Two rings are worn on the little finger and middle finger of the left hand, while the other two rings are worn on the ring finger and middle finger of the right hand. (c) The corresponding relationship of the fingers and keys in standard typing method.

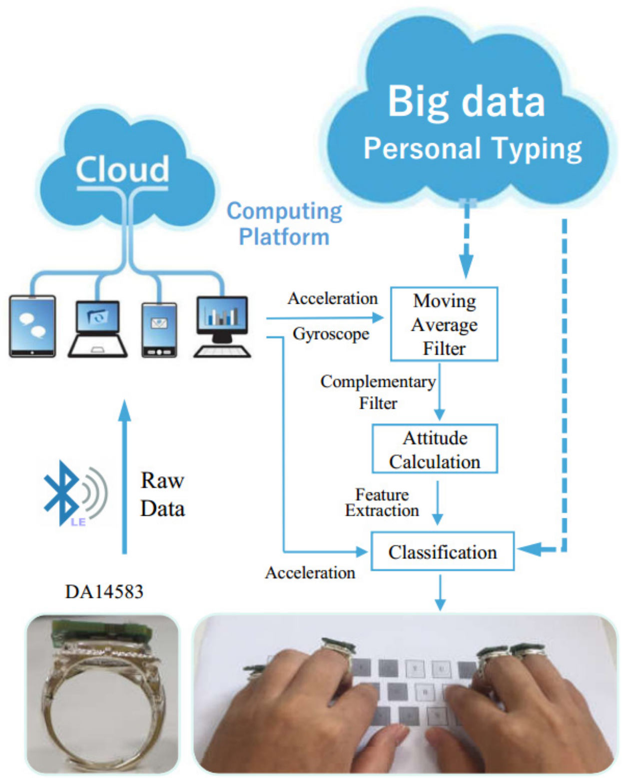

FIGURE 2. The schematic diagram of the keystroke recognition process.

impacts of psychological and other factors, the subjects are required to look at the monitor during typing.

III. EXPERIMENTAL METHOD

A. DATA PREPROCESSING

To remove the Zero drift of sensors, the accelerometer and gyroscope of the ring were calibrated separately before the experiment. After the motion data was received, we applied a zero-bias compensation to eliminate the zero bias. The algorithm is shown as following the equations:

$$x' = \frac{1}{m-n}\sum_{i=n}^{m} x_r(i) \tag{1}$$

$$x(i) = x_r(i) - x', \quad i = n, \ldots, m \tag{2}$$

where x_r is the raw data of accelerometer and gyroscope, n is the starting point of the sampling sequence, m is the ending point, and $x(i)$ is the value after zero bias compensation [38].

Next, a moving average filter was applied to eliminate the high-frequency noise of accelerometer data and smooth the waveforms. The filter is shown in the following equation:

$$y(i) = \frac{1}{M}\sum_{j=0}^{M-1} x[i-j] \tag{3}$$

where $y(i)$ is the output signal, and M is the size of the moving window of the average filter [39].

B. FEATURE SELECTION

From the comparison of the waveforms collected from typing different keys using the accelerometer, angular velocity, and magnetometer data, we found that none of the three can produce an acceptable accuracy of keystroke recognition. As discussed by prior research results, accelerometer data could be used to easily distinguish some finger and hand gestures [40]–[43], such as up, down, left and right. But it is still difficult to recognize the keys with high accuracy because of the high similarity among these adjacent keystrokes and the changing typing speed. Keystroke recognition using the angular velocity data also has the same problems. And, the magnetometer data is easily affected by environmental noise.

