ThumbRing: Private Interactions Using One-handed Thumb Motion Input on Finger Segments

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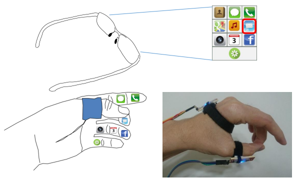

Figure 1: Thumbring, sliding and touching on the finger segments. 10 items are arranged on the 10 finger segments. The panel is shown on the smart glass. Right: prototype with 2 IMUs on the thumb and back of the hand.

MobileHCI '16 Adjunct, September 06-09, 2016, Florence, Italy
 ISBN 978-1-4503-4413-5/16/09$15.00
DOI: http://dx.doi.org/10.1145/2957265.2961859

Abstract

We propose an input device, ThumbRing, for items selection on head-mounted displays (HMDs) or smart glasses. ThumbRing is a ring with an inertial measurement unit (IMU) worn on the thumb to track the motion. By arranging an item to a finger segment, users touch and slide finger segments to select the items. To resist shake in mobile conditions such as walking, another IMU is attached to the back of the hand to compute relative angles between the hand and the thumb. Sliding and touching the segments with the thumb in the hand provide privacy, subtlety, natural haptic feedback and similar input area to smartphones. A pilot study is performed to obtain users' preference finger segments. We evaluate the performance of ThumbRing in different conditions and commitment approaches in a user study. The results show that accuracy are 92.3% and 89.7% in the sitting and walking conditions, respectively.

Author Keywords

Mobile; private input; subtle; finger ring.

ACM Classification Keywords

H.5.2. [Information Interfaces and Presentation (e.g. HCI)]: Input devices and strategies (e.g., mouse, touchscreen)

Introduction

Head-mounted displays (HMDs) and smart glasses have good visual output but unsatisfied input approaches. Google Glass provides voice input with little privacy and a touch pad on the side offering limited gestures, making users fatigued when lifting the hand to touch. Other HMDs require extra wired controllers held, which is inconvenient. We propose a wearable input device for HMDs and smart glasses providing privacy, subtlety and high mobility. Many studies provide input methods using wearable devices which can be used as HMDs and smart glasses input. Using a magnetometer [1, 3, 4, 7] or a camera [2, 11, 12, 14, 15] to track finger motion and pose are common approaches.

In this paper, we propose a wearable input device ThumbRing for HMDs and smart glasses. ThumbRing detects thumb motion and pose using a ring with an inertial measurement unit (IMU). The finger segments, nature landmarks, are arranged with items so users slide and touch the segments to select items on HMDs or smart glasses with the thumb. The pose is the similar to use smartphones with one hand. To make ThumbRing work in mobile conditions such as walking, another IMU attached on back of the hand in Figure 1 is used to obtain relative angles between the thumb and the hand. We observe users preference of finger segments in a pilot study at first, and further evaluate performance ThumbRing in different conditions and commitment approaches in a user study.

ThumbRing provides following contributions. (1) Privacy and subtlety using sliding and touching gestures on the segments in the hand. (2) Sufficient input area is similar to smartphones. (3) Haptic feedback is provided by finger segments, natural landmarks, on the hand. (4) High social acceptance wearable device due to the ring form-factor. (5) High mobility is supported by relative angles from two IMUs.

Related Work

We discuss wearable devices for gesture input, private and subtle input, and input methods using finger segments.

Wearable Devices for Gesture Input

Magnet motion tracking is widely used to track a single finger. Two devices are worn to attach a magnet and a magnetometer, respectively. The magnet is attached to the finger tip to track the finger motion and pose. The magnetometer is worn on the wrist in Abracadabra [7], nail in FingerPad [3] or ring finger in uTrack [4] to provide 1D, 2D and 3D input, separately. Magnet motion tracking is usually interfered by magnetic field noise. The magnetometer moving also affects the tracking such as the ring finger in uTrack.

