WRIST: Watch-Ring Interaction and Sensing Technique for Wrist Gestures and Macro-Micro Pointing

Hui-Shyong Yeo
School of Computer Science
University of St. Andrews
Fife, United Kingdom
hsy@st-andrews.ac.uk

Juyoung Lee
Graduate School of Culture Technology
KAIST
Daejeon, Republic of Korea
ejuyoung@kaist.ac.kr

Hyung-il Kim
Graduate School of Culture Technology
KAIST
Daejeon, Republic of Korea
hyungil@kaist.ac.kr

Aakar Gupta
Cheriton School of Computer Science
University of Waterloo
Waterloo, Canada
aakar.gupta@uwaterloo.ca

Andrea Bianchi
Department of Industrial Design
KAIST
Daejeon, Republic of Korea
andrea@kaist.ac.kr

Daniel Vogel
Cheriton School of Computer Science
University of Waterloo
Waterloo, Canada
dvogel@uwaterloo.ca

Hideki Koike
Department of Computer Science
Tokyo Institute of Technology
Tokyo, Japan
koike@c.titech.ac.jp

Woontack Woo
Graduate School of Culture Technology
KAIST
Daejeon, Republic of Korea
wwoo@kaist.ac.kr

Aaron Quigley
School of Computer Science
University of St. Andrews
Fife, United Kingdom
aquigley@st-andrews.ac.uk

ABSTRACT

To better explore the incorporation of pointing and gesturing into ubiquitous computing, we introduce WRIST, an interaction and sensing technique that leverages the dexterity of human wrist motion. WRIST employs a sensor fusion approach which combines inertial measurement unit (IMU) data from a smartwatch and a smart ring. The relative orientation difference of the two devices is measured as the wrist rotation that is independent from arm rotation, which is also position and orientation invariant. Employing our test hardware, we demonstrate that WRIST affords and enables a number of novel yet simplistic interaction techniques, such as (i) macro-micro pointing without explicit mode switching and (ii) wrist gesture recognition when the hand is held in different orientations (e.g., raised or lowered). We report on two studies to evaluate the proposed techniques and we present a set of applications that demonstrate the benefits of WRIST. We conclude with a discussion of the limitations and highlight possible future pathways for research in pointing and gesturing with wearable devices.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Pointing devices**; **Pointing**; **Gestural input**.

KEYWORDS

Smartwatch; wrist gesture; distal pointing; large displays

ACM Reference Format:
Hui-Shyong Yeo, Juyoung Lee, Hyung-il Kim, Aakar Gupta, Andrea Bianchi, Daniel Vogel, Hideki Koike, Woontack Woo, and Aaron Quigley. 2019. WRIST: Watch-Ring Interaction and Sensing Technique for Wrist Gestures and Macro-Micro Pointing. In *21st International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '19), October 1–4, 2019, Taipei, Taiwan.* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3338286.3340130

1 INTRODUCTION

Interacting with large public displays or small on-body wearable devices, such as smartwatches remains a challenge. The nature of interaction with large public displays or a "display ecosystem" [59] presents many challenges from non-interactivity, requires vision-based sensing (e.g., camera, depth sensor) or requires specific input devices (e.g., pointer,

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

MobileHCI '19, October 1–4, 2019, Taipei, Taiwan

© 2019 Association for Computing Machinery.

ACM ISBN 978-1-4503-6825-4/19/10…$15.00
https://doi.org/10.1145/3338286.3340130

remote) for interaction at a distance. At the smaller, and more intimate scale, interacting with a wearable device is challenging when we consider the range of interaction, device size, device type, social context and physical constraints. For example, interacting with a smartwatch or fitness tracker often necessitates two hands, one to wear the device and another one for touching the screen or pressing buttons.

The range of human motions have often been considered in isolation, rather than as part of a continuous interaction experience with such devices. The human hand, fingers and wrist afford us a wide range of gestures, including pointing, that can support proximate, distant and hybrid interactions. Indeed, the dexterity of the human wrist joint with flexion-extension, radioulnar deviation, and rotation typically allows people a broad range of movements, making it one of the most dexterous parts of the human body and promising to consider for input and interaction [38, 46].

We introduce the **W**atch-**R**ing **I**nteraction and **S**ensing **T**echnique (WRIST). It can measure very small changes in the wrist orientation at high refresh rate by using a sensor fusion approach that combines IMU data from two orientation sensors, one on the wrist and one on the finger. Further, we leverage the dexterity of the human wrist and enable new types of interactions with wearable devices and distant displays, using only one hand. While our proposed approach requires two devices (smartwatch + smart ring), wearing watches and jewellery is commonplace. Hence, we envision future scenarios where WRIST technology is incorporated into day-to-day smart wearable devices in use.

In WRIST we make the following contributions: 1) we study macro-micro distal pointing without explicit mode switching which relies of natural forearm and wrist movements; 2) we explore robust single-handed wrist gestures recognition with simple hardware and sensor fusion, and study the orientation and movement invariant input; 3) we developed several applications demonstrating the benefits of the proposed input techniques. These techniques are studied in a lab setting with a large projected display for pointing and a treadmill for gesture recognition while on-the-go.

2 RELATED WORK

Our work lays at the intersection of three areas of human-computer interaction, including distal pointing, single-handed gestures, and wearable input device research. Here we give an overview of each topic with the most relevant work.

Sensing of Single-Handed Gestures

Currently, interacting with a wrist-worn smart device (e.g., smartwatch or fitness tracker) often necessitates two hands. As a result, researchers are currently exploring the design of single-handed gestures [8, 23] and at-your-side interaction [35, 54]. Techniques such as tilting, flicking or shaking of

Figure 1: (left) Assembled custom smart ring device (right) when worn on finger together with an Android smartwatch.

devices are also explored. Indeed, many smartwatches have such gestures built-in as part of the operating system. However, these gestures are discrete and non-continuous, where each flick or tilt triggers only one action, which is limited in terms of interaction capabilities and expressiveness.

Research has also explored various sensing techniques to detect single-hand gestures, such as Electromyography [51], Infrared [19, 37], motion [20, 60, 66], vision [9, 28], magnet [11, 12], force [17, 34], acoustic [32, 73–75], electrical impedance [76] and capacitive [48]. However, each of these techniques is not without limitations, such as complex sensor requirements, high computational demand, use of repetitive gestures and the need for audible signals for acoustic sensing. Most importantly, they typically only support discrete and non-continuous input. Alternative input modalities such as speech recognition or blowing air to trigger an input [13, 50] are also possible, but they can suffer from background noise or can be socially awkward to perform in the public.

Our approach aims to support continuous input for single-handed interaction, while using only IMU information, which is already available in most off-the-shelf wearable devices.