Due to the differently positioned keys in a keyboard layout, the typing path of each keystroke should be unique, and which should lead to different finger gestures and motions. And, assuming that the typing motion of fingers is stable and consistent, it is possible to recognize keystrokes by analyzing the gestures of fingers. We hypothesize that during the typing process, the attitude angles of the fingers can be used to express the gestures of fingers. Therefore, we used attitude angles as the features to describe the typing motion of fingers. There are three kinds of attitude angles: *pitch* angle, *roll* angle and *yaw* angle. To obtain the attitude angles, we adopted angle complementary filter for angle estimation [45] (for only the *pitch* and *roll* angles). The algorithm is shown as follows:

$$\theta_{Angle} = (1-\alpha)^* a_{Acc} + \alpha^*(\theta_{Angle} + \omega_{Gyro}{}^* dt) \tag{4}$$

where θ_{Angle} is the final estimated attitude angle, a_{Acc} is the angle estimate based on measured accelerometer data, and ($\theta_{Angle} + \omega_{Gyro}{}^*$dt) is the angle estimate based on measured angular velocity integration over time, α is the weight coefficient, which is determined by the following equation:

$$\alpha = \frac{\tau}{\tau + dt} \tag{5}$$

where τ is the time constant of the filter. As for yaw angle, we only estimated the angle roughly using the angular velocity, because the angle is not affected by the acceleration data.

To verify the stability and consistency of the angles, we carried out a series of experiments, and collected 50 sets of data for typing each alphabetic key. Focusing on the relative values of the attitude angles, the initial angle is shifted to zero. In Fig. 3, as examples, we show the calculated attitude angles as a function of time of the motions of different fingers of the left hand as they are used to type three different keys. The red lines represent the average attitude angles of these data sets. We can see evident differences among different keystrokes using this method. And, as shown in the experimental data in Fig. 3, the change of attitude angles of a finger is consistent while typing a particular key. We adopted the difference between the angles before and after a keystroke as the features for keystroke recognition. Despite the differences

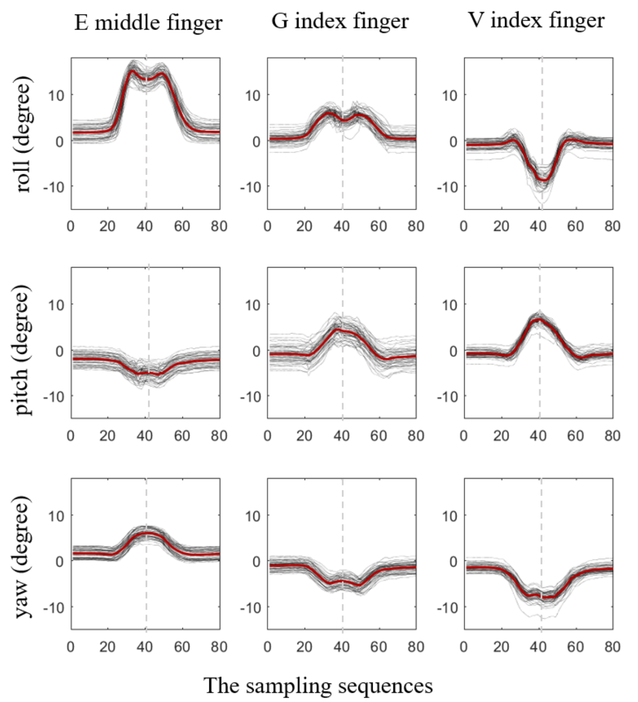

FIGURE 3. The waveforms of 50 sets of time-series attitude angles data for the keys 'E', 'G', and 'V' typed by the left hand. The roll and pitch angles were calculated based on Eq. 4, and the yaw angle was calculated by integrating the angular velocity data from the gyroscope.

of the measured attitude angles among keystrokes of typing the same key (i.e., from typing the same key 50 times), the dynamic trend in attitude angles of a specific key is the same.

C. FEATURE EXTRACTION

In Fig. 4, we present the change in the attitude angles of four fingers for both hands when typing different keys. By using a keyboard typing monitor software developed by our team and repeated experiments, we found a peak or valley in the middle of the attitude angle waveforms, which only occurs at the moment of typing. At the same time, a sharp change occurs in the waveforms of the acceleration data, which indicates that the finger is pressing a key. Therefore, these peaks or valleys of the angle waveforms were used as the basis for feature extraction.