Rather than tracking a single finger, camera-based methods are usually used to track gestures from the whole hand. An infrared (IR) camera in Digits [12], PinchWatch [14], proximity sensors in LightRing [11], iRing [15] and a fisheye camera in Cyclopsring [2] are used to distinguish single- or multi-fingers gestures. Camera-based methods, such as Digits, PinchWatch and Cyclopsring, generally suffer from the occlusion problem. iRing has limited input area. LightRing is limited in mobile conditions due to a gyroscope.

Except camera-based approaches, various techniques detect the whole hand gestures using slight contour change or biosignal. Gesturewrist [17] recognizes two gestures using the bio-capacitive sensing technique based on the wrist contour change. Electromyography (EMG) [8] and bio-impedance [18] are also used to detect gestures. Detecting slight form change on the back of the hand using strain gauges, BackHand [13] provides hand gesture sensing. These techniques require gesture training after wearing the devices each time. Slightly changing the wearing position causes different signals from the same gesture. While reproducibility is claimed in [8], four gestures are recognized.

Private and Subtle Interactions on Wearable Devices
Nenya [1] provides subtle 1D input by tracking magnet ring motion when users spin it. The unpowered ring and subtle interaction are great contributions of Nenya; however, two-handed commitment and 1D input are the limitations. FingerPad [3] also provides a subtle interaction using magnet motion tracking with a nail-mounted magnet. It allows users to perform 2D input using the pinch gesture. It is similar to a small 2D touchpad with haptic feedback on the thumb. However, nail-mounted devices reduce social acceptance. Similarly, NailO [10] provides touch input on nails using capacitive sensing technique. Combining with fashionable nail art stickers, NailO is preferred by female users.

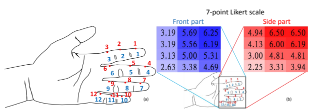

Figure 2: The results of the pilot study. Left: red for side and blue for front part of finger segments. 12 segments are enumerated. Right: Preference mean scores using a 7-point Likert scale.

Wearable Devices interacting with Finger Segments
Imaginary Phone [6] propose that using finger segments and the palm assist users to learn imaginary interface [5]. Users map icons and buttons on smartphones to finger segments, which are natural landmarks on the hand. The transfer learning improves the learning performance. PinchWatch [14] also leverages the finger segments as buttons and provides one-handed smartwatch input. However, both studies require a camera for detection. The occlusion problem and camera's field-of-view (FOV) are the limitations.

Design
Due to ubiquitous smartphones, people are accustomed to performing touch input with the thumb when using smartphones with one hand. We leverage the thumb and finger segments to propose a subtle input method for item selection on HMDs in ThumbRing. The users, wearing ThumbRing on the thumb, maintain the same pose when using smartphones but touch finger segments instead of touchscreen as input. We assign an item to a finger segment, as shown in Figure 1. Using the IMU in the ring, ThumbRing is able to track the thumb pose and recognize which finger segment is touched. Users slide the thumb on fingers to move to the target segment and commit with the proposed commitment gesture. Finger segments provide nature landmarks for touch input. Therefore, during the whole procedure, the users keep the thumb contacting with fingers to maintain haptic feedback and reduce jitter problem. The item selection procedure in the hand is private and subtle, and TumbRing provides similar input area to smartphones.

Pilot Study
Users might not be able to easily and comfortably reach all finger segments with the thumb due to the thumb length and dexterity. Therefore, we performed the pilot study to obtain the proper finger segments, comfort zone, as the input area. Except a thumb, a total of 12 finger segments were in one hand, as illustrated in Figure 2. Although DigitSpace [9] also investigated how to use the front part of finger segments as input area, by observing the pose using smartphones with one hand, we supposed that the side part of finger segments might be more proper as the input area. Therefore, we also compared these two parts in the pilot study. The results shown which finger segments most users desired to arrange a button on.