Wrist and Finger Interactions

As the human wrist is dexterous with flexion-extension, radioulnar deviation, and rotation movements [16, 46], some approaches such as WristWhirl [19] and "With a Flick of the Wrist" [57] explore the idea of leveraging the wrist joint as a controller, which is aligned with our approach. Indeed, many of the distal pointing related tasks [22, 61] involve the combination of the arm and wrist motions. This also gives rise to text entry techniques based on wrist tilting [24, 45, 67] and tilt-based gesture typing [21, 71].

The growing availability of smartwatches and smart rings have prompted researchers to explore new forms of human-computer interaction and augmentation. Duet [14], VibRing [3] and Expressy [68] leverage the smartwatch or smart ring to add expressiveness to touch-based interactions on a phone or tablet device. Digital digits [52] and "Ring Form Factor" [15] surveyed and explored the design space of smart rings for interaction. Webb et al. [64] explored using wearable devices such as a smart ring as context for surface and pen-based interaction. Magic Finger [70] and TouchCam [56] enables users to interact with surfaces using optical sensor embedded in a wearable ring form factor. DeformWear [65] is a tiny finger worn device that enables precise input using pressure, shear and pinch deformations.

PredicTouch [33] and Moschetti et al. [40] explore the combination of wrist and finger IMU for reducing touch screen latency and for recognition of daily gestures but these are not focused on single-handed interaction. SynchroWatch [49] uses rhythmic correlation between a user's thumb movement (magnet ring) and on-screen blinking controls (smartwatch). In WRIST we explore combining data from a smartwatch and smart ring for distal pointing and gesture interaction.

Distal Pointing

There is an extensive literature on pointing interaction for large displays, using laser pointers [43], WiiMote controllers [47, 53], and everyday smart devices [55]. Kopper et al. [29] studied four possible models for a distal pointing task whereas Jota et al. [25] compared different ray pointing techniques for very large displays. "Put-that-there" [4] is the first project that explored free hand pointing combined with voice recognition. Vogel and Balakrishnan [63] introduced free hand pointing and clicking techniques for distant display. The idea was later applied to a single wearable EMG-based armband (Myo) in [22]. Watchpoint [26] and TickTockRay [27] employ a commodity smartwatch for pointing in ubiquitous display or virtual reality environments. However, to enable clicking without requiring the second hand, it uses wrist rolling as the trigger, which can be difficult to maintain accurate pointing.

By contrast, WRIST pointing is largely based on the idea of allowing users to perform both coarse and precise modes in pointing. For example, the MAGIC pointing technique [72] uses eye tracking for coarse contextual pointing combined with a regular pointing device for precision tasks. Hybrid-Pointing [18] lets users easily switch between absolute and relative pointing with a pen. Cao et al. [6] also explored hybrid pointing devices that combined both finger and hand movement to control the cursor. Nancel et al. [42] formally define Dual-Precision pointing which explicitly divide pointing tasks into a coarse phase and a precise phase, requiring explicit mode switches. Tsandilas et al. [61] explored the physical constraints of the wrist and extend the range of its input based on rate control, thus without requiring explicit mode switching mechanisms. Our work support hybrid coarse and fine pointing *without* explicit mode-switching.

3 PROTOTYPE

To leverage the dexterity of the human wrist, our system measures human wrist in terms of flexion/extension, radial/ulnar deviation, pronation/supination and maps the measurement as an input, akin to a joystick controller. Due to the hand biomechanics and limited range of freedom around the wrist joint [16, 46], the horizontal movement is more challenging than vertical movement. As observed in WristWhirl [19], drawing a circle shape resulted in an oval shape instead.

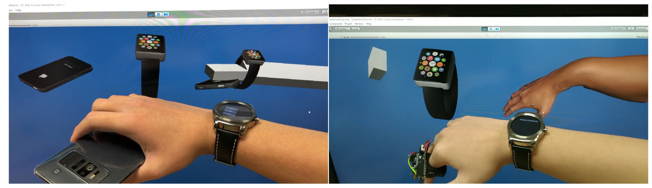

Figure 2: (left) Initially we tried with a smartphone imitating a ring and controlling primitive blocks. (right) Trying with a custom assembled ring and controlling a 3D hand model.

To support different contexts such as hand-front, hand-up and hand-down interaction, it is important that our technique works with any arm orientation. This is where using only one watch or one ring falls short, due to lack of a reference point. When using only one ring, it cannot distinguish between a whole arm gesture or just the wrist gesture.

Prior work such as the WristWhirl [19] prototype is not sensitive to small wrist movement near to neutral position. Therefore, users needed to exert more tilt for the infrared sensors to pick up the wrist motion. This led to potentially larger gestures and longer gesture times. We hypothesize that using IMUs should overcome these issues.

Hardware

Initially we tested the idea by simply holding a smartphone in the hand and combining the sensor's readings with those of a smartwatch. By tilting the wrist we were able to manipulate a primitive hand model consisting of cubes (Figure 2 left). We then created our own prototype ring (Figure 1 & 2 right) using simple hardware for the flexibility in accessing the IMU data. Nonetheless, we envision this could be miniaturized, as already shown in various commercial smart rings (Oura [44], Motiv [41], Talon [58]) and wearable IMU (Meta [36]).

For the custom smart ring, we employed a Bosch IMU (BNO055) with the Arduino platform with WiFi (ESP8266). All the components are mounted on a 3D printed C-shape ring (Figure 1). As a result, the ring is self-contained, and works without cable tethering to another device. The ring weighs about 18gram in total including a 105mAh lithium ion battery. We used the LG Urbane (Android Wear) smartwatch. Both IMUs are updating at 50Hz. We use a force sensitive resistor (FSR) which acts a button that only requires a light press from the thumb. In second iteration we also replaced the 3D printed ring with a Velcro strap for better fitting.

Software

We extract the orientation of the watch and the ring using the Android SDK and Arduino library, respectively. The IMU data from the ring is streamed to the smartwatch through WiFi, where the calculation of the xy position is computed locally. Optionally, all data are streamed to a PC for i) visualization by gesture trail points (Figure 10) and hand deformation (Figure 2) and ii) saving for offline analysis. The experiment software is written in Python whereas the demo applications are written in Android and Unity game engine.

To find the difference in the rotation matrix, we rotate the reference IMU towards the target IMU. We take the target rotation matrix and multiply with the inverse of the reference rotation matrix, as shown in the following equation.

$$R_{Diff} = R_{Target} \ x \ Inverse(R_{Reference})$$

Then we convert the rotation matrix to Euler angles. We compared the angles to the initial angles obtained during a neutral pose and map the difference to xy position. For controlling a cursor we can use absolute or relative mapping.