The first step for angle extraction was to interpret the waveform of each keystroke by accurately detecting the starting and ending points. From Fig. 4, we see that the amplitude of attitude angle change of some keys is small, and hence it is not easy to detect the starting and ending points of each peak and valley directly. Since the change in the raw angular velocity data from the gyroscope are more obvious for these cases, the starting and ending points were detected by using the raw angular velocity data if the amplitude change of the attitude wave form is too small. For example, from Fig. 5(a), we can see that the angular velocity data of a particular finger is stable when no key is pressed. Once a key is pressed, the angular velocity in all 3 axes changes sharply. And, when the typing is finished, i.e., the typing finger moves back to its original position, the angular velocities return to their normal values again. Therefore, the starting and ending points can be detected by the forward difference method easily, as shown in equation (6):

$$\Delta\omega_k = \left|\omega_{x_k} - \omega_{x_{k-1}}\right| + \left|\omega_{y_k} - \omega_{y_{k-1}}\right| + \left|\omega_{z_k} - \omega_{z_{k-1}}\right| \quad (6)$$

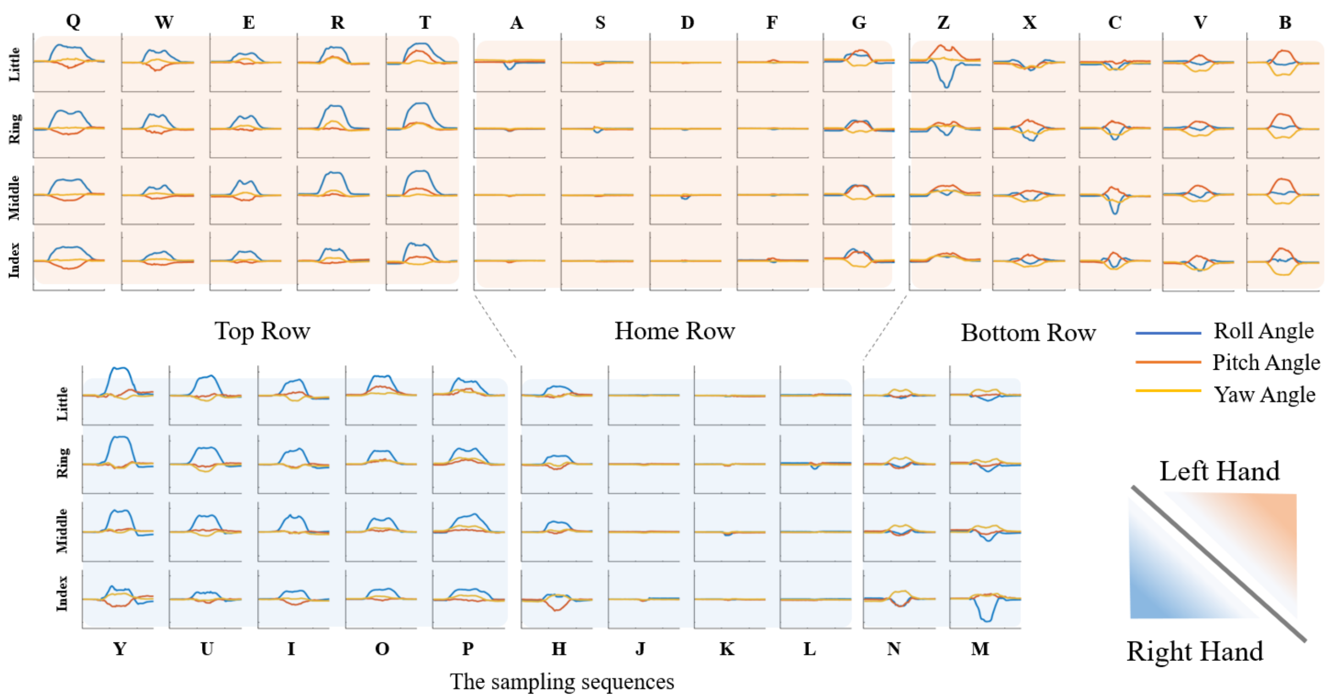

FIGURE 4. The attitude angle waveforms for all 26 alphabetic keys as typed by different fingers of each hand.

