Keep the Phone in Your Pocket: Enabling Smartphone Operation with an IMU Ring for Visually Impaired People

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Previous studies have shown that visually impaired users face a unique set of pain points in smartphone interaction including locating and removing the phone from a pocket, two-handed interaction while holding a cane, and keeping personal data private in a public setting. In this paper, we present a ring-based input interaction that enables in-pocket smartphone operation. By wearing a ring with an Inertial Measurement Unit on the index finger, users can perform gestures on any surface (e.g., tables, thighs) using subtle, one-handed gestures and receive auditory feedback via earphones. We conducted participatory studies to obtain a set of versatile commands and corresponding gestures. We subsequently trained an SVM model to recognize these gestures and achieved a mean accuracy of 95.5% on 15 classifications. Evaluation results showed that our ring interaction is more efficient than some baseline phone interactions and is easy, private, and fun to use.

CCS Concepts: • **Human-centered computing → Accessibility technologies**; *Gestural input*.

Additional Key Words and Phrases: accessibility, gestural input

ACM Reference Format:
Guanhong Liu, Yizheng Gu, Yiwen Yin, Chun Yu, Yuntao Wang, Haipeng Mi, and Yuanchun Shi. 2020. Keep the Phone in Your Pocket: Enabling Smartphone Operation with an IMU Ring for Visually Impaired People. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 2, Article 58 (June 2020), 23 pages. https://doi.org/10.1145/3397308

1 INTRODUCTION

Smartphones are an indispensable tool for visually impaired (VI) people. As shown in Figure 1(a), VI users operate smartphones via a screen reader (e.g., VoiceOver or Talkback), following a touch and listen model. Previous studies have demonstrated that VI users encounter the following issues when using a smartphone. Getting the phone out of a pocket is inconvenient and time-consuming [8, 43]. It's difficult for VI users to access or locate smartphones in a timely manner [32]. When using smartphones, VI people are constrained to two-handed interaction: one holding the phone, the other one interacting with the screen by performing gestures or touch-and-explore [39]. Therefore, using a smartphone is difficult when only one hand is available, such as when walking with a cane or

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2474-9567/2020/6-ART58 $15.00
https://doi.org/10.1145/3397308

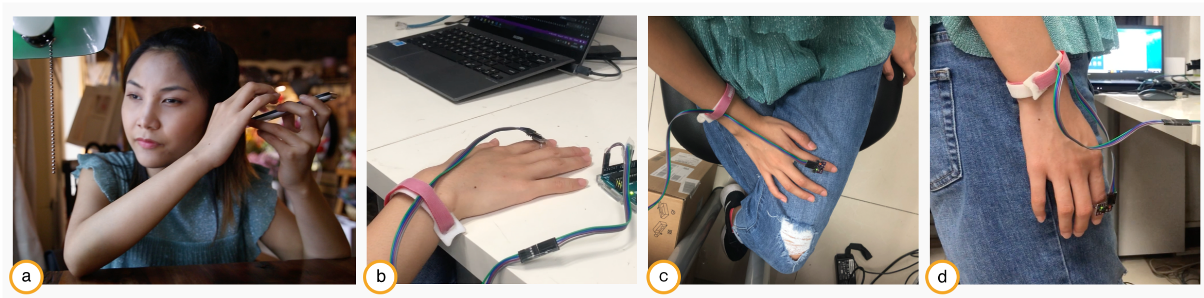

Fig. 1. (a) A visually impaired user operates a smartphone. (b), (c) and (d): Using an IMU ring to perform gestures on a table, on the top of the thigh, and on the side of the thigh to operate the phone without taking it out of her pocket

a dog. To address these issues, we can develop a socially acceptable phone controlling system that allows users to use one hand to interact with smartphones without touching the phone.

Prior works have provided a handful of wearable solutions. Previous studies using wristband-based interaction [43] allowed users to perform a set five of predefined gestures on a wristband to operate a smartphone. This interaction method addressed the pain points of acquiring the phone but failed to provide one-handed interaction. Ring-based surface-specific interaction [8], in which users wear a ring embedded with sensors worn on the index finger and use their thumb to rub on the side of the index finger, allowed users to perform gestures to issue six commands to screen reader software. Location-specific on-body interaction [31, 35], enabled users wearing a ring equipped with a camera, IMU, and IR reflectance sensors, to quickly complete simple tasks like checking the date and time by performing different gestures on different body locations such as the thighs, ears, and so on.

In this paper, we present a ring-based gesture input system to enhance phone interaction. Our system uses a smart ring with a single Inertial Measurement Unit (IMU) to sense gesture inputs and delivers feedback to the user via earphones. Wearing the ring on the middle phalanx of the index finger, users can perform 15 subtle gestures on any surface (e.g., tables, thighs) to operate their phones. This interaction not only addresses the pain points associated with fishing a phone out of a pocket and one-handed operation, but also mitigates privacy and social concerns, such as unintentionally exposing personal data to bystanders, and unwanted attention in public settings due to special postures used to operate the phone [39, 43].

We use an IMU ring as a gesture sensing device. Compared with other sensing form factors like wrist-worn devices [15, 21, 40, 51], when using the index finger to perform gestures on a given surface, a ring is better at sensing subtle gestures like taps and swipes. We believe it reduces interaction fatigue and is more efficient, for one-handed, subtle, and socially inconspicuous interaction.

We address three research questions in this work: 1) What gestures should be included for ring-based interactions that work on any surface? 2) What is the optimal technical implementation to recognize those gestures? 3) How usable is this interaction?

To address the first question, we conducted focus groups to obtain a set of 15 versatile commands for phone operation. We then designed a gesture vocabulary and conducted a gesture ease-of-use scoring study to understand the participants' preferences. Finally, we mapped gestures to commands based on the idiomatic gestures of existing screen reader software, semantic relationships between commands and gestures, and gesture ease-of-use score.

Our interaction surfaces include the user's thighs, which are soft, not flat, and covered with the user's clothing. For the second question, we collected data from 20 participants with different types of clothing. We then used this training data to identify the moment when a user's finger touches down on the interaction surface [10], trained an SVM model, and achieved an average of 95.5% accuracy on 15 classifications.

For the third question, we evaluated the gestures' practice time, compared the accuracy and efficiency on three interaction surfaces (table surfaces, top of the thigh, side of the thigh), and compared the efficiency with the baseline – phone interaction. Results showed that users acquired ring interaction gestures in less than 10 minutes; When the phone was in the user's pocket, the ring interaction was more efficient than the baseline interaction on all three surfaces.

Specifically, our contributions are as follows:

(1) This work enables VI people to operate smartphones via gestures input on any surface with an IMU ring for the first time. Based on data we collected from user studies, we designed a set of versatile commands and suitable gestures to control smartphones.
(2) This work shows that a ring with a single IMU sensor has a good performance on recognizing 15 touch gestures on three different surfaces.
(3) This work provides empirical results for usability evaluation, demonstrating that our ring interaction is learnable and and is more efficient than the baseline interaction when the phone is in the user's pocket.

2 RELATED WORK

In this section, we briefly review prior research, including input techniques that enable users to operate a smartphone without touching it, use smart rings to control devices, and phone-free interaction for VI users.

2.1 Input Techniques for a Smartphone Operation without Touching It

In the future, smartphones will become smaller and smaller and even allow for invisible integration into ubiquitous surfaces and human skin [28]. In anticipation of this trend, some researches have explored phone-free interaction. For example, OmmiTouch [14] and Imaginary Phone [12] focused on using a projector to project the phone's interface onto an ordinary surface (e.g., wall, hand, etc.), and then using a camera to track users' hands to enable input.

In terms of smartphones' current form, screen-touch is the primary input method. However, this kind of interaction is difficult in some scenarios (e.g., when users' hands are wet). Therefore, many researchers have explored screen-touch-free interactions, such as mid-air gesture input [7, 11], lip-motion input [36], acoustic input [50] and so on. These interactions need to be performed near the device, which requires users to take their phone out of their pocket before operating.