Technical Evaluation

We performed a set of tests to measure the accuracy of the system. For ground truth data, we employ the SteamVR tracking system which consists of a HTC Vive tracker and light house system that can provide low latency and sub-millimeter accuracy [62]. We affixed the Vive tracker together with smartwatch and smart ring on a wooden hand, using masking tape and hot glue, as shown in Figure 3.

The first test is to evaluate the total drift that occurs after extensive motion, by measuring the initial orientation and compared with the final orientation over the course of the test. We place the wooden hand at an initial position and orientation, then re-center all the sensors orientation to a virtual cube in the software. Then we take the wooden hand and swing it freely in random motion while walking around in different directions within the tracking space of Vive light house, which is about 2x2 meter. After that we place it back at the initial position and orientation (marked by pen) and make sure the difference in orientation (in quaternion) was close to zero (±0.5 degree) by comparing the current Vive tracker's orientation with the initial orientation recorded. We then measure the angular differences of the smartwatch and smart ring with respect to the ground truth data (i.e., the angles required to rotate this quaternion to the reference quaternion). We did this 14 times and found an average difference of 1.13 degrees (SD: 0.56) for smartwatch and 1.58 degrees (SD: 0.96) for the smart ring.

In a second test, we mounted the sensors on a platform that is capable of rotating in 3 degrees of freedom (Figure 3 right). With the Vive tracker acting as the reference, we measure the quaternion angular difference between the smartwatch vs. tracker and smart ring vs. tracker in real-time, while we rotated the platform randomly in all 3 DoF. Through this process, we collected about 50k data points. We found the mean difference to be 3.09 degrees (SD: 2.29) for smartwatch and 8.27 degrees (SD: 3.19) for smart ring.

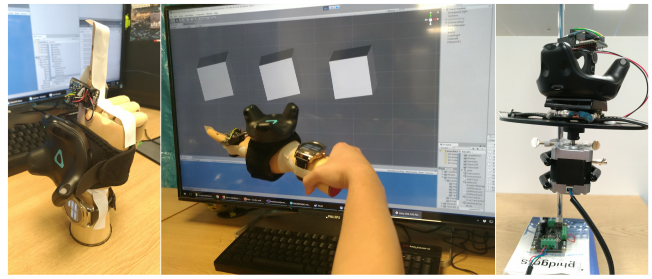

Figure 3: (left) Wooden hand with sensors affixed. (middle) Visualization of real-time orientation of the sensors. (right) Sensors placed on a platform that supports 3 DoF rotation.

Regarding the higher error in the second test, subsequent analysis suggested that the motorized platform used in the second test contains ferrite core. Therefore, it has affected the sensor fusion technique that combines data from accelerometer, gyroscope and epspecially magnetometer. Also, we neglected to account for network delays from the smartwatch and smart ring using WiFi compared to a Vive tracker which streams data using a dedicated Bluetooth dongle. Hence, during fast motion, the watch+ring data was not synchronized with the ground truth data, causing higher error rates to be recorded. Furthermore, the higher error on the ring is potentially caused by misalignment and the higher distance from the center of the Vive tracker due to the physical constraint in mounting the sensors together on the platform. Therefore, we should treat this result of the second test as the worst case scenario where network delays and ferrite elements exist, such as in real-world environments.

4 WRIST POINTING FOR LARGE DISPLAYS

Large displays are increasingly commonplace as a means to broadcast and distribute content. However, such displays typically do not offer any interaction capabilities for their users. Here we explore how our technique can enable macro-micro pointing on such displays without explicit mode switching. Pointing at interfaces on displays, called distal pointing, is commonly achieved with forms of raycasting with laser pointers or mobile devices [47]. However, such techniques have inherent precision problems, due to natural hand jitter, lack of support surface and the so called "Heisenberg effect" in spatial interaction [5] where the cursor position is unintentionally changed when the button is clicked. These issues are further amplified when the display area or the distance

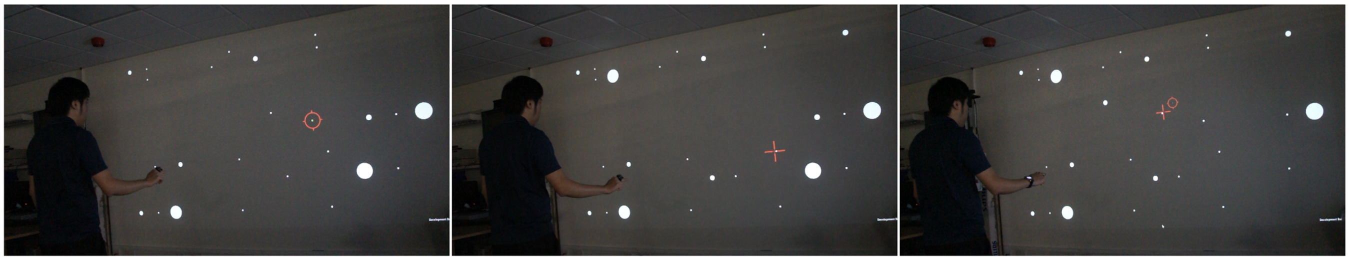

Figure 4: (left) Raycasting (middle) Laser+Gyro in precision mode (right) WRIST pointing where the circle area cursor and the crosshair are visible at the same time, the forearm controls the circle while the wrist controls the crosshair.

to the display gets larger. Existing research has proposed numerous enhancements, including input filtering, area cursors, zoom in on an area, or relative pointing with clutching. In particular, hybrid or dual-precision techniques [42, 63] have shown great potential, which WRIST is based on.

Typically, the first phase of a distal pointing task consists of a ballistic movement [39] that prioritizes direction and velocity. As the cursor approaches a target, it slows down and a finer control is required to select or stay within the target, which is the second phase. Dual-precision techniques [42] explicitly separate these two and the transition between them into a coarse mode and a precise mode, using an explicit mode switch, triggered by a second button or hand posture.

WRIST's Macro-Micro Pointing Design Space

In WRIST, the wrist and finger movements can be independently tracked from the forearm movement, allowing us to consider various two-tier techniques such as those explored in the multimodal interaction literature (e.g., Gaze+Gesture [10] and Pinpointing [31]). Here we apply this type of interaction to continuous macro and micro pointing, without explicit mode switching. The forearm controls an area cursor that points at a coarse location while the wrist or finger controls a precise crosshair independently pointing at a finer location, as shown in Figure 4 (right). We speculate that this allows more accurate pointing at smaller targets while avoiding the time required for explicit mode switching. Indeed, Balakrishnan and MacKenzie [2] found that the wrist or forearm performs better than the index finger alone in pointing tasks, which motivates our approach that uses the forearm for coarse pointing and wrist/finger for precise pointing.