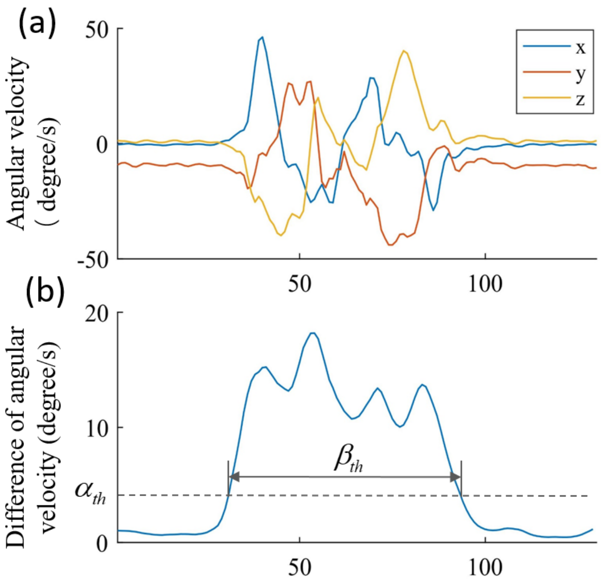

FIGURE 5. The starting and ending points detection for the recognition of the angular waveforms of keystrokes. (a) 3-axes angular velocity data. (b) The sum of the absolute difference values of the angular velocity on 3-axes.

where $\Delta\omega_k$ is sum of the absolute difference of 3-axes angular velocities at k point. A moving average filter is applied again to smooth the differential sequence of angular velocity, which is then defined as:

$$S(k) = \frac{1}{N}\sum\nolimits_{i=k-N}^{k} \Delta\omega_k \tag{7}$$

where N is the window size of the moving filter [46].

Thresholds α_{th} and β_{th} were set to detect the starting and ending points of the waveforms, where β_{th} is a length threshold of the motion time used to eliminate the accidental jitters of the fingers. For the sampling sequence after difference, if any point satisfy the condition $S(k) > \alpha_{th}$, we will consider $S(k)$ as a starting points or ending point. Then, an extra condition was added to judge the attribution of the point:

$$\begin{cases} S(k) > S(k-1), & S(k-3) \\ S(k) < S(k+1), & S(k+3) \end{cases} \tag{8}$$

$$\begin{cases} S(k) < S(k-1), & S(k-3) \\ S(k) > S(k+1), & S(k+3) \end{cases} \tag{9}$$

If $S(k)$ satisfied the set of conditions in (8), it was considered as the starting point. Similarity, if $S(k)$ satisfied the conditions in (9) it was identified as the ending point. However, the hand jitter and environmental noisy may cause disturbance on the recognition of motion patterns. Hence, β_{th}, which was used to denote the holding time of pressing a key, was also used to restrict the length of the data sampling window. If we define the starting point as k_1, and the ending points as k_2, then the limitation of the keystrokes window can be described as the inequality equation:

$$k_2 - k_1 > \beta_{th} \tag{10}$$

Then, the final typing point k can be selected by the relationship below:

$$k = (k_1 + k_2)/2 \tag{11}$$

The angle values of the 3 axes at point k were extracted as the feature vector for recognition. To explore a suitable classifier for keystroke recognition, we compared four typical classifiers: the distance-based *k-Nearest Neighbor* (k-NN) algorithm, the probability estimation-based *Naive Bayes* (NB), the SRM (Structural Risk Minimization) principle-based *Support Vector Machine* (SVM) algorithm, and the *Random Forest* (RF) algorithm that consists of multiple decision trees [47]. In our comparative analysis, *accuracy*, *recall* and *precision* were adopted as the indicators to evaluate the performance of these algorithms.