Prior work focused on enabling in-pocket smartphone operation relates more closely to our work. Nandakumar et al. presented FingerIO, a finger tracking solution for around-device and in-pocket phone interaction without any wearable sensors. Researchers achieved this by transforming the device into an active sonar system, which transmitted inaudible sound signals and tracked the echoes of finger taps through microphones [27]. Saponas et al. presented a capacitive sensing prototype called PocketTouch. Mounted on the back of a smartphone, PocketTouch enables eyes-free multi-touch finger input through a variety of garments [34]. Ronkainen et al. presented Tab Input, which could detect hand directional taps via an accelerometer to support through-pocket gestures [33]. Hudson et al. developed Whack Gestures: An external device that could be plugged into a phone in the user's pocket. Users could interact with this peripheral device which remained exposed outside of the pocket to operate the phone [16]. The interactions of these works need to be performed on a specific surface or space with a limited size around the phone. Our ring interaction allows user input on any surface.

Some sensing techniques using wearable devices to recognize gestures can also be used for phone-free operation of smartphones. For example, Zhang et al. [51] developed Skintrack, a wearable system that enables continuous touch tracking on the skin. It consists of a ring, which emits a continuous high frequency AC signal, and a sensing wristband with multiple electrodes. This system allows the arm to be appropriated for continuous on-skin touch tracking, expanding interaction beyond the small confines of a smartwatch touchscreen. Harrison et al. [15]

presented Skinput, a wearable armband with a bio-acoustic sensing array built in. It could appropriate the human body for acoustic transmission, allowing the skin to be used as an input surface. Laput et al. [21] developed a custom smartwatch kernel that boosts the sampling rate of a smartwatch's existing accelerometer to 4 kHz. Using this new source of high-fidelity data, they uncovered a wide range of applications. For example, using bio-acoustic data to classify hand gestures such as flicks, claps, scratches, and taps. Wen et al. [40]presented Serendipity, a new technique for recognizing subtle and fine-motor finger gestures using integrated motion sensors (accelerometer and gyroscope) in off-the-shelf smartwatches. The system demonstrated the potential to distinguish five fine-motor gestures like pinching, tapping and rubbing fingers with an average f1-score of 87%. However, when performing gestures on any surface with the index finger, a ring has a higher accuracy in detecting subtle gestures like single swipe, back-and-forth swipe, and tap. This is because the ring is worn on the finger, and it is easier to detect the fine movement of the finger than the wrist-worn device. In this work, we want to explore the feasibility of using a single-IMU-sensor ring to detect subtle gestures, and provide a new one-handed input method for VI people to operate smartphones.

2.2 Smart Ring for Controlling Devices

Smart ring is a lightweight and portable wearable device. Equipped with different sensors, such as an electric field sensor [41], an infrared reflection sensor [19, 29, 35, 49], a magnetic field sensor [1, 5, 46], a camera [3, 4, 26], an inertial measurement units sensor [18, 38], contact microphone [47, 48], pressure sensor [22] and so on, that can be used to detect gestures in many different scenarios.

For example, in the context of smart-home interaction, Magic Ring [18] can detect the subtle finger gestures and routine daily activities by using an inertial sensor, and acts as a remote controller to control TV, radio, and lighting. With a particle filter integrated magnetic sensing technique, TRing [46] can compute the fingertip's position relative to an embedded magnet. Placing magnets on plain surfaces, users can interact with fabricated and existing objects. Example applications of this technique are personalized office desk and furniture remote controller. Gheran et al. [9] conducted gesture elicitation studies to obtain a set of ring-based gestures to complete everyday tasks such as adjusting the lights in a home environment. In the domain of head-mounted display controls, ThumbRing [38], leveraged an IMU sensor to enable users to touch and slide finger segments to select items. TouchRing [37] uses printed electrodes and the capacitive sensing technology to detect touch input. Worn on the index finger, it allows multi-touch using the thumb and middle finger to control smart glasses. For smartwatches, PairRing [6] and Nenya [1] allows users to scroll through lists by turning the ring on their index finger with their thumb. Smart Rings can be used for identification and cross-device interaction. Bianchi et al. [2] proposed a technique to augment human touch using a smart-ring. When the finger wearing a ring is in contact with the touchscreen, a unique ID is transmitted through vibration patterns from the ring to the target device. This enables the device to distinguish touches from different users, or to associate different meanings with different touches from the same user. PickRing [42] is a wearable sensor that allows seamless interaction with devices through predicting the interaction intention through the device's pick-up detection.

In the space of smartphone interaction, Plex [45] and TIMMI [44] are finger-worn textile sensors for phone-free interaction that focus mainly on music playback controls (e.g., volume, advance, previous, etc.). There are few works that focus on using a ring as a general input method for the phone. Our work broadens this field: We conducted a series of studies to obtain a set of commands and gestures for VI users and designed an algorithm to recognize 15 gestures with a single IMU, with an accuracy of 95.5%.

2.3 Phone-free Interaction for Visually Impaired People

As we mentioned in the introduction, VI users face additional difficulties in the tasks of acquiring a phone from their pocket, two-handed interaction, and keeping personal data private in a public setting [8, 30, 39, 43].

Prior solutions focus on developing a wearable device as a controller for phone-free interactions. Ye et al. [43] studied current and future mobile and wearable devices used by VI people. Their study confirmed that VI people are readily to adopt wearable devices. Following the study, they designed a wristband with five commands as a prototype to gain a richer understanding of accessibility issues and the use of wearable devices. Feng's [8] work showed that most of the participants prefer using wrist and hand-mounted systems for operating their phones. They then developed a ring prototype with six commands to help VI people operate smartphones while on the go. Oh et al. [31] and Stearns et al. [35] developed a ring which consisted of a camera, an LED, two IR reflectance sensors, and an IMU to recognize location-specific on-body gestures to quickly access daily tasks on a smartphone. Outside of the wearable solutions above, Patil et al. developed GesturePod [32], which was attached to a cane. This device allowed VI people to perform gestures with the cane (e.g., tap the cane on the floor twice) to trigger tasks on their smartphones. To the best of our knowledge, our work enables users to control smartphones on any surface using gesture input with a single IMU for the first time.

Besides, comparing to interactions on a physical device, some works have affirmed the superiority of on-body interaction. Oh et al. [30] conducted a performance comparison of on-hand versus on-phone eyes-free input with blind and sighted users. They highlighted that the on-body input has a high potential to support accessible non-visual mobile computing. Gustafson et al. [13] studied palm-based imaginary interfaces. Results showed that the eyes-free on-skin interface was superior to the on-device interface, which could benefit VI people as well. Inspired by this research, our ring interaction allows users to touch any surface (including the body) to operate their phones.

3 STUDY 1: COMMANDS AND GESTURES DESIGN

The goal of this study was to design a versatile command set for phones and a suitable gesture set for ring-based interactions on any surface.

3.1 Phase 1: Commands Design

To design the commands, we conducted two focus groups with 15 VI participants. We recruited participants from a local online forum for VI people based on the following criteria: being visually impaired, being a screen reader software user, interested in our project, and willing to share ideas. There were eight participants (three male, five female, aged from 22-32) in group 1. All of them were blind. Half of them were Android users, and the rest were iOS users. There were seven people in group 2 (three male, four female, aged from 24-38). Five were blind and two were low vision. Four were Android users, and three were iOS users. Each focus group lasted for 90 minutes and followed the procedure below:

Step I: Query Scenarios. We introduced the idea of the ring interaction to participants and asked them to brainstorm scenarios where a ring might be useful. Participants mentioned the following scenarios when using a phone is inconvenient and might be made easier with a ring input method. 1) For time-sensitive tasks, such as answering a phone call, it's time-consuming for users to physically locate and open their phone. Our ring interaction could reduce this phone-acquisition time. 2) When one hand is occupied, such as when walking with a cane or a dog or handling a handle for stability on public transit, our ring interaction input method could make one-handed phone operation easier. 3) In settings where the normal operation of a phone might be socially inappropriate, such as during a meeting or while attending a lecture, our ring-based interaction method enables the wearer to use subtle gestures to operate their phone inconspicuously. 4) Operating a capacitive touchscreen requires a dry and clean finger. When hands are covered (e.g., wearing gloves), wet, or dirty, our ring interaction input allows users to issue commands to their phone via gestures on any surface.

Step II: Brainstorm commands. We set out to identify versatile commands that could complete a wide range of tasks, rather than shortcuts for a limited set of specific operations. To inform our selection of commands for our ring-based interaction, we referred to the commands of existing screen reader software, asking participants to recall the commands that they used most frequently. After that, moderators collected the results and identified 17 commands (group 1 mentioned 13 commands, group 2 mentioned 15 commands, 11 were the same). Our ring-based input method cannot support the following types of commands, which we consider to be design limitations: 1) Commands that can only be completed by screen-touch interactions (e.g., typing, dragging and dropping an icon on the home screen). 2) Commands that can only be finished by operating hardware devices (e.g., taking photos.). In this study, we used voice input instead of touch interaction to facilitate text input.