Baseline Performance Techniques for Pointing

For comparison, we re-implemented three other pointing techniques including i) Raycasting, ii) Relative pointing with clutching [22] and iii) a dual-precision technique (Laser+Gyro [42]). Hence, in total we tested four different techniques. In each case distinct sounds are played for click-down and click-up events. Various design choices such as using a long click as the trigger and linear mapping are incorporated into our implementations as described below. Since employing IMU for pointing can be negatively affected by hand tremor and the Heisenberg effect, we apply 5 correction and filtering techniques that are inspired by previous work [22]. The first 3 are applied to all pointing techniques while the last 2 are only applied to WRIST pointing.

Trigger. For the Relative technique that require clutching and the Laser+Gyro technique that require mode switching, initially we employed a secondary button as the trigger, as in prior work. However, during pilot study this proved confusing for the users and resulted in too much of the Heisenberg effect. As a result, for our studies we instead used a long click as the trigger, which is a sufficiently distinguishable event. While this single button solution reduces confusion, the trade-off is it introduces a delay. Here, while the button remains clicked, it is in clutching or precise mode. Once the button is released, there is a short delay before switching back to non-clutching (400ms) or coarse mode (800ms).

Linear Mapping. For the relative technique, we did not use an acceleration function that was employed by previous work [42, 63]. As with desktop pointing, in practice acceleration can be customized to each user, making it easier to traverse a long distance. However, to maintain consistency here we employ a linear mapping function. The control to display (CD) ratio was tuned so that a user can reach anywhere on the screen comfortably with just one full clutch.

Cursor position filtering. We used the 1 Euro filter [7] in all four techniques, with suitable parameters tuned during our pilot study. For the Raycasting technique, we needed to use more filtering due to the extreme difficulty in pointing and clicking on the smallest targets (16mm). This decision was made to avoid high levels of user frustration during our studies. However, this level of filtering may introduce lag and slow down the pointing speed across all 3 target widths.

Click position correction. Clicking a button on the smart ring caused the Heisenberg effect [5], where the cursor appears to "jump", making it difficult to click a small target at a distance. This is especially difficult if both the click-down and click-up have to be within a small target to be considered correct. To minimize this effect, we saved the cursor positions in a buffer and used the position from the previous 10 frames for click-down and 15 frames for click-up. In addition, we use a pressure sensor that acts as the button to reduce this effect as it does not require a strong force to activate.

Temporal click filtering. There might be an unintentional click immediately after an activation, or after successfully clicking on a target. If such a click occurred within within 400ms after a trial or activation, they are ignored.

Locking the area cursor. In WRIST macro-micro pointing, the crosshair (micro) is controlled by the wrist and finger, and it is tethered to the center of the area cursor (macro) which is controlled by the forearm. As such, the crosshair can appear to be jittering if there are movements of the forearm. To avoid this, we lock the position of area cursor (macro) when the crosshair deviates from the center more than a predetermined threshold, which indicates that a micro pointing is occurring. This makes the crosshair fully stable and only controlled by the wrist/finger movement. Now, minor forearm movements and arm shake do not move the area cursor at all until the crosshair returns to the center. This can be overridden by a sufficient forearm movement that unlocks the area cursor caused by macro pointing.

Reset the crosshair to center of area cursor. In WRIST pointing, the crosshair might deviate slightly from the center of the area cursor at different parts of the screen due to misalignment between the two IMUs, and it accumulates over time due to IMU drift. We adopted a strategy whereby the crosshair will always reset to the center if there is large forearm movement - which occurs when user is aiming for the next target using the forearm. However, this strategy introduces an issue if the user did not physically reset the wrist posture after a trial when the crosshair resets to center. For example, if the user already bent their wrist to the left for current trial, and further moved the forearm to the left for the next trial without resetting the wrist posture, while the crosshair has reset to the center, then the user cannot bend the wrist to the left anymore. This can be overcome if the participant changes the wrist posture to the natural posture and then make a sufficient large forearm movement.

5 USER STUDY: POINTING INTERACTION

In order to evaluate the potential of WRIST for pointing on a large display, we conducted a user study. The goal of this study is to compare the task completion time and error rate between the four pointing techniques: *RayCast* (RC), *Relative* (R), *Laser+Gyro* (LG) and *WRIST* (W).

Participants and Apparatus

We recruited 12 participants (4 females) aged between 20 and 27 (Mean: 22.0, SD: 1.96) from our university. 3 of them were left-handed but use computer mouse with their right hand. Participants were compensated $15 for their time. They stood 2 meters in front of a front-projected display. We use a short throw FHD projector (1920x1080). Our wall surface is 3.5 by 2.0m with area of 7.0m^2 compared to MyoPoint's 4.6 by 1.4m with area of 6.44m^2 [22]. Our pixel density is smaller but we ensured the smallest target (16mm) is clearly visible.

Task and Procedure

We followed the study design used in MyoPoint [22], which also follows Vogel and Balakrishan [63] where there are sets of a Transition task followed by a Sequence task. The current target appears as a white circle on a black background and the next target appears as a white outline (see video figure).

Transition task. simulates transitioning from resting to pointing. It requires the participant to activate the technique first and then select the target. One minor difference from previous design is our cursor always appears at the center of the screen when activated.

Sequence task. simulates continuous pointing usage. Immediately after the transition target is selected, 6 more targets appear in sequence after each other, at controlled distances and random directions. After the sequence task, participants lower their hand and deactivate to transition back to the non-pointing task. Due to randomized controlled distances, there might be a lack of range within the display to show the next target if the current target is towards the middle while the next controlled distance is the largest one (2680mm). Hence, we create a yellow experiment "guiding" target that does not require a click. As the name implies, it guides the participants to point to an appropriate location before the next target appears at a controlled distance from there.

Study Design

We try to follow closely the three levels of distance (D) and width (W) as in MyoPoint [22] and Vogel and Balakrishnan [63]: D_L = 4020mm, D_M = 2680mm and D_S = 1340mm; W_L = 144mm, W_M = 48mm and W_S = 16mm. However, due to the shorter horizontal length of our wall display, we have to replace the longest distance (4020mm) to a smaller one (670mm). In addition, the cursor always starts at the center of the display after activation, hence for the *Transition task* we use only 1340mm for amplitude. We use *Technique*, *Distance* and *Width* as independent variables.

For each technique, participants were given time to practice for up to a maximum of 5 minutes, followed by 2 blocks of measured trials. Each block consists of 3 sections of tasks,

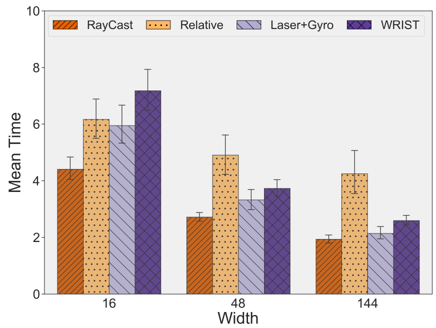

Figure 5: Mean selection times by width for different techniques.