IV. EXPERIMENTAL RESULT

A. COMPARISON BETWEEN DIFFERENT CLASSIFIERS AND SUBJECTS

For experimental results presented below, three subjects typed in their own typing speed and finger gesture for data collection. The 26 letters in four different pre-determined orders of letter sequence were typed using the paper keyboard and the angular velocity data were collected. That is, we have defined 4 sequences of how each subject should type the 26 letters, where the order of the letters in each sequence was randomly chosen. Then, each subject performed 100 sets of typing experiments, with 25 sets of experiments for each sequence of letters. We randomly selected 20 sets of data as the template and applied the other sets of data for classification. As mentioned before, four typical classifiers, i.e., k-Nearest Neighbor (k-NN), Naive Bayes (NB), Support Vector Machine (SVM) and Random Forest (RF), were adopted and evaluated to recognize the keystrokes. The recognition accuracy of each algorithm is shown in Table 2.

TABLE 2. The recognition accuracy of four classifiers for three different subjects of each hand.

Type		k-NN	NB	SVM	RF
	A	98.0%	97.7%	97.1%	97.2%
Left Hand	B	99.1%	98.3%	98.3%	98.1%
	C	95.6%	94.8%	92.8%	94.2%
	A	98.3%	96.3%	95.0%	97.8%
Right Hand	B	96.8%	96.9%	92.6%	95.3%
	C	95.0%	93.5%	91.8%	95.2%

As shown in Table 2, the recognition accuracy is different among the three subjects A, B, and C, which is caused by the variability of their individual typing motions. However, the overall accuracy rate for each subject can be as high as 95% for all 26 keystrokes. The classifier k-NN delivers a higher accuracy than the other classifiers as shown in Table 2 and Fig. 6. Hence, we will present and discuss our experimental results using the k-NN as the classifier below.

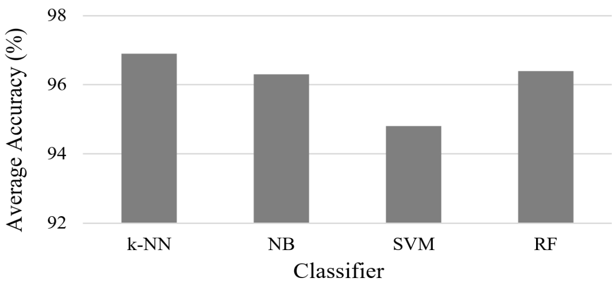

FIGURE 6. The average accuracy of three subjects for both hands based on different classifiers.

TABLE 3. The confusion matrix of recognition results. The data of subject C wearing four rings was utilized on both hands for keystroke recognition.

Left Hand

(a)

KEY	A	B	C	D	E	F	G	Q	R	S	T	V	W	X	Z	Recall(%)
A	70					3				6					1	88
B		80														100
C			76									1		3		95
D	1			67		6				5				1		84
E					76						1		3			95
F	5			1		74										93
G							80									100
Q					1			78	1							98
R									80							100
S				1		3				76						95
T					4						76					95
V												80				100
W					2								78			98
X			3											77		96
Z	1														79	99
Precision(%)	91	100	96	97	92	86	100	100	99	87	99	99	96	95	99	

Right Hand

(b)

KEY	H	I	J	K	L	M	N	O	P	U	Y	Recall(%)
H	80											100
I		79						1				99
J			72	5	3							90
K			3	77								96
L			6		74							93
M						78	2					98
N							80					100
O		1						78			1	98
P									80			100
U		2						2		73	3	91
Y	3	5						1	1	5	65	81
Precision(%)	96	91	89	94	96	100	98	95	99	94	94	