A total of 16 participants (12 male) aged 23-58 (mean 27.63) were recruited. The 12 finger segments were enumerated, as shown in Figure 2 in left hand, and the numbers were in mirrored positions in right hand. A finger segment was further divided into two parts: front and side. The participants were required to press on both parts with the thumb. During the pilot study, they slid the thumb back and forth on the finger and stayed on the certain finger segment for a few seconds. Based on comfort and ease to touch or press, they gave a score to each segment orderly in both parts, blue one and red one in Figure 2, using a 7-point Likert scale. At last, we interviewed them for feedback and comments.

The mean scores of the segments in front and side parts were shown in Figure 2. The segments around the thumb got higher scores because the participants did not need to bend the thumb hard to touch. In terms of the parts of segments, the mean scores in segment 1 to 6 (index and middle fingers) in the side parts were higher. However, the scores in segment 7 to 12 (ring and pinky fingers) in the front parts were higher. We found that the thumb rotated inward gradually when bending toward the pinky finger. When the thumb bended toward the fingers around it (index and middle fingers), the front part of the thumb were approximately parallel to the side part of the fingers. On the contrary, when the thumb bended toward the fingers far from it (ring and pinky fingers), the front part of the thumb were approximately parallel to the front part of the fingers. Thus, different scores for different parts on the same segment.

The side part of segment 1 to 9, i.e. index, middle and ring fingers, were chosen as the comfort zone. The segments were acceptable for most participants and the side parts got higher scores in these segments. In fact, the side part of the segments were closer to the thumb than the front part so it was easier to touch on them. Segment 10 to 12 (pinky finger) had lower scores. Besides, we observed that when touching the pinky finger, many participants slightly moved the pinky finger toward the thumb. This made the pinky finger position similar to the ring finger position. Nevertheless, we still adopted the front part of segment 12, less affected by pinky finger moving, as a special segment to assign the item less frequently used or required to avoid false positive (e.g., the activation button) in our design. As a result, ten finger segments including the side part of segment 1 to 9 and the front part of segment 12 were used in ThumbRing.

Finger Segments Recognition

Touching different segments with the thumb causes different thumb poses. The IMU in ThumbRing detects the orientation of the thumb in three degrees of freedom (3DoF), including yaw, pitch and roll angles. Nevertheless, in mobile conditions such as walking, the body or hand shake. It results that different orientations are detected in the same touch gesture. To overcome the problem, we leverage another IMU attached to the back of the hand to construct a relative angular coordinate system. These two IMUs obtain similar relative angles in different hand poses only if touching on the same segment, which means that the relation between the thumb and the segment does not change a lot.

To obtain relative angles from these two IMUs, we use the rotation matrix, Direction Cosine Matrix (DCM) [16], of each IMU to further compute a transform matrix. The transform matrix allows us to obtain the relative angles of one IMU based on the other. The definition of DCM:

$$V_G = RV_S \tag{1}$$

where V is certain kinds of vector, including directions, velocities or accelerations. V_S, a vector V based on a sensor coordinate, can be transformed from the sensor based coordinate to the ground based coordinate, V_G, by multiplying R, a DCM rotation matrix. We obtain angles based on the ground coordinate from elements in R. Based on definition of R, the transform matrix can be further deduced as:

$$R_A^B = R_A^G R_G^B = (R_G^A)^{-1} R_G^B = (R_G^A)^T R_G^B \tag{2}$$

where R_G^A and R_G^B represent R from sensor A and B based on the ground coordinate G, which are what we know. R_A^B means R in sensor B based on sensor A coordinate, the transform matrix we desire. R^{-1} is equal to R^T based on the definition of rotation matrix R. With the transform matrix, we get relative angles of IMU B based on IMU A.

Although touching the same segment, different relative angles might be detected due to slightly different thumb poses and noise from IMUs. Thus, after collecting relative angles when touching each finger segment, we build a training model using a machine learning approach K-nearest neighbors algorithm (KNN). When performing item selection, the relative angles are classified into proper segments.

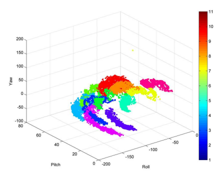

Figure 3: A totol of 1100 relative angles collected from the 11 classes from a participant for training. Three axes are angle of yaw, pitch and roll in degrees.