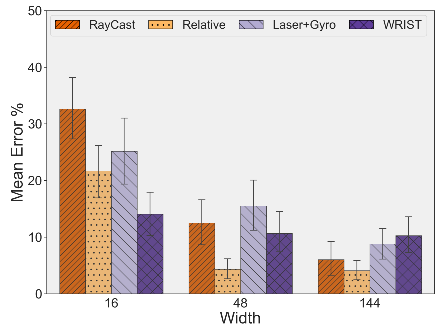

Figure 6: Mean error rates by width for different techniques.

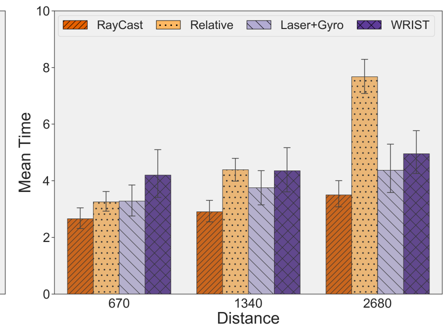

Figure 7: Mean selection times by distance for different techniques.

where each section uses a different width that is held constant throughout the section. The order of width sections was Latin square balanced. Each section had 3 sets of 2 tasks (1 Transition target and 6 Sequence targets). For the *Sequence task*, target distances were randomized an equal number of times within each section. For our *Transition task*, the distance is always at 1340mm from the center. Participants rest between techniques and complete a NASA TLX form. Participants did not report substantial fatigue during the 90 minutes experiment. In summary, the experimental design was: 12 participants x 4 techniques x 2 blocks x 3 sections of target widths x 3 sets of 7 targets (1 + 6) = 6048 trials.

Following the stringent protocol used in MyoPoint [22], trials were only considered successful if both click-down and click-up were inside the target during the first attempt. Otherwise, the trial is recorded as an error. Participants only proceed to next trial after successfully clicking the target, perhaps after multiple attempts. In total we recorded 825 error trials out of 6048 trials, which is 13.6% and is in line with the results in both MyoPoint (17.9%) and Vogel and Balakrishan's (18.4%) study. Of the 825 error trials, there are 2.2 misses per trial until it is finally succeeded (if both a click-down and a click-up occurred outside the target, it is counted as 2 misses). Error trials are excluded from our subsequent timing analysis.

Results

Results for selection time and error were analyzed with a repeated measures 3-way ANOVA. Greenhouse-Geisser correction was used where Mauchly's test of sphericity was significant. Bonferroni corrections were applied for post-hoc analyses. Figures 5 and 7 show the mean selection time while Figure 6 shows mean error rate. Error bars are 95% CI.

Selection Time. We found significant main effects of Technique, Width, and Distance and significant interaction effects of Technique*Width ($F_{(1.589, 17.482)} = 10.308$, $p<.005$, $\eta^2 = .484$) and Technique*Distance ($F_{(2.117, 23.282)} = 50.910$, $p<.001$, $\eta^2 = .822$) on selection time. Due to the interaction effects, we ignored the main effects and ran 1-way ANOVAs for each Width on Technique and for each Distance on Technique. The effect of Technique on selection time was significant for each of the three widths and each of the three distances. We then run pairwise comparisons to see where the significant differences lie. Table 1 shows these results.

The pairwise comparisons show that for medium and large width targets, *RayCast* is significantly faster than *Relative* and *WRIST*. Further, *Laser+Gyro* is significantly faster than *Relative* for medium and large targets, and significantly faster than *WRIST* for large targets. *Relative* is significantly slower than others for the largest width. For Distance, *RayCast* is significantly faster than *Relative* and *WRIST* for medium and large distances. *RayCast* is also significantly faster than *Laser+Gyro* and *WRIST* for the shortest distance.

Selection Error. We found significant main effects of Technique, Width, and Distance and a significant interaction effect of Technique*Width ($F_{(2.406, 26.470)} = 6.676$, $p<.001$, $\eta^2 = .378$) on selection error rate. No interaction effects involving Distance were found and therefore the main effect of Distance is useful ($F_{(2, 22)} = 6.432$, $p<.01$, $\eta^2 = .369$). The mean error rates across all techniques for the small, medium, and large distances were 13.7% (95% CI: 10.4-17%), 11.5% (95% CI: 8.4-14.7%), and 15% (95% CI: 11.4-18.7%) respectively. Pairwise comparisons show that the largest distance caused significantly higher errors than medium distance (p<0.01) across all techniques.

Due to the Technique*Width interaction, we ignored the main effects of Technique and Width and ran 1-way ANOVAs for each Width on Technique. The effect of Technique was significant for Width = 16, 48 but not 144. The significant effect results are shown in Table 2, along with the pairwise comparisons. Figure 6 shows the graph. The pairwise comparisons show that *RayCast* had a significantly higher error rate than *Relative* and *WRIST* for the smallest width.

Table 1: 1-way ANOVA on Selection Time for Sequence task (only showing significant pairwise comparisons). For instance, the first row shows the 1-way ANOVA on the effect of Technique on selection time for the smallest width, with the corresponding F-statistic, p-value, and effect size. RC<R indicates that pairwise comparisons showed that RayCast had a significantly lower selection time than Relative along with its p-value.

Effect of TECH	F-value	p-value	η^2
WIDTH=16	$F(3, 33) = 10.633$	<0.001	0.492
Pairwise	RC<R	<.005	
WIDTH=48	$F(3, 33) = 24.744$	<0.001	0.692
Pairwise	RC<R, R>LG, RC<W	<.001, <.005, <.005	
WIDTH=144	$F(1.642, 18.057) = 33.081$	<0.001	0.750
Pairwise	RC<R, R>LG, RC<W, R>W	<.005 for all	
DISTANCE=670	$F(3, 33) = 15.492$	<0.001	0.585
Pairwise	RC<LG, RC<W, LG<W	<.05,<.001,<.05	
DISTANCE=1340	$F(3, 33) = 18.192$	<0.001	0.623
Pairwise	RC<R, R>LG, RC<W	<.005,<.005,<.001	
DISTANCE=2680	$F(3, 33) = 34.886$	<0.001	0.760
Pairwise	RC<R, R>LG, RC<W	<.005 for all	

Table 2: 1-way ANOVA on Selection Error (Only showing significant pairwise comparisons), RC: Raycast, R: Relative, LG: Laser+Gyro, W:WRIST.