As an example, the detailed recognition results of subject C for typing each of the 26 alphabets are shown in the *confusion matrix* of Table 3. For a particular key typed, the column data represents the false-positive (FP) recognitions while the row data shows the false-negative (FN) recognitions. The diagonal elements of the confusion matrix are the true-positive (TP) recognitions. For convenience, the results from left hand are discussed as an example. The overall ***accuracy*** of keystroke recognition from typing with the left-hand fingers is above 95% (i.e., sum of TPs/total no. of samples, where the total number of samples is 15keys x 80samples/key). However, the ***recalls*** (TP/(TP + FN)) of the keys 'A' and 'D' were below 90%. Keys such as 'A', 'S', 'D' and 'F' were misidentified due to their similar feature patterns. Take the key 'F' for example, it was misidentified as key 'A' five times and as key 'D' for one time. Hence, the ***recall*** for typing the "F" key is about 93%, and the ***precision*** (TP/(TP + FP)) is only 86%. Low precision was also found in another two groups of keys: 'W', 'T' and 'E', and 'C' and 'X'. They could be easily mistaken as each other because of the similar typing motions of the subject. These problems also occurred when the keys were typed using the right hand. Our analysis of the experimental process indicates that the habit of typing is very hard to change for individuals. However, the feature vectors of typing each key can be improved to produce more differentiable differences in separating the typing motion data. Therefore, it became necessary to find other new features to improve the recognition accuracy as discussed in the following sub-section.

B. IMPROVEMENT OF FEATURE VECTORS

The raw acceleration data proved to be effective for improving the accuracy of keystroke recognition. This is because the typing finger will induce a greater fluctuation in acceleration data than the other fingers, especially for typing the Home Row Keys. In Fig. 7, we show the acceleration data measured from different fingers of each hand when they typed the Home Row Keys.

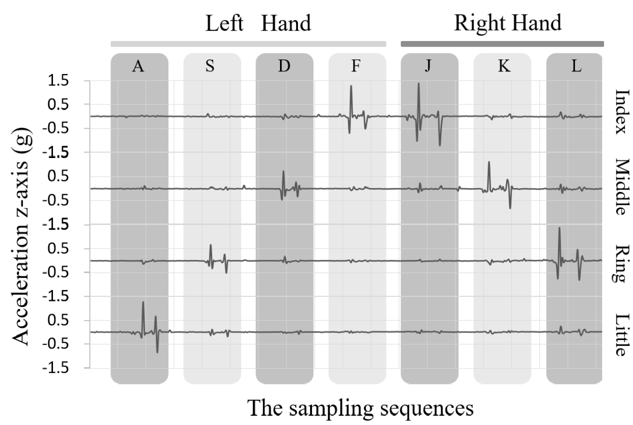

FIGURE 7. Comparison of acceleration data from different fingers of each hand when they typed the home row keys.

Take the key 'S' for example, when it is typed, the typing finger (*ring* finger) shows a much bigger fluctuation in acceleration. Therefore, besides being factored into the calculation of attitude angles, the z-axis acceleration data was also added into the keystroke feature vectors. After the recognition of keystrokes using machine learning algorithm, we adopted the maximum of acceleration data on z-axis to assist the recognition of the Home Row Keys, as shown in Fig. 7. With these acceleration features, we improved the recognition accuracy of the Home Row Keys by identifying or excluding the candidate keys.

Table 4 shows the final recognition results for each hand after adding the acceleration data. As shown, the new feature vectors, which include the acceleration data, can greatly increase the accuracy of keystroke recognition. By using this method, the overall recognition accuracy for typing all

TABLE 4. The accuracy of keystroke recognition before (type 1) and after (type 2) the improvement of feature vectors with acceleration data on each hand.

Type		A	B	C
Left hand	1	98.0%	99.1%	95.6%
	2	99.5%	99.4%	98.2%
Right hand	1	98.3%	96.8%	95.0%
	2	99.0%	97.7%	96.8%

TABLE 5. Accuracy of wearing the IoT rings on different combinations of two fingers. (Notations: 1-Little finger, 2-Ring finger, 3-Middle finger, 4-Index finger).

Type		1,2	1,3	1,4	2,3	2,4	3,4
Left Hand	A	94.3%	96.7%	90.1%	95.9%	95.0%	94.2%
	B	96.1%	98.2%	96.4%	94.9%	92.6%	94.3%
	C	91.6%	91.6%	89.7%	89.7%	86.7%	84.6%
Right Hand	A	91.4%	92.0%	86.5%	96.8%	92.5%	88.2%
	B	86.0%	87.8%	81.5%	94.3%	88.9%	89.4%
	C	83.5%	87.4%	88.1%	90.5%	88.5%	90.2%

26 keys on the paper keyboard is increased to 98% on average for the 3 test subjects. This method is more effective for subject C than it is for subjects A and B in terms of improving the accuracy of keystroke recognition. This means that the more the features, the broader applicability the method has.