Commitment Approach
After moving the thumb to the target segment, the users perform a tap gesture to commit the target. In our design, when touching on the target segment, the users lift the thumb to the position similar to the thumbs-up gesture. After it is detected, commitment is ready to be triggered. The thumb then taps back to the finger segment. No matter it taps on the target segment or not, the commitment is triggered. Certainly, when lifting, the thumb may be misclassified into incorrect the finger segments. Therefore, we infer the target segment using a short pause that the users stay the thumb on the target segment to check whether it is the right one and change the gesture from touch to commitment. The pause is usually longer than 120 ms. If the thumb stays on a segment longer than the time threshold and successfully lifts to the required position, the target is committed after tapping back. Combining the ten finger segments and tap gesture, eleven classes are required for training using the machine learning approach KNN.

User Study

To obtain performance of ThumbRing in different conditions and commitment approaches, we designed the user study.

Apparatus and Participant
Two 9DoF IMUs were used. The IMU, SparkFun 9DoF Sensor Stick, consisted of an ADXL345 accelerometer, a HMC5883L magnetometer, and an ITG-3200 gyroscope. Each IMU was connected to an Arduino Nano. Each DCM element and 3DoF orientation data were further delivered to a laptop in sample rate 50Hz. The laptop also was used to simulate the HMD and smart glass visual feedback. The visual feedback was displayed on the sub-region of the laptop in 3 inches. A total of 12 participants (9 male) aged from 23-36 (mean 26) were recruited to the experiment. Three of them worn ThumbRing on the right thumb. They received some incentives after the experiment.

Experiment Design and Procedure
Two main factors, including conditions and commitment approaches were considered in the experiment.

Condition
Sitting and walking conditions were considered. In the sitting condition, the participants sat in front of the laptop and were allowed to lay the hand on the leg to reduce fatigue. We expected to obtain the performance in a static condition. In walking condition, the participants trod in the same path when walking in front of the laptop as walking on a treadmill. They were allowed to lean the elbow on the side of the body similar to the pose using smartphones to reduce fatigue. It was used to simulate the shake caused by walking.

Commitment Approach
Although tap was proposed to commit in this paper, we did not want the performance of commitment to influence the performance of finger segment selection. Consequently, we added keyboard commitment as a baseline. It represented the performance of segment selection with the best commitment approach. Participants pressed SPACE to commit.

Procedure
The experiment was a 2 x 2 x 10 (*Condition* x *Commitment Approach* x Segment Position) with-in subject design. Each combination had 5 repetitions so there were a total of 200

Figure 4: The experiment results. Selection time (up) and error rate (down) in different conditions and commitment approaches.

trials for each participant. *Conditions* and *Commitment Approaches* were counterbalanced, and segment positions were randomized. 2 IMUs were worn on the thumb and attached to the back of the hand respectively, as shown in Figure 1. The visual feedback was displayed on the subregion of the laptop. Before the experiment, we collected 3DoF relative angles from the 2 IMUs in 11 classes from each participant for training. In data collection, participants stood in front of the laptop and touched with the thumb on side of the finger segments from class 1 to 10 and lifted the thumb as a thumbs-up gesture in class 11 orderly. We suggested them to divide the space in five planes in five pitch orientations. 200 data in each plane. They moved the forearm or hand leftwards and rightwards on each plane while maintaining the gesture in each class. It simulated the relative angles in different hand positions in front of the laptop caused by walking, jittering and noise from the IMUs. A total of 11000 labeled data, 3DoF relative angles (Figure 3), were trained by KNN using the function provided by OpenCV. After the training data collection from each participant, we randomly chose 100 data from each class to perform the leave-one-out-validation and obtained the training data accuracy. The mean accuracy was 92.10% (SD = 8.27%) from all participants.

In the experiment, 10 blue rectangles representing 10 segments were shown on the laptop screen. One of them turned into yellow meaning the target button. A red dot on one of the rectangles was a cursor representing which finger segment the thumb touched. The committed rectangle turned into green, and the next target was shown. Selection time (ST) and error rates (ER) were recorded during the experiment. The experiment, including data collection, took approximately an hour for each participant.