Step III: Remove unnecessary commands. Participants independently rated the necessity of the commands (5 = most necessary). According to the score, we removed two commands with a mean score of less than 3. They were "read the item currently under finger" (M=2.93, SD=0.96), which is not applied to gesture input, and "read from the first item" (M=2.6, SD=0.74), which could be duplicated combining the following two commands "Move to the first item" and "Read from the current item". We adopted the remaining 15 commands shown in Table 1.

Basic commands	*Additional commands*	*Registration*
Previous item (5 (0))	Move to the first item on screen (4.07 (0.8))	Registration (5 (0))
Next item (5 (0))	Move to the last item on screen (4.07 (0.8))	
Select focused item (5 (0))	Scroll up (4.33 (0.72))	
Back (5 (0))	Scroll down (4.33 (0.72))	
Voice input (5 (0))	Scroll left (4.13 (0.92))	
Open hidden menu (5 (0))	Scroll right (4.13 (0.92)	
	Read from the current item (3.4 (0.83))	
	Short-cut menu (3.8 (0.77))	

Table 1. Command list. (5 (0)) denotes the mean score of the command is 5, and the standard deviation is 0

- **Basic command (M=5)**. Users can complete most tasks on their phones only using the basic commands. Particularly, using "previous/next" to browse the information on the interface linearly, using "select focused item" to select an item, using "back" to return to the previous page, using "voice input" to compose and send messages, and using "open hidden menu" to view the sub-menu for a specific item.
- **Additional command (3 < M < 5)**. As a supplement to basic commands, additional commands help users complete tasks on their phones more efficiently. For example, by "scrolling down", users can turn a page with one gesture. Otherwise, using only basic commands, users would have to turn the page by performing the "next item" command until they reach the ultimate item, which is less efficient.
- **Registration (M=5)**. We designed a registration command to enter and exit ring operation mode to prevent users from unintentionally issuing commands while wearing the ring.

3.2 Phase 2: Gesture Design

In order to design gestures that are easy to learn and use, we took users' phone operation habits and semantic relationships between commands and gestures into consideration. We also sought to understand user preferences for gestures. In this phase of the study, we designed a gesture vocabulary first, and then asked participants to rate the ease-of-use.

3.2.1 Gesture Vocabulary. We designed a gesture vocabulary in the following design spaces:

- **Posture type** We define two posture types: finger pulp (FP) posture and fingertip (FT). We define FP posture as when the fleshy part of the index finger makes contact with a surface while the index finger is extended (e,g., swipe left using FP posture). We define FT posture as when the tip of the finger touches the surface while the index finger is bent (e.g., swipe left using FT posture). Figure 2) shows the gesture performing postures.

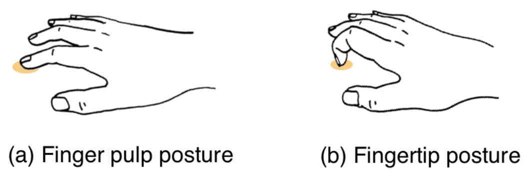

Fig. 2. Gesture performing postures

- **Single posture or double posture** Only using FP or FT to perform one gesture is defined a single posture, e.g., swipe right by FP. Using both FP and FT to perform one gesture is a double posture, e.g., tap by FP then tap by FT.
- **Gesture type** There are four types of gestures: single swipe, back-and-forth swipe (e.g., swipe left then right), angle swipe, and tap. Angle swipe is an L-shaped gesture with different orientations, such as swipe down then right or swipe up then right.
- **Single gesture type or double gesture type?** Only using one of the gestures defined above (i.e., single swipe, back-and-forth swipe, angle swipe, and tap) to perform one operation is a single gesture type (e.g., swipe left). Using the combination of the above gestures to perform one operation is a double gesture type(e.g., tap then swipe right).

We removed gestures that were obviously difficult and time-consuming to perform in double gestures and double postures, such as single swipe then back-and-forth swipe, back-and-forth swipe then angle swipe, swipe by finger pulp then swipe by fingertip and so on. After researching existing user behaviors, we decided not to put the single tap in the gesture vocabulary. In widely-used screen reading software, in order to avoid accidental touches, users have become accustomed to triggering commands with multiple taps. We did not define angle swipe using only fingertip or finger pulp. When designing the subtle gestures, we designed the index finger movement with the finger base as the axis. Angle swiping requires constant changes in the angle of the finger. Asking users to distinguish the fingertip or finger pulp postures will cause difficulty in use. We kept 32 gestures that are relatively easy to use and reasonable as our gesture vocabulary (see table 2). We then conducted an ease-of-use scoring study to understand user preferences for them.

3.2.2 Ease-of-use Scoring Study. 20 VI people participated in this study (12 male, 8 female; aged from 22-45). 15 of them were blind, and five of them were low vision. Fifteen of these participants also participated in the command design study.

During the study, we taught the gestures from our gesture vocabulary to the participants one by one and then asked them to perform these gestures in sequence. After that, we asked them to use a Likert scale to rate the subjective ease-of-use of each gesture (1 = most difficult, 7 = easiest). Figure 3 shows the action diagram of the gesture as well as their ease-of-use score.

Following the examples of [10, 36, 39], we used Non-parametric tests to analyze participants' subjective scores. We used a Wilcoxon signed-rank test to analyze two paired samples, using Friedman test to analyze three or more paired samples. p value less than 0.05 denotes statistically significant effects.

A Wilcoxon signed-rank test showed that there is no significant effect of posture type (FP posture or FT posture) on subjects' gesture preferences. For the number of postures (single posture or double posture), a Wilcoxon signed-rank test showed single posture gestures (M=5.55, SD=1.46) are easier than double posture

		Single posture		**Double posture**
		Finger pulp	Fingertip	Finger pulp and fingertip
Single gesture type	**Single swipe**	swipe L swipeR	swipe L swipe R	swipe U swipe D
	Back-and-forth swipe	swipe L then R, swipeR then L	swipe L then R swipe R then L	swipe U then D swipe D then U
	Angle swipe	–	–	swipe D then L swipe U then R swipe D then R swipe R then D swipe L then U swipe U then L
	Tap	double tap triple tap quadruple tap	double tap triple tap quadruple tap	tap by FP then tap by FT tap by FT then tap by FP
Double gesture type	**Tap and single swipe**	tap then swipe L tap then swipe R	tap then swipe L, tap then swipe R	tap then swipe U tap then swipe D

Table 2. Gesture Vocabulary. FP denotes the finger pulp posture; FT denotes the fingertip gestures; L, R, U, D denote the swipe directions, which are left, right, up, down.

gestures (M=4.92, SD=1.6) with $z = -2.987, p = .004$. For the gesture type, a Friedman test showed a significant effect on subjective preference with $\chi^2 = 14.862, p = .002$. A Bonferroni correction post-hoc analysis with $\alpha = 0.05$ showed that the ease-of-use of single swipe (M=6.18, SD=0.99) is greater than an angle swipe (M=4.84, SD=1.58) with $p = .001$. For gesture type (i.e. single type or double type), a Wilcoxon signed-rank test showed the ease-of-use of single gestures (M=5.48, SD=1.53) is higher than that of a double gesture (M=4.70, SD=1.51) with $z = -2.841, p = .008$. Thus, when designing the mapping of commands to gestures, we focused on gestures with single posture type and gesture type.