C. KEYSTROKE RECOGNITION WITH TWO RINGS ON EACH HAND

From the experiments, we also found a significant correlation between the motion of the finger touching a key on the paper keyboard (i.e., the finger that the user utilized to type a particular key) and some of the fingers that do not touch the keyboard. That is, when one finger is typing on a key, the other fingers will move with it naturally, which makes it possible to recognize keystrokes with fewer rings. Therefore, different combinations of fingers wearing rings were tested. As we reduced the number of rings from four to one, the accuracy rate gradually decreased as expected, while the accuracy for the scenario where three or two rings are used are more acceptable. A summary of the experimental results based on two rings for each hand is provided in Table 5.

Table 5 shows the recognition accuracy on each hand of the 3 test subjects. For all these three subjects, the combination of rings worn on the *little* finger and *middle* finger of the left hand shows a higher accuracy than each of the other combinations. While for the right hand, the best combination of rings is worn on the *middle* finger and *ring* finger of the right hand. Moreover, experiments also showed that the difference in the accuracy of different subjects increased when a smaller number of rings were used; this is because more rings are required to provide enough information for recognizing different ways of typing. When the number of rings was reduced to one, the keystroke recognition accuracy sharply decreased to a very low level, i.e., as high as only 87.3% accuracy and as low as 63.5% accuracy, as shown in Table 6. The accuracy rate of different keys varied significantly. For subjects A and B, the highest accuracy can reach up to 87.3%, when the ring is worn on the middle finger. But when wearing the ring on the other fingers, the accuracy dropped to a low level. For example, the recognition accuracy of the keys such as 'W', 'E', 'S', and 'F' was below 50%.

TABLE 6. Accuracy rate based on wearing one ring on the left hand.

Subject	little	ring	middle	index
A	70.6%	81.8%	86.0%	69.0%
B	82.2%	80.9%	87.3%	71.9%
C	72.6%	64.5%	67.6%	63.5%

TABLE 7. Comparison of overall accuracy of typing all 26 keys.

Type		A	B	C	Average
Left Hand	4 ring	99.5%	99.4%	98.2%	99.0%
	2 ring	96.7%	98.2%	91.6%	95.5%
Right Hand	4 ring	99.0%	97.7%	96.8%	97.8%
	2 ring	96.8%	94.3%	90.5%	93.9%
Both Hands	4 ring	99.3%	98.7%	97.7%	98.6%
	2 ring	96.7%	96.6%	91.2%	94.8%

D. FURTHER DISCUSSION: TWO AND FOUR RINGS

Here, we compare the recognition results of the left hand, the right hand and with both hands while wearing two and four rings per hand. The IoT rings were worn on the *middle*, *little*, *ring*, *index* fingers for the four ring per hand experiments. When typing the 26 alphabetic keys with both hands, the final average accuracy of three subjects with four rings on each hand is 98.6% and that with two rings is 94.8%, as shown in Table 7.

When the number of rings worn on a hand is reduced, the keystroke accuracy rate declines. However, this declining accuracy is dependent on individual users. For example, the difference of recognition results for wearing 2 or 4 rings for subject C was considerably lower for subject C, i.e., approximately 6.5% drop in accurate recognition when less rings were used. A possible explanation is that subject C may have a low proficiency in typing, i.e., the subject's typing pattern was not stable or consistent enough. The low typing proficiency may have led to the inconsistency of the calculated attitude angle waveforms in typing the same keys during the experiments. This problem could have been further aggravated by the lack of supporting motion data when only two rings were used on each hand. Increasing the sample quantity may be helpful in improving the accuracy.