Effect of Technique	F value	p value	η^2
WIDTH=16	$F(1.819, 20.007) = 7.709$	<0.001	0.412
Pairwise	RC>R, RC>W	<.05, p<.005	
WIDTH=48	$F(3, 33) = 5.848$	<0.005	0.347
Pairwise	R<LG	<.05	

Clutching and Precise Mode. For the *Relative* technique, on average participants performed 0.73 clutch-events per trial with average clutch time of 1.06 second. As expected, participants clutch more for longer distance than smaller distance ($D_L = 1.44$, $D_M = 0.58$, $D_S = 0.25$). Participants also clutch less for larger targets than smaller targets ($W_L = 0.66$, $W_M = 0.75$, $W_S = 0.79$). This can be explained as we observed participants tend to be willing to go to extreme postures for large targets because it is easy to click, but for the smaller targets, they tend to perform a clutch first and then employ a relaxed posture to point and click.

For *Laser+Gyro* technique, on average participants switched into precise mode for 0.47 times per trial. As expected, participants switched less for larger targets than smaller targets ($W_L = 0.016$, $W_M = 0.244$, $W_S = 1.165$). Interestingly, participants switched more for longer distances than shorter distances ($D_L = 0.525$, $D_M = 0.471$, $D_S = 0.431$) when the different widths are presented an equal number of times for different distances.

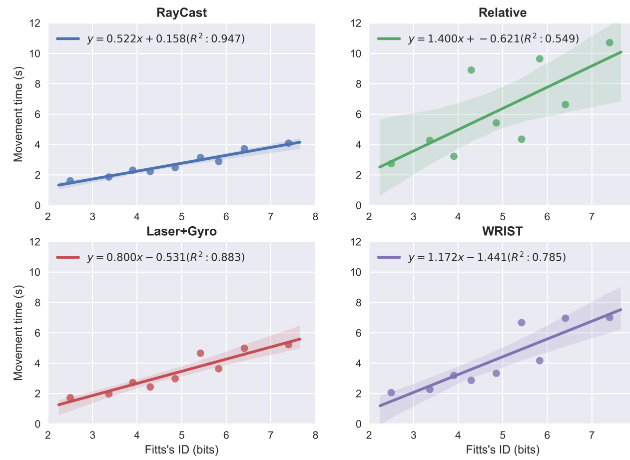

Figure 8: Movement time by Fitts's ID.

Pointing Results Discussion

Due to the absence of clutching or a precise mode, *RayCast* performs better than the rest on selection time, but has higher error rates at least for the smallest width. Our error rate on *RayCast* for the smallest target is 32%, which is lower than Vogel and Balakrishan's 56% [63]. We attribute this to heavier filtering that we employ (lower fcmin in 1 Euro filter [7], which reduces jitter but increases lag). While Vogel and Balakrishan argued that *Raycast*'s high error rates prevent it from being a practical technique, our results show that with more filtering, it is actually usable, at the cost of higher lag. Indeed, some participants favor it due to its simplicity.

In contrast to *RayCast*, *Relative* has significantly slower speeds which can be explained by its clutching time (mean 1.06s). Overall, no one technique emerges as the perfect technique across all widths and distances, for both time and error. However, given *RayCast's* significantly high error rates and *Relative's* significantly slow speeds, *Laser+Gyro* and *WRIST* offer a better balance of speed and accuracy. Yet, *Laser+Gyro* requires explicit switch to the precise mode while *WRIST* does not. In addition, *WRIST* appeared to be most accurate for the smallest width but the differences are not significant.

While we followed an established experimental protocol, it is worth noting that the white outline visualization for next target was on occasion quite confusing and misled the users. In addition, the button position is not ideal and is difficult to reach for some participants. Especially when bending the wrist to the right, the button is now further away from the thumb and it became more difficult for the thumb to click on the button (assuming right handed). Alternative forms of click sensing may address this in future work.

We fit both sets of task data to Fitts' models (Figure 8). The movement time of *Relative* technique in our implementation is slower compared to MyoPoint [22], which indicate that

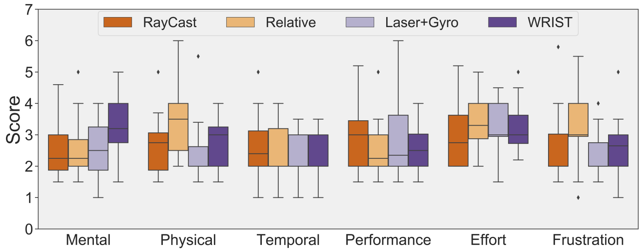

Figure 9: NASA TLX score for 4 techniques, lower is better.

indeed acceleration function plays an important role as an improvement for easier traversing of long distance while maintaining accuracy when selecting small targets.

Subjective Ratings and Feedback

We conducted Friedman tests on the NASA-TLX ratings. There were no statistical significant differences between the four techniques for any of the six metrics. Figure 9 shows the results. Participants were divided in their opinions. Some participants prefer *RayCast* overall, as it is the most straightforward technique. They expressed that although clicking on a very small target is more difficult using *RayCast*, they suggest that in real-life there is rarely a need to click on very small target on a large display from a large distance. *"The laser (RayCast) was good, even for small targets it is relatively okay"* (P6). *"Laser (RayCast) was quite accurate in most ways and quite fast. Even for really small target, that depends on your finger and the way you use it but it is manageable still for small target"* (P5).

Participants did not like *Relative*, commenting that while it may be good for short distances, it is frustrating for longer ones, especially for large targets that can be easily clicked. *"The last one (Relative) I felt it was actually quite a lot of effort to move it all, I can see like depends like where you use it, a bit say like in a real world kind of place, that kind of exaggerated movement will get put off, cause it might get a bit odd"* (P8).

For *Laser+Gyro*, participants expressed concern that the 800ms delay was too short to perform a click before switching back to coarse mode. *"For laser+gyro, once you miss it you have to do it again and it takes longer"* (P6). It was a compromise that we designed to avoid a long waiting time before moving on to next trial during the user study.

Participants noted that *WRIST* has a learning curve but were also positive that given more practice they would become faster. For *WRIST*, some participants developed a strategy to always point coarsely above the target and then move the wrist/finger down, as wrist vertical flexion has a wider range of motion, and is hence easier to perform. *"I like the WRIST most. Even though it took longer to getting used to, but once I am getting into it it felt like it was faster. I just like it, it's fu."* (P3). *"Once you get pass the learning, then it does actually becomes quite fast. For small target it is actually really good. For bigger target you don't really need to, it is just the same as the others. So in that way it is not bad at all"* (P5).

6 WRIST GESTURES FOR SINGLE-HANDED INTERACTION

Encouraged by the positive results of using WRIST for pointing on large screens and the wide range of motions participants demonstrated we decided to explore whether the same system can be used for robust gesture recognition in semi-realistic conditions (e.g., walking on a treadmill). The primary motivation here is to evaluate if there is potential of using WRIST for gestures interaction, then it can be also combined with pointing to afford hybrid pointing+gesture interaction. For example, a user could point a location on a large screen, and then fluidly switch to a different tool (e.g., a marker) using a gesture and finally highlight some information on the screen.