3.3 Phase 3: Commands to Gesture Mapping

We designed the mappings as follows: First, we leveraged VI users' pre-existing vocabulary of idiomatic gestures on existing screen reading software. We chose "swipe left by FP", "swipe left by FT", and " double tap by FP" to map "previous item", "next item", and "select focused item", respectively, as they are commonly used in screen reader software. We then explored the semantic relationships between commands and gestures. Specifically, we matched "swipe left then right by FP" to "back", because this gesture is like wiping something away, which is in line with a certain negative meaning such as cancellation and revocation. We matched "swipe up", "swipe down", "swipe left by FT", and "swipe right by FT" to scroll "up", "down", "left", and "right", respectively, as they form relatively natural mappings . We matched "swipe left then right by FT" and "swipe right by FT" to "move to the first item" and "move to the last item", respectively, as the user effectively draws arrows in performing the gesture. Third, we balanced the possibility of confusing gestures with natural motion and ease-of-use score, and

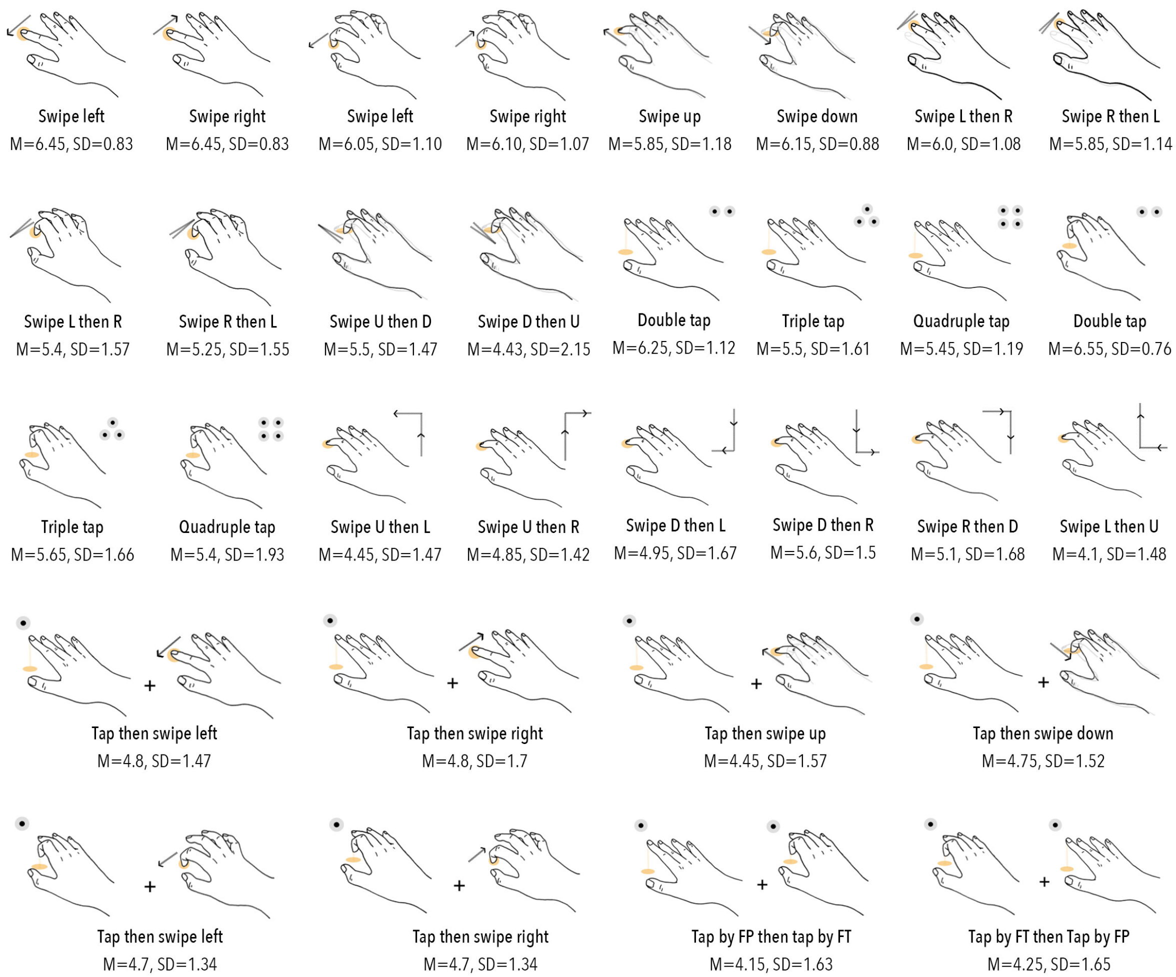

Fig. 3. The action diagram of the gesture and ease-of-use score. L denotes left, R denotes right, U denotes up, D denotes down

mapped “triple-tap by FP” to our “registration” command. Finally, we selected four single posture gestures with the highest ease-of-use score from the remaining gestures to map the remaining commands. Table 3 shows the final mappings.

4 STUDY 2: GESTURE RECOGNITION

The goal of this study was to obtain users’ gesture data, around which we could design an algorithm to recognize ring-based gestures.

Commands	*Gestures*
Previous item	Swipe left by finger pulp
Next item	swipe right by finger pulp
Select focused item	Double tap by finger pulp
Back	Swipe left then right by finger pulp
Voice input	Triple tap by fingertip
Open hidden menu	Quadruple tap by finger pulp
Move to the first item on screen	Swipe left then right by fingertip
Move to the last item on screen	Swipe right then left by fingertip
Scroll up	Swipe up
Scroll down	Swipe down
Scroll left	Swipe left by fingertip
Scroll right	Swipe right by fingertip
Read from the current item	Double tap by fingertip
Shortcut menu	Quadruple tap by fingertip
Registration	Triple tap by finger pulp

Table 3. The mapping between commands and gestures.

4.1 Design and Procedure

We recruited 20 VI participants (12 male, 8 female, aged from 20 to 35). All the participants were right-handed. None of them took part in the prior study. Figure 4 shows the experimental setup of study 2. Participants performed the 15 gestures in table 3 in three sessions. In session one, participants performed the gesture on a table while seated (figure 1b). In session two, participants performed gestures on the top of their thigh in a sitting position (figure 1c). In session three, participants performed gestures on the side of their thigh in a standing position (figure 1d).

Fig. 4. The experimental setup of study 2. The participant wore the IMU ring and performed gestures on a physical surface.

Participants wore the IMU ring on the middle phalanx of the index finger. Before performing the gestures in a sitting position, participants adjusted the chair to a comfortable position. Each session consisted of 15 ring gestures in random order. For each gesture, participants heard the gesture's name and then performed the gesture five times in a two-seconds interval. We asked participants to perform the gesture in their preferred way, e.g., with preferred strength. For each participant, we collected $3session \times 15gestures \times 5trials = 225$ samples. Participants rested for five minutes between two sessions to avoid fatigue. As participants' attire was varied, we collected data for gestures performed on different materials, such as skin, denim, gauze, waterproof fabric, and so on.

In addition, we collected negative samples of the registration gesture (triple tap), including three types of task: 1) on-table gestures such as grabbing and dropping objects like cups, phones, and books; 2) gestures performed by touching different parts of the body (e.g., putting on and taking off glasses, playing with hair) 3) unintentional gestures such as finger stretching, curling, shaking, trembling, and arbitrary mid-air gestures. Each participant performed each type of task for one minute. The experiment lasted for 40 minutes. Each subject was paid USD $15 for their participation in the study.

4.2 Apparatus

The IMU ring was a 9-axis IMU (GY-91, 1000Hz) attached to a normal ring. We connected the IMU to an Arduino Uno R3, which we connected to a computer, with Dupont lines.

We sampled 3-axis raw acceleration and 3-axis angular velocity from the IMU. We used Madgwick Filter [24] to split raw acceleration into linear acceleration and gravity. The Madgwick Filter also provided pitch angle (i.e., the angle between the forward direction and the horizontal plane). In total, we sampled 11 dimensions of motion data: timestamp, 3-axis linear acceleration, 3-axis angular velocity, 3-axis gravity, and pitch angle.

4.3 Implementation

4.3.1 Touch sensing. We sought to design an algorithm that could recognize when the user touched his or her finger to any given surface, as this event is crucial in recognizing the start of ring-based gestures. To sense touch down, we followed a paper [10], which used SVM to sense the vibration at the moment of touchdown.

There were some differences in our reproduction. First, we used an IMU sensor with a higher frequency (1000Hz). Second, we included the human body as an interaction surface. As we explored the feasibility of touch sensing on the body, we could not acquire a ground truth via touch screen as presented by paper [10]. Instead, we learned the pattern of touchdown data given by paper [10] and labeled all the touchdown events manually.

For all the gestures we collected, we selected intervals of 50 ms centered around the touchdown event as positive samples. We conducted a small experiment to collect negative samples of touchdown events following the example of [10]. The negative samples are random intervals of 50 ms in mid-air gestures such as drawing circles, swiping, and Hololens gestures. We extracted the maximum, minimum, mean, skewness, and kurtosis of the 3-axis angular velocity, 3-axis acceleration, and 3-axis gravity dimensions, and concatenated them to obtain a feature with 45 dimensions. Then, we trained the SVM classifier.