In Fig. 8, we compare the average key-recognition accuracy of three subjects for typing on the paper keyboard

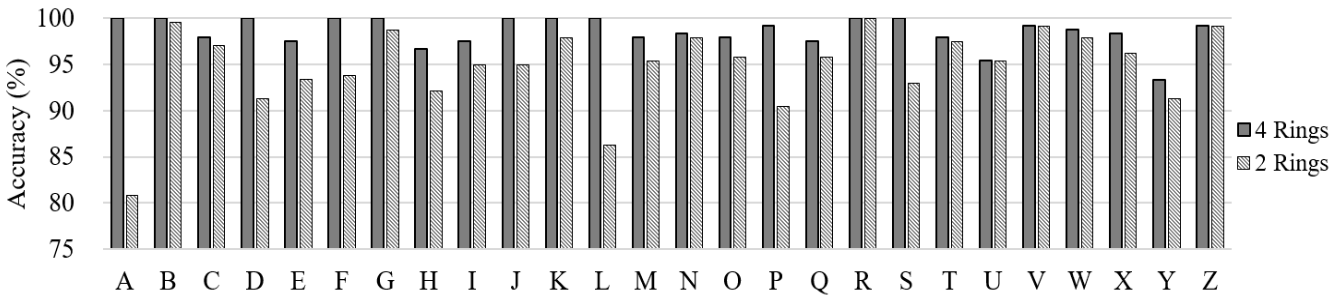

FIGURE 8. Comparison of the average accuracy of typing 26 alphabetic keys conducted by three subjects while wearing 2 rings and 4 rings per hand.

while wearing 2 rings and 4 rings per hand, respectively. The accuracy for recognizing keys such as 'A', 'D', 'H', and 'L' is significantly lower when only two rings were used on each hand. This is because the reduction of acceleration data from other fingers when only 2 rings are worn on each hand, but the accuracy could be improved if much higher resolution acceleration sensors are used in the future. That is, the variations of accelerations between some keys cannot be clearly distinguished by the sensor data from only two fingers, unless the sensors are much more sensitive to the motions of the non-ring fingers. Therefore, identifying new keystroke features and correlation between different finger motions and implementing sensors with higher sensitivity will be the key factors to improving the recognition accuracy if fewer rings are worn on each hand.

Since the typing habit of each subject could also vary significantly, it is difficult to establish a unified model for all subjects. Consequently, utilizing a specific model for each subject is an efficient way to improve keystroke recognition. Thus, techniques customizing a paper-based keyboard for individual subjects based on their own typing habit should also developed in the future.

In the experiments, users were allowed to just type one single key at a time, i.e., once a user types a letter using a particular finger, all fingers must return to the positions on the Home Row Keys. If a user types continuously without returning the fingers to the positions of Home Row Keys, the waveforms of the attitude angles will be overlapped, and it will be very difficult to decouple and recognition them.

The accuracy of our proposed scheme also can be affected by other factors, such as the gap between the keys, the shape of keyboard, and even the layout of keyboard. But our paper keyboard can be customized easily to meet the habits of different people.

V. CONCLUSION

We present a new approach to implement a "virtual keyboard" for human-computer interaction using wireless IoT sensing rings and a "paper keyboard" in this paper. This wearable virtual keyboard is implemented by using micro-motion sensors, which have the benefits of portability, ease of implementation, and low-cost. In the experiments, attitude angles and acceleration data were selected and extracted as features for keystrokes recognition. The highest accuracy of keystroke recognition (of 26 alphabets) with four rings worn on each hand was 99.3% for a particular subject and was 98.6% on average for 3 different subjects. When only two rings are worn on each hand of the test subjects, a subject achieved 96.7% typing accuracy, and the average accuracy for three subjects was 94.8%. In addition, our experiments indicate that rings worn on the *little* finger and *middle* finger on the left hand, and *ring* finger and *middle* finger on the right hand, were the best combination of ring-wearing fingers for keystroke recognition for all subjects. With improvements in typing accuracy and continual reduction of overall ring size, we expect this new type of virtual input method to find many applications in human-computing interactions devices in the future.

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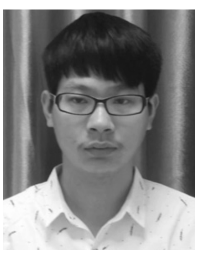

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