For the evaluation with gestures, we largely follow protocol in [19] which uses a gesture recognition task. In order to achieve a higher ecological validity we chose to test a semi-realistic condition with users walking on a treadmill, while the hand was placed in three different postures (hand-front, hand-down, and hand-up). In total, our experiment consists of eight gestures tested for each of the three hand postures.

Participants

We recruited 6 participants (2 females) between the ages of 24 and 29 (Mean: 26.5) from a local university. They are all right-handed and were compensated $10 for their time.

Task and Procedure

We selected 8 gestures: left, right, up, down, triangle, rectangle, circle and question mark. In each trial, the name of a gesture was shown to the participants on a laptop placed beside the treadmill (Figure 11 right). Participants were asked to perform the gesture using the wrist of the non-dominant hand, by holding the pressure button with the thumb while performing the gestures. Since we only study the walking condition, we asked the participants to walk on a treadmill with speed set at 3km per hour. We limit the practice time to 10 minutes and we collect a set of templates (one for each gesture) after the practice. Each template is used in a $1 gesture recognizer [69] for real-time recognition during the actual study. We also conduct offline analysis afterwards.

Study Design

The experiment employed a within subject design with three hand-postures (hand-front, hand-down and hand-up) and eight gestures (4 directional and 4 shape). Each condition was repeated 10 times with gestures presented in counterbalanced order following a Latin square design. During the

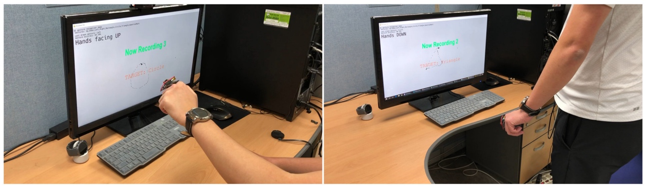

Figure 10: Experiment software interface with different postures: hand-front and hand-down).

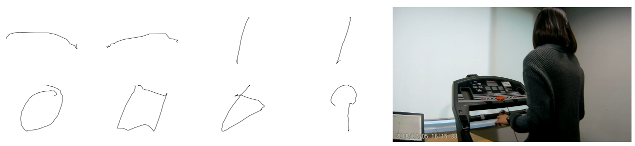

Figure 11: (left) Sample gestures from user study, 4 directional and 4 shapes. (right) Participant performing gesture trials while walking on a treadmill.

first 4 trials, participants look at the display with a GUI presenting the real-time gesture trails and gesture recognition result while performing the gestures. On the last 6 trials, participants do *not* look at the display but use their muscle memory and imagination while performing the gestures. In total, we collected 3 hand postures x 8 gestures x 10 repetitions x 6 participants = 1440 trials.

Results

Task Completion Time. The task time was recorded when the button was pressed until it was released. Overall, participants spent on average 1304ms per gesture (Figure 12). Directional gestures (858ms) took less time than shape gestures (1750ms). Within all gestures, the rectangle took the longest time (2068ms). Interestingly, one-way ANOVA shows hand postures did not have a significant effect on the task completion time ($F_{(1,5)}$ = 1.65, p>0.05).

Shape gesture recognition accuracy. We used the $1 gesture recognizer [69] for accuracy measurement. Using only a single template collected during the practice session, the real-time recognition result is 73.06%. Using a 6-fold random cross-validation, the result increases to 88.75%. Using the same user data to train and test (3-fold cross-validation), the result increases to 90% (user-dependent). Finally, using a leave-one-user out for training and testing on the remaining user, the average accuracy is 81.8% (user-independent).

Directional gesture recognition accuracy. We can measure the accuracy of directional marks by fitting the line using linear regression. We calculate the R-squared (R^2) coefficient and standard error (SE). The average R^2 is 0.76 (SD: 0.29) and SE is 0.12 (SD: 0.13). Hand posture did not have a significant

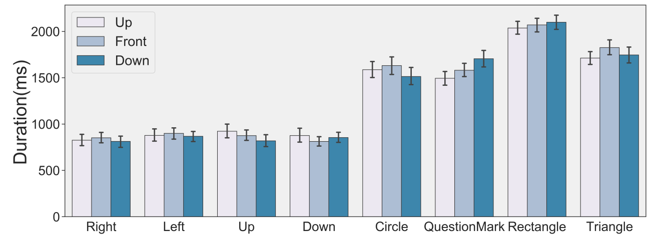

Figure 12: Task time shown by gestures and hand posture.

effect on both R^2 (p = 0.59) and SE (p = 0.90). By taking the line slope and compare against the ideal mark, we calculate the angular error as 5.27 degrees (SD: 17.69). Figure 11 shows example gestures recorded during the study.

Subjective Ratings and Feedback

To assess physical exertion, we asked participants to rate each posture on the Borg CR10 scale. On average, the scores are 4 (hand-front), 3.5 (hand-down) and 5.67 (hand-up). There were some interesting points of feedback from the participants. Indeed, 2 participants mentioned that hand-down was the easiest posture, and another 2 participants prefer hand-front posture for visual feedback and stability. Most participants rated the hand-up as the hardest condition.

P4 and P5 commented that they felt it was easier to perform the gesture without looking at the screen with real-time gesture trails feedback, although they were not sure about its accuracy. *"I could focus my mind on the gesturing (imagining my gesture)"* (P5). *"Maybe just only me, when check the screen, it is more difficult, because imagining and checking are difficult"* (P4). Indeed, we observed that P1 could *never* perform the triangle gesture properly in the hand-down posture when looking at the screen (during practice and during their first four trials), but could perform triangle gesture when hand-front and hand-up. Then, surprisingly to us and also P1 himself, during the fifth trial - when we removed the screen from him, he could perform the triangle gesture perfectly in the hand-down posture using only his imagination. On the other hand, P3 commented that visual feedback was helpful to assist him in drawing the correct shape.

P3 and P5 also commented about the bad positioning of the button, due to their short thumbs. P6 said the ring is quite heavy and would prefer haptic feedback that tells him if the gesture is accepted or recognized. Finally, P5 said that she would like to use her right hand since she is a right-handed person. *"I'm sure I'll rock with my right hand!!!"* (P5).

Gesture Results Discussion

Our study shows that participants can use the wrist as an input controller with our system, and it is accurate and robust to walking motion. Surprisingly, participants can perform the gestures equally fast in the three different postures we studied, although hand-up posture was rated the most difficult. In general, participants commented the system was not difficult to learn or familiarize themselves with.