Leave one person out cross-validation showed that the precision of our classifier was 97.8% and the recall rate was 98.1%. We further packed the classifier into a touchdown sensing algorithm:

- The algorithm ignores a touch event if there has been an event within the past 50 frames (50 ms).
- The algorithm recognizes a touch event only if the classifier detects ten consecutive frames of with a touch event.

We simulated the algorithm on the data of three interaction surfaces: table, top of the thigh, and side of the thigh. The recall rates were 98.26% (SD=1.83), 96.99% (SD=2.19), and 96.08% (SD=3.36), respectively.

We used RM-ANOVA for data analysis. Following papers [17, 20]etc., we used Mauchly's test to assessed sphericity. If Mauchly's Test of Sphericity was violated, Greenhouse-Geisser corrections were employed. If any independent variable or combinations had statistically significant effects ($p < 0.05$), we used Bonferroni-corrected post-hoc tests to determine which pairs were significantly different.

RM-ANOVA showed a significant effect of interaction surface on the recall rate ($F_{2,38} = 7.463, p = .002$). Touch events on the table, having more pronounced vibration, had a higher recall rate on than those on the top ($p = .028$) and side ($p = .012$) of the thigh. The average delay was 8.72 ms (SD=0.83). The algorithm reported 37 false positive touch events during a 60-minute negative sample.

4.3.2 Registration. Users perform the registration gesture–a triple tap on any surface with the pulp of the index finger–to enter ring operation mode. The registration collects the pitch angle $Pitch_0$ when the user touches down on the surface using the pulp of his or her finger so that the system can better distinguish between touch gestures using finger pulp and fingertip. The system calculated $Pitch_0$ as the average pitch angle of the three touchdown events. In the following description, $Pitch$ is the difference between the raw pitch angle and $Pitch_0$.

The system reported a registration event when three touch events occurred within a 450 ms window. The simulation showed that the recall rate of this classification method was 97.6%. In a 60-minute negative sample, the classification method triggered 42 false positive registrations.

4.3.3 Recognition. We sampled 20 participants × 225 gestures = 4500 ring gestures from the raw data. All gestures began at touchdown, so we ran the touch sensing algorithm to identify the starting times. We defined the end of a gesture as when its angular speed was lower than 50 rad/s for more than 200 ms. We used the rules above to find 97.8% of the samples successfully and identified the others by manual labeling.

We designed the features according to five criteria:

(1) **Category**: Does the gesture belong to tap, swipe left / right, or swipe up / down?
(2) **Touches**: How many touches does the gesture include?
(3) **FP or FT**: Finger pulp or fingertip gesture?
(4) **L or R**: Does the gesture belong to swipe left, swipe right, swipe left then right or swipe right then left?
(5) **U or D**: Swipe up or swipe down?

Criteria	Features
Category	$max(\|Gy\|_{begin+20:end})$, $max(\|Gz\|_{begin+20:end})$, $\|Pitch_{end} - Pitch_{begin}\|$
Touches	The number of touches, The number of zero points
FP or FT	$Pitch_{begin}$, $mean(Pitch_{begin+20:end})$, $max(Pitch_{begin:end})$, $min(Pitch_{begin:end})$
L or R	$sign(Gx_{begin}), sign(Gx_{begin+\frac{end-begin}{9}}), \ldots, sign(Gx_{end})$, $sign(Gy_{begin}), sign(Gy_{begin+\frac{end-begin}{9}}), \ldots, sign(Gy_{end})$
U or D	$Pitch_{begin}, Pitch_{end}, mean(Gy_{begin+20:end})$

Table 4. Features of every criteria

Table 3 shows the features of every criteria, where G_x, G_y, G_z denotes the angular velocity for the three-axes, $Pitch$ denotes the pitch angle, $Touch$ denotes the number of detected touches, *begin* and *end* denotes the beginning and ending timestamps, respectively. We used subscript to represent the data at a moment or in a period, for example, $Pitch_t$ denotes the pitch angle at moment t, $Pitch_{t1:t2}$ denotes the pitch angles in the time window $[t_1, t_2]$.

We discuss the logic of the feature design below. 1) The timestamp $begin + 20$ was widely used in our features, because the motion data in the first 20 ms after the touch event was unstable. Some features ignored the motion data in the first 20 ms. 2) As the criteria "L or R" shows, we sampled ten values from $sign(G_x)$ and $sign(G_y)$ with equal interval. The number of sampled values was an empirical value, which was obtained by simulations aiming to optimize the performance of the classifier.

We concentrated all the values in table 3 to form a feature with 32 dimensions. We then normalized the data and trained the SVM classifier. The single classifier can recognize the 15 gestures on the three surfaces we tested. Leave one person out cross-validation showed an accuracy of 96.0% (SD=3.81), 95.4% (SD=4.21), and 95.5% (SD=4.55) on the table, thigh top, and thigh side data sets, respectively. RM-ANOVA showed the type of surface had no significant effect on accuracy. Table 5 shows a confusion matrix for the three surfaces.

As shown in the confusion matrix, our system's recognition accuracy is listed below in descending order.

(1) Recognition are most accurate for quadruple tap using finger pulp (4TFP) and swipe right using finger pulp (SRFP), at 99.3%, and 99.2%, respectively.
(2) Recognition of swipe up (SUP) and swipe down (SDN) is highly accurate, at 96.1%, and 98.8%, respectively.
(3) Tap-based gestures (including multiple taps) are also highly accurate: 96.0% for fingertip gestures and 97.7% for finger pulp gestures.
(4) Swipe left or swipe right gestures, excluding swipe right using finger pulp (SRFP), are less accurate at 93.9%.
(5) Back-and-forth gestures are the least accurate at 91.9%.

Finally, the system struggled the most with recognizing swipe left or swipe right vs. back-and-forth swipe, due to the finger's involuntary movement in the opposite direction after performing a single swipe gesture.

	SLFP	*SRFP*	*SLRFP*	*2TFP*	*3TFT*	*4TFT*	*2TFT*	*SLRFT*	*SRLFT*	*SUP*	*SDN*	*SLFT*	*SRFT*	*4TFP*	*3TFP*
SLFP	**94.4**	0	5.2	0	0	0	0	0	0	0	0.4	0	0	0	0
SRFP	0	**99.2**	0.4	0	0	0	0.4	0	0	0	0	0	0	0	0
SRLFP	2.5	0.8	**93.4**	0.4	0	0	0	0.8	0	0	0	0	0.4	0	1.7
2TFP	0	0	0.3	**97.9**	0	0	0	0	0	0.3	0	0	0	0	1.4
3TFT	0	0	0	0	**95.8**	2.1	0.4	0	0	0.4	0	0	0	1.4	0
4TFT	0	0	0	0	1.8	**97.5**	0.4	0	0	0	0	0	0	0	0.4
2TFT	0	0	0	0.4	0	1.4	**94.6**	0.7	2.5	0.4	0	0	0	0	0
SLRFT	0	0	0.4	0	0	0.4	3	**90.1**	2.6	0	0.9	1.3	1.3	0	0
SRLFT	0	0.8	0	0	0	0.4	1.2	0.4	**92.1**	1.7	0.4	0.4	2.5	0	0
SUP	0.4	0.4	0	0	0	0.4	2.9	0	0	**96.1**	0	0	0	0	0
SDN	0	0	0	0	0	0	0.8	0	0	0	**98.8**	0	0.4	0	0
SLFT	0.8	0	0	0	0	0	0.8	2.9	0	0	0.8	**94.6**	0	0	0
SRFT	0	0.4	0	0	0	0	0.4	1.9	3.1	0.8	0.4	0.4	**92.6**	0	0
4TFP	0	0	0	0	0.3	0	0	0	0	0	0	0	0	**99.3**	0.3
3TFP	0	0	0	2	0	0	0	0	0	0	0	0	0	2	**95.9**

Table 5. Confusion matrix. FP denotes the finger pulp posture; FT denotes the fingertip gestures; S denotes swipe; L, R, LR, RL, UP, DN denote the swipe directions, which are left, right, left then right, right then left, up, down; T denotes tap; 2, 3, 4 denote the number of taps. For example, SLRFT is swipe left then right using fingertip, 2TFP is double tap using finger pulp.

4.3.4 *Lower Frequency.*

We used 1000Hz as the IMU frequency in the table above, which represented the highest performance of our algorithms. In real use, a practical system may be better off using a lower frequency to save battery life. We evaluated the algorithms with frequencies of 1000Hz, 500Hz, 200Hz, and 100Hz. Figure 5 shows the accuracy rates of touch sensing and gesture classification in different settings.