Results and Discussion

Mean selection time (ST) for all trials without errors was 1763.59 ms (SD = 386.89 ms), and the error rate (ER) was 16.13 %. The details were shown in Figure 4. Repeated measures ANOVA (RM-ANOVA) and Bonferroni correction for post-hoc pairwise tests were used for the analysis.

In terms of conditions, there was a significant effect on ST ($F_{1,9}$ = 9.43, p = 0.01) but not on ER ($F_{1,9}$ = 0.08, p = 0.79). We observed the unexpected results that the ST and ER in the walking condition was better than in the sitting condition except ER in keyboard commitment. The possible reason was that the participants laying the hand on the leg caused the hand squeezed and deformed. Therefore, the hand pose was no longer the same as the pose in data collection. It increased ST and ER in the sitting condition.

Regarding commitment approaches, significant effects were revealed on both ST ($F_{1,9}$ = 39.24, p $<$ 0.01) and ER ($F_{1,9}$ = 17.18, p $<$ 0.01). Some participants indicated that the tap gesture was intuitive. Due to the proposed tap detection, they had to lift the thumb in to the certain position. It made the segments around the thumb (index finger) were committed easily and even a little bite prone to cause false positives. On the contrary, touching the segments on fingers far from the thumb, they had to lift the thumb in a long distance to trigger the tap detection. It caused fatigue easily. Furthermore, some participants accidentally supinated the hand when lifting the thumb. It caused that the 2 IMUs rotated to the same direction and the relative angles were not classified to the tap gesture class. We believed that it could be improved using better tap detection or commitment approaches. The keyboard commitment showed the ThumbRing performance that was not affected by commitment approaches in the sitting (ST: 1522.47 ms, ER: 7.67%) and walking (ST: 1343.41 ms, ER: 10.33%) conditions.

Limitations and Future Work

Due to noise from the IMUs, a training model is needed for classification. The sample rate, 50Hz, of our IMUs is not high enough to provide more accurate orientation. We will use IMUs with a higher sample rate to alleviate the problem. For the attachment problem, we will fabricate a 3D printed ring to fix the IMU. In terms of the machine learning method, we observed that KNN outperformed support vector machine (SVM) with linear and radial basis function (RBF) kernels. However, other machine learning methods (e.g., SVM with polynomial kernel and sigmoid kernel) will be compared in the future. We will also improve the tap detection using angular velocity and time thresholds instead of the thumb-up position. Thus, users will not have to lift the thumb in a far distance from middle finger and ring finger.

Although Visual feedback is provided in the current ThumbRing design, ThumbRing providing haptic feedback from the natural landmarks, finger segments, can also offer eyes-free interactions. In addition, discrete input is provided in current ThunbRing. With more accurate classification methods above-mentioned, ThumbRing can recognize more classes, which means that we can arrange more than an item on a finger segment. ThumbRing can even provide continuous 2D input using a regression model in the future.

Conclusion

ThumbRing is a wearable input device provides privacy, subtlety and sufficient input area. It tracks the thumb motion using relative angles from two IMUs, which makes ThumbRing tolerant in mobile conditions such as walking. By leveraging the finger segments arranged with items, ThumbRing provides haptic feedback. 10 finger segments (9 side and 1 front parts) are defined as the comfort zone in the pilot study. The results, as shown in Figure 2, can be guidelines in item arrangement on the finger segments for app developers. The user study evaluates the performance of ThumbRing in different conditions and commitment approaches. The proposed commitment approach tap is an intuitive gesture but the detection approach can be further improved. We also envision that ThumbRing provides eyes-free interactions and continuous input in the future.

Acknowledgements

This work was supported in part by the Chiang Ching-kuo Foundation for International Scholarly Exchange, Ministry of Science and Technology, Taiwan, National Taiwan University and Intel Corporation under Grants 04HT946001, MOST 105-2633-E-002-001 and NTU-105R104045.

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