Our results are encouraging, considering that we conducted the gesture study on the non-dominant hand, as we believe it better represents the real-world conditions, and provides a lower-bound performance. Moreover, in practice most people wear watches on their non-dominant hand on a daily basis. We do expect the result to fare better on the dominant hand as it is usually more dexterous and agile. For example, an input controller device for mobile AR/VR headset (Oculus Go or Google Daydream) that is mainly used by the dominant hand, can take advantage of our technique.

Another interesting point is that we also only considered the walking condition, which is indeed a challenging semi-realistic situation for evaluating a new prototype. Furthermore, a system like WristWhirl [19] is susceptible to lighting conditions, as there are infra-red sources in the environment including natural daylight. Our system which employs IMU does not suffer from lighting conditions, but it is more sensitive to motion, especially while walking. Nonetheless, our result (walking) is actually comparable to WristWhirl [19] (standing). More work is needed to understand the usability of this system in real-world conditions.

7 APPLICATIONS

We demonstrate several applications with WRIST to explore the potential of single-handed pointing and gesture-recognition interactions in different usage scenarios, as shown in Figure 13, 14, 15 and the video figure.

Smartwatch Applications

The first set of applications run on the smartwatch and use gestures only. (i) **Gesture Shortcuts** (Figure 13 left) afford a simple, yet rapid, means to customize and quickly access specific applications on the smartwatch. (ii) **Map Navigation** (Figure 13 middle) with WRIST supports rate-control of a range of map navigation methods, such as zooming and panning, operated with only one hand. (iii) **Analog Clock** (Figure 13 right) with WRIST supports rate-control of the minute hand for setting an alarm or timer conveniently with only one hand.

Cursor Control and Gaming for Distant Display

The second set of applications are for interaction with a range of distant display such as a desktop computer or public display, based on controlling a cursor. (i) **Gesture-based Game** (Figure 14 left) WRIST can take advantage of suitable wrist gestures, as they require pulling, flapping or throwing with the wrist. (ii) **Cursor-based Game** (Figure 14 middle) WRIST allows a single hand to input by controlling a cursor,

Figure 13: (left) Gestures recognizer for shortcut commands, (middle) 2D map navigation, (right) Analog clock.

Figure 14: Example applications on the PC: (left) Swiping game (middle) Angry bird and (right) MS Paint application.

without relying on a physical mouse. Thus enabling cursor-based games such as Angry Bird. (iii) **MS Paint** similarly, the ability to control cursor allows various type of painting application. Beyond these, we suggest that future work such as WRIST interaction in virtual reality or text entry with shape writing/gesture typing [30, 71] are possible.

Hybrid Macro Pointing and Micro Gestures

The last set of applications are based on hybrid interactions, combining pointing with gestures. (i) **Smart home and IoT control** (Figure 15 left) allows user to point at smart devices at home and then perform intuitive wrist gesture to control different settings, such as lamp's brightness, speaker's volume or a TV's channel. (ii) **Pie and Marking Menus** (Figure 15 middle) are common and useful in graphical user interface (GUI). WRIST allows user to point at different menus, and then uses wrist gesture to select the second level menu. This can be particular useful in multi-device, multi-display environments. (iii) **Gesture Checklist** (Figure 15 right) allows convenient pointing at list of tasks and perform a check or a cross gesture to mark them.

The example applications demonstrate the potential of pointing, gesturing and hybrid interactions which rely on simple single handed input.

8 DISCUSSION, LIMITATIONS AND FUTURE WORK

Our two studies have explored both a range of gestures and macro-micro pointing with a smartwatch and smart ring. However, there are a number of limitations. The presented gesture study has a limited scope of testing a small set of

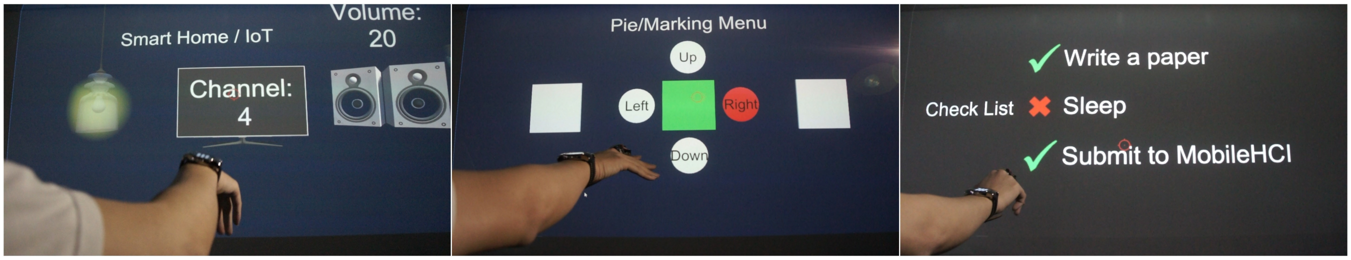

Figure 15: Example applications using hybrid pointing and gestures: (left) Multiple pie/marking menu without require clicking (middle) Point at smart devices to control without clicking (right) Checklist that interprets different gestures, a check or a cross.

simple gestures. Future work should include more complex gestures. In addition, the $1 gesture recognizer can be replaced by more advanced techniques such as machine learning. Further filtering may reduce the effect of motion.

It is important to highlight limitations in the study design of such pointing techniques. The use of a long press for clutch and lack of acceleration function are design choices which impact on the ability to compare such techniques. For example, prior work on dual-precision technique uses a mouse with two buttons that are operated by different fingers. For a ring intended to be wore on the index finger, using two buttons that are operated by different fingers would be infeasible, hence the choice of relying on a single button with long press. Further, since the ring is worn on the inner end of the finger near the MCP joint, the movement can be a mixture of finger or wrist movement, but the horizontal finger movement is more restricted than vertical movement. During the user study, the participants were free to decide how to use the finger or wrist movement. Further studies should evaluate the different techniques with a range of other parameter choices from acceleration to clutching.

A further limitation is that this form of smart ring has to be self-powered using a battery. This limits how much miniaturization may be possible. Advances in energy harvesting continue and may address this problem to some extent. In addition, jewellery in the form of a smart ring is quite personal and does not suit everyone. Future work aims to explore a passive ring, and in particular, a ring with a magnet [1, 49].

Here we only explored a single ring. Yet people wear multiple rings, on multiple fingers and hands. Our future work aims to study multiple rings for more expressive gestures such as twisting a virtual dial with two fingers. Rings on different hands, can enable bi-manual interaction or allow for the recognition of which hand is touching a surface. Finally, motion correlation using wrist gestures [49] for sensor fusion is another topic of interest for the future work.

While there are a number of limitations, one of the contribution of WRIST is its position and orientation invariance. Now users can perform a gesture even when their hands are facing down or behind their back, thus can be more subtle and discreet. Although not validated through user study, we believe WRIST has the following advantages over other input techniques or modalities: i) eyes-free