Results show that there is a tradeoff between the frequency and the performance. Two-factor RM-ANOVA shows significant effect of frequency on both the performance of touch sensing ($F_{3,57} = 10.336, p < .001$) and gesture classification ($F_{3,57} = 19.938, p < .001$). Touch event detection had a higher recall rate on the table

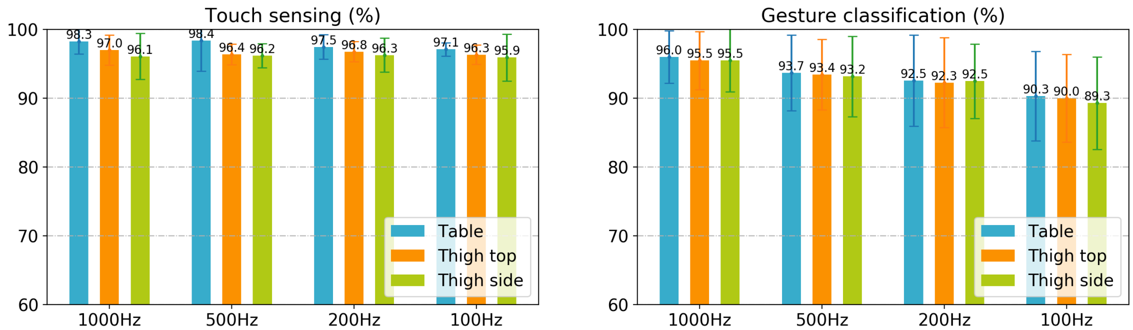

Fig. 5. The performance of touch sensing and gesture classification over IMU frequencies. Error bars indicate standard deviation.

compared to those on the top ($p = .029$) and side ($p = .04$) of the thigh. There is no significant effect of touch position on the performance of gesture classification.

5 STUDY 3: USABILITY EVALUATION

The goal of this study was to evaluate the usability of the ring-based interaction, including accuracy, efficiency, and participants' subjective feedback.

5.1 Participants and Apparatus

We recruited 12 VI participants (six male, six female, aged from 19-38). Half of them were Android users, and the rest were iOS users. None of them had participated in the previous studies. Our ring input system was identical to the apparatus used in Study 2: a 9-axis IMU GY-91 (1000Hz sample rate) attached to a regular ring with adjustable size. The ring was connected to an Arduino Uno R3 with Dupont lines. For phone interaction, we provided users with a 6.4-inch Huawei Honor smartphone.

5.2 Phase 1: Learning Commands and Gestures

5.2.1 Procedure. At the beginning of this phase, we gave a verbal explanation of the commands and gestures in about 15 minutes as follows:

Step I: Teaching gesture performing postures, including finger pulp posture and fingertip posture, as figure 2 shows.

Step II: Teaching 15 kinds of gestures. We divided them into three groups based on performing postures. 1) Finger pulp gestures, including swipe left, swipe right, swipe left then right, double tap, triple tap, and quadruple tap. 2) Fingertip gestures, including swipe left, swipe right, swipe left then right, swipe right then left, double tap, triple tap, and quadruple tap. 3) Double postures gestures, including swipe up, and swipe down.

Step III: Teaching 15 commands. We divided the commands into five groups based on functions. 1) registration. 2) linear browsing, including previous item, next item, and select focused item. 3) Page scrolling, including scroll up, scroll down, scroll left, and scroll right. 4) Focus jumping, including back, move to the first item on screen, and move to the last item on screen. 5) Other commands, including voice input, open hidden menu, shortcut menu, and read from the current item.

Step IV: Teaching the mapping of commands to gestures. We divided the mappings into four groups. 1) "triple tap by FP" for "registration". 2) mappings commonly used in screen reader software, including "swipe left by

FP" for "previous item", "swipe right by FP" for "next item", and "double tap by FP" for "select focused item". 3) mappings with semantic relationships, including "swipe left then right by FP" for "Back", swipe "up", "down", "left", and "right" for scroll "up", "down", "left", and "right" , respectively, "swipe left then right by FT" for "move to the first item", and "swipe right then left by FT" for "move to the last item". 4) tap-related mappings, including "triple tap by FT" for "voice input", "quadruple tap by FP" for "open hidden menu", " double tap by FT" for "read from the current item" , and "quadruple tap by FT" for "shortcut menu".

In the above process, participants performed gestures according to our explanation and asked questions. We also corrected their finger postures while explaining. After that, we asked participants to put on the ring and practice the gestures using an interactive program to further solidify the training. Participants listened to the command name read out by the program and performed the corresponding gestures on the table surface in a comfortable sitting position. When the system identified the gesture as correct, the program read out the name of the next command and asked participants to perform the corresponding gesture. When the system identified the gesture as incorrect, the program played an audio reminder to signal the error. Participants then needed to perform correct gesture in order to move on to the next task. There were 15 randomly-ordered tasks in each round. Participants ended the practice when they felt confident that they had learned all the gestures. We recorded the practice time in each round to measure the learnability potential of the gestures.

5.2.2 Result. All practice times were less than 10 minutes (M=230.24s, SD=138.63), ranging from the shortest 121.01 seconds to the longest 568.45 seconds. The mean number of practice rounds was 4.17 (SD=1.70). The result showed that users could learn the gestures and issue commands using ring-based interaction relatively quickly.

5.3 Phase 2: Accuracy and Efficiency

5.3.1 Procedure. We asked participants to finish eight daily tasks [39] using ring and phone in turn. Table 6 summarizes the tasks as well as how they are performed using ring and phone.

At the beginning of the study, we gave participants 5-10 minutes to learn how to use the ring and Talkback (Android native screen reader software) to finish tasks, respectively.

For ring-based interactions, participants completed three rounds of tasks on three different surfaces in random order: table surface in sitting position, the top of the thigh in sitting position, and the side of the thigh in standing position. There were eight tasks in each round with a randomized presentation order. Participants started the tasks by performing the registration gesture (triple tap using finger pulp). We recorded this process by video for subsequent accuracy evaluation.

For phone interactions, participants completed one round of tasks with a randomized presentation order. Participants started the tasks by taking the phone out of their pockets and performing a two-finger swipe starting from the bottom of the screen to unlock the phone. We allowed participants to operate phones using the posture and way they felt most comfortable with (e.g., two-handed explore-by-touch in sitting position).

Therefore, each participant needed to finish tasks in four interaction modes – ring on the table (M1), ring on the top of the thigh (M2), ring on the side of the thigh (M3), and phone interaction (M4).

Our implementation of the ring interaction, as well as the phone interaction, is a "closed-loop" in a sense that if some error occurs, a user can always recover from the error and perform the task again, just like a sighted user does on a smartphone. For example, if a contact is mistakenly chosen in a messaging app, the user can return to the previous contact page (by performing "Back") and select the desired contact. During the study, participants handle errors by themselves in this way, and the time for handling errors is counted as a part of overall completion time.

5.3.2 Result 1: Accuracy of the Classifier. We used $1 - \frac{errors}{steps}$ to calculate the accuracy of classifier for participants' use. *Errors* denotes the numbers of classification errors for each task, and *steps* denotes each task's operating steps.

Listen to time	
Ring	3TFP to registration and access time
Phone	Take out the phone -> tap the volume button to access time
Answer a phone call	
Ring	Registration and listen to the numbers (3TFP) -> answer the phone (2TFP) -> hang up the call (Swipe LR (FP)
Phone	Take out the phone and listen to the numbers -> answer the phone (double tap) -> hang up the call (double tap)
Open a messaging App, find a friend in the chat list and send a voice message to him / her	
Ring	Registration (3TFP) -> find target App on the home screen (swipe L or R (FP)) -> open (2TFP)-> find target friend (swipe L or R (FP)) -> enter chat page (2TFP)-> initiate voice input (3TFT) -> speak -> send this message (2TFP)
Phone	Take out the phone and unlock -> find target App (explore-by-touch or linear browse) -> open (double tap) -> find target friend (explore-by-touch or linear browse) -> enter chat page (double tap) -> initiate voice input (long press) -> speak -> send this message (lift finger)
Open a map App, input a destination by voice and start navigation	
Ring	Registration (3TFP) -> find target App on the home screen (swipe L or R (FP))-> open (2TFP) -> initiate voice input (3TFT) -> speak -> select the travel mode (swipe L or R (FP))-> confirm and start navigation (2TFP)
Phone	Take out the phone and unlock -> find target App on the home screen (explore-by-touch or linear browse)-> open (double tap) -> initiate voice input (find the button and press) -> speak -> select the travel mode (explore-by-touch or linear browse)-> confirm and start navigation (find the button and double tap)
Listen to News	
Ring	Registration (3TFP) -> find target App on the home screen (swipe R (FT))-> open (2TFP) -> initiate "read from current item" (2TFT) -> listen -> enter the news (2TFP)
Phone	Take out the phone and unlock -> find target App on the home screen (explore-by-touch or linear browse)-> open (double tap) -> initiate "read from current item" (draw an L to open a menu and find the button) -> listen -> enter news details (double tap)
Play music	
Ring	Registration (3TFP) -> find target App on the home screen (swipe LR (FT))-> open (2TFP) -> turn to target page (swipe U or D) -> find the target music (swipe L or R (FP)) -> play (2TFP)
Phone	Take out the phone and unlock -> find target App on the home screen (explore-by-touch or linear browse)-> open (double tap) -> turn to target page (swipe U or D) -> find the target music (explore-by-touch or linear browse) -> play (double tap)
Browse mail and delete spam	
Ring	Registration (3TFP) -> find target App on the home screen (swipe L or R (FP))-> open (2TFP) -> browsing the mails and find unnecessary ones (swipe L or R (FP)) -> open hidden menu (4TFP) -> find the button "delete" (swipe L or R (FP)) -> confirm (2TFP)
Phone	Take out the phone and unlock -> find target App on the home screen (explore-by-touch or linear browse)-> open (double tap) -> browsing mail and find spam (explore-by-touch or linear browse) -> open hidden menu (long press) -> find the button "delete" (explore-by-touch or linear browse) -> confirm (double tap)
Short-cut menu	
Ring	Registration (3TFP) -> start the menu (4TFT) -> find the target feature (swipe L or R (FP)) -> select (2TFP)
Phone	Take out the phone and unlock -> start the menu (draw an L) -> find the target feature (explore-by-touch or linear browse) -> select (double tap)

Table 6. Tasks and Operations

Our program recorded the number of steps. For error counting, we labeled the classification results of each step by watching the video and then comparing them with the results given by the program. The mean accuracy of M1 was 95.16% (SD=3.47), M2 was 94.66% (SD=3.16), and M3 was 95.08% (SD=2.25) for 15 classifications. RM-ANOVA showed there is no significant effect of mode on accuracy.

5.3.3 *Result 2: Efficiency Comparison between M1, M2, M3, and M4.*

We used the task completion time as a measure to evaluate the interaction efficiency of the four interaction modes, including registration time and net completion time. For M1, M2, and M3, we recorded the time from task start to registration as registration time, and the time from registration to task completion as net completion time. For M4, we recorded the time from task start to the moment when participants took the phone out of their pocket and unlocked the screen as registration time, and the time from screen unlock to task completion as net completion time.

The mean registration time per task was 1.59s (SD=0.79) for M1, 1.38s (SD=0.54) for M2, 1.26s (SD=0.54) for M3, and 5.81s (SD=3.51) for M4. RM-ANOVA showed that mode has a significant effect on registration time with $F_{3,33} = 17.605, p = .001$. Bonferroni correction post-hoc tests showed significant differences between the following mode pairs: M1-M4 ($p = .006$), M2-M4 ($p = .009$), M3-M4 ($p = .007$), which indicated that our ring-based interaction can significantly reduce the amount of time required for the registration event.

The mean net completion time per task was 8.62s (SD=2.34) for M1, 10.13s (SD=1.62) for M2, 8.99s (SD=1.81) for M3, and 11.63s (SD=2.03) for M4. RM-ANOVA showed that mode has a significant effect on net completion time with $F_{3,33} = 7.144, p = .001$. Bonferroni correction post-hoc tests showed significant differences between the following mode pairs: M1-M4 ($p = .01$), M3-M4 ($p = .03$), which indicated that the ring interaction is faster than the phone interaction when the input surfaces are tables and the side of the thigh. In addition, there was no significant difference between input surfaces (M1, M2 and M3).

5.3.4 *Result 3: Task-based Efficiency Comparison between Ring and Phone.*

As shown in Table 7, for registration time, the efficiency of ring interaction is higher than that of phone interaction for all eight tasks. This result supports the conclusion above: that ring interaction is significantly more efficient than the user removing the phone from their pocket.

	Ring	Phone	RM-ANOVA
Time	1.46 (SD=0.86)	4.58 (SD=1.69)	F(1,11)=25.14, p<.001*
Phone	1.44 (SD=0.86)	6.13 (SD=4.28)	F(1,11)=13.36, p=.004*
Message	1.77 (SD=1.42)	5.53 (SD=3.36)	F(1,11)=32.14, p<.001*
Navigation	1.06 (SD=0.49)	6.56 (SD=6.1)	F(1,11)=9.524, p=.01*
News	1.29 (SD=0.83)	6.51 (SD=4.56)	F(1,11)=15.174, p=.002*
Music	1.31 (SD=0.85)	5.95 (SD=3.66)	F(1,11)=16.787, p=.002*
Mail	1.27 (SD=0.51)	6.15 (SD=3.68)	F(1,11)=20.538, p=.001*
Short-cut Menu	1.71 (SD=0.64)	5.05 (SD=2.20)	F(1,11)=23.134, p=.001*

Table 7. Registration time comparison. * denotes significant effect

As shown in Table 8, for net completion time, the efficiency of ring interaction is higher than phone interaction in “Navigation”; lower than phone interaction in “Music” and “Short-cut menu”; has no significant difference with phone interaction in “Phone call”, “Message”, “News” and “Mail”.

(1) Navigation: with phone interaction, participants had to touch and explore the interface with numerous small widgets to find the target item, which is frustrating and time-consuming. By contrast, with ring interaction, participants could finish these tasks by performing a series of gestures and didn’t have to manually search for the target’s position. In the Navigation task, participants could perform triple-tap using fingertip instead of searching for the voice input button to evoke voice input command.

	Ring	Phone	RM-ANOVA
Time	–	–	–
Phone	4.89 (SD=1.79)	5.67 (SD=1.74)	F(1,11)=1.088, p=.319
Message	11.61 (SD=2.19)	12.85 (SD=4.04)	F(1,11)=1.457, p=.253
Navigation	13.48 (SD=2.17)	24.95 (SD=6.22)	F(1,11)=57.923, p<0.001*
News	9.65 (SD=3.00)	12.33 (SD=4.44)	F(1,11)=2.993, p=.112
Music	12.87 (SD=3.03)	8.79 (SD=3.28)	F(1,11)=8,295, p=.015*
Mail	13.86 (SD=2.76)	11.48 (SD=5.68)	F(1,11)=1.659, p=.224
Short-cut Menu	7.65 (SD=1.7)	5.32 (SD=2.06)	F(1,11)=10.222, p=.008*

Table 8. Net completion time comparison. * denotes significant effect

(2) Music and Short-cut menu: with ring interaction, participants had to linearly browse the list by performing swipe right by finger pulp repetitively to find the target item. With phone interaction, participants could easily touch the target position without having to perform the same gesture repetitively. For example, in the Music task, using ring interaction, participants needed to perform swipe right continuously to find the target song; while using phone interaction, they could touch the position of target song relatively easily.
(3) Phone call, Message, Mail, and News: There was no significant difference between ring and phone interaction on efficiency. Because ring and phone interaction have the same task flows, the same numbers of operating steps, and similar performance times for each step involved in these tasks.

5.4 Phase 3: Subjective Evaluation

5.4.1 Procedure. After finishing the tasks above, we asked participants to complete two 7-point Likert scale questionnaires. The first questionnaire asked participants to rate the experience of M1, M2, and M3 in the dimensions of “easy to use” and “efficient to use”, respectively. The second questionnaire asked participants to rate the overall experience of the ring (M1, M2, M3) and the phone (M4) interaction, respectively. The dimensions were easy-to-use, enjoyment, efficiency, privacy, convenience with respect to one-handed interaction, learnability (ring-only), and willingness to use the ring interaction (ring-only). As participants were already familiar with phone interaction, we did not ask them to give a response to the last two questions.

5.4.2 Results. Table 9 shows the subjective score for the experience of M1, M2, and M3. Friedman test showed that there are no significant effects of input surface on user preference in the dimensions of "ease-of-use" and "efficiency." As the thigh surfaces are softer than the table surfaces and covered with different clothing materials, participants mentioned that the force to perform gestures on such surfaces is a little greater than on the table surface, but it did not affect their experience. For example, P2 said: *"As the table is hard, I only need to use a very light force to operate. However, on the thigh, I need to apply a little more force intentionally, but the difference is acceptable."*

	Ease-of-use	Efficiency
M1 (table)	6.83 (SD=0.41)	6.67 (SD=0.52)
M2 (the top of thigh)	6.50 (SD=0.84)	6.17 (SD=0.75)
M3 (the side of thigh)	6.67 (SD=0.52)	6.33 (SD=0.52)

Table 9. Subjective score of M1, M2, and M3. 1=disagree strongly, 7=agree strongly

Table 10 shows the subjective feedback of the overall experience of the ring and phone. Wilcoxon signed-rank test showed that the ring interaction outperforms the phone interaction in the dimensions of "fun-to-use" ($z = -3.115, p = .002$), "private" ($z = -3.089, p = .002$), and "facilitates for one-handed interaction" ($z = -2.76, p = .006$).

	Ring	Phone
Easy to use	6.43 (SD=1.02)	5.79 (SD=1.31)
Fun to use*	6.64 (SD=0.50)	5.21 (SD=0.80)
Efficient	5.93 (SD=0.93)	5.79 (SD=1.19)
Private*	6.77 (SD=0.43)	4.50 (SD=1.79)
Facilitates one-handed interaction*	6.27 (SD=0.83)	4.93 (SD=1.27)
Easy to learn	6.64 (SD=0.50)	-
Willingness to use	6.64 (SD=1.08)	-

Table 10. Subjective score of the overall experience of ring and phone. 1=disagree strongly, 7=agree strongly. * denotes significant effect

We used different finger postures (finger pulp or fingertip postures) to form a rich set of swipe and tap gestures and then mapped them to screen reading commands. As the difference between the finger posture and mapping relationship of ring interaction and phone interaction, users need learning time. However, compared to mid-air gestures and finger-rubbing gestures(e.g., using the thumb to rub against the index finger), the ring interaction uses the finger to interact with any surface directly, which can bring users an experience similar to interacting with a screen. We also consider the idiomatic gestures on screen reading software and semantic relationships between commands and gestures. Therefore, users can adapt to these gestures after short learning and practicing time. During the study, three participants mentioned it was a little harder to memorize the mapping of the commands and gestures at first. However, it was natural, easy, and memorable to use them in practical tasks. For example, P5, the participant with the longest practice time, said: *"Initially, I was worried that I could not remember them. However, in performing the tasks, I had a familiar feeling of operating a phone, and I could recall the gestures in every step when needed. It was a surprising experience."*

We found that although the gestures of "swiping up, down, left, and right" naturally map to directional commands like "scroll up, down, left, right", users often reversed the mappings in practice, i.e., swiping up to scroll down, swiping left to scroll right, etc. This is most likely because this inverse mapping is widely adopted by screen reading software. Upon making errors, users could perform reverse gestures to navigate back to the previous page. In the future, we can provide a custom mode that allows users to adjust the mappings according to their own habits.

All participants expressed interest in using ring-based interactions in their daily lives. They hoped that the ring could be put into production as soon as possible and be widely used by VI people.

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6 DISCUSSION

We present a ring-based input interaction. It enhances phone interactions by allowing for input on any surface and serves as a supplementary input method to relieve VI people from the task of acquiring the phone from their pocket, to facilitate one-handed interaction, and to mitigate social concerns.

VI users do not want to attract additional attention in social settings, and care about the physical appearance of the ring [23]. During the studies, participants often asked us "what will this ring look like?", and "how much will this ring cost?". The IMU (the ring's sensor) is low-cost and small-sized. Its small size leaves room for design optimizations to alleviate users' concerns about appearance. In addition, IMUs are already widely used in commercial rings. Our IMU-based gesture sensing technique can be easily embedded into commercial smart rings.

Our ring-based interactions are also beneficial to the general population. Ring interaction can alleviate widely recognized pain points such as the sticky hand problem [25] or operating a phone discreetly in socially sensitive situations. For example, when cooking, users can perform gestures on the counter and listen to recipe information. Moreover, as performing gestures only requires the movement of the index finger, our interaction method can also benefit people with motor impairments (e.g., people with ALS disease). Therefore, the ring interaction is universal in design, which is also in line with VI people's desire to use things that the general population uses rather than separating themselves from society [23].

In addition, we discuss concerns regarding the ring's form factor, size, and power consumption:

Ring form factor. Many smart devices can be used to control smartphones, such as Bluetooth headsets with voice input and smartwatches [15, 21, 40, 51]. Compared with these alternatives, a ring has unique benefits in some aspects and will serve as a new alternative for phone-free interaction for VI people.

Compared with Bluetooth headsets with voice input, our ring interaction suffers less from privacy concerns, and is more efficient for simple operations such as "moving to the previous or next item."

Compared with smartwatches in one-handed interaction scenarios, a ring can sense subtle swiping and tapping finger gestures with greater accuracy than a wrist-worn device. This input method provides improved usability (e.g., less fatigue and higher efficiency). As users can perform gestures on the watch screen worn on the opposite wrist, smartwatches have the advantage of being able to provide rich and high-precision gestures for phone-free interactions for VI users in two-handed scenarios. Some researches have explored watch-based one-handed sensing techniques that use relatively larger finger movements to control daily devices, such as flicks, scratches, pinch, rubbing fingers, etc [21, 40]. However, these works focus on sensing techniques, rather than addressing the issues of smartphone use for VI people. We believe a watch-based phone-free input method for VI users warrants further research.

Size and power consumption. Improvements in hardware will mitigate size and power consumption issues. A direct example is Oura Ring (https://ouraring.com/). It contains Infrared optical pulse measurement, 3D accelerometer, gyroscope, body temperature sensor, Bluetooth, and battery, with 4-6 grams in weight, 7.9mm wide, and 2.55mm thick. The battery life is up to one week. Our ring has fewer sensors compared to the Oura. We're aware of the power consumption caused by the ring's 1000Hz sample-rate. We believe the development of improved battery technology will eventually solve this problem.

7 LIMITATIONS

Affected by the curvature, softness, and clothing material, the force to perform gestures on the thigh is a little greater than on the table surfaces. According to the participants' subjective feedback, this difference in force is acceptable. In the future, we'll study the impact of different materials on force and user preferences.

Preventing unintentional touches via the triple-tap registration gesture is not reliable enough. In the future, we'll add a physical button on the ring. Users will need to interact with this button to enter and exit the ring input mode.

Our ring prototype is not small enough and is connected to the Arduino via the Dupont line, which affects user experience. In the future, we'll add Bluetooth and battery modules to the ring remove all physical wire connections.

We choose a sample of daily behaviors that might be confused with our gestures as negative sample (three categories mentioned in Study 2). We collected as much data as possible in each category. The results of Study 2 show that the recognition accuracy is satisfactory. We agree that it is hard to collect all possible negative samples and prevent false positives with 100% certainty.

We used voice input instead of typing in this study, which may raise privacy issues to some extent. However, this issue is not particular to VI people, but a common problem raised by voice interaction. In the future, we'll explore ring-based typing input methods for VI people.

Limited by a single IMU, we could not sense sustained gestures (e.g., long press). Rather, our main contribution is demonstrating the feasibility of ring-based input and its usefulness to VI users. In the future, we will explore new sensing techniques (e.g., adding a camera) to sense more gestures and enhance the user experience.

8 CONCLUSION

In this paper, we present a ring-based input interaction for visually impaired people, which enables in-pocket smartphone operation on any surface. We designed commands and gestures through participatory studies, then designed gestural recognition algorithms and achieved an average accuracy of 95.5% for 15 gesture classifications. Finally, we conducted a study to evaluate usability, including accuracy, efficiency, and subjective feedback. Results show that this interaction provides an easy, efficient, private, ubiquitous, and one-handed way to bring users a phone-free experience. In a broader sense, it is a promising study that expands the HCI community's work of using wearable devices to address the issues of visually impaired people.

ACKNOWLEDGMENTS

This work is supported by the National Key Research and Development Plan under Grant No. 2016YFB1001200, the Natural Science Foundation of China under Grant No. 61521002 and No. 61672314, and also by Beijing Key Lab of Networked Multimedia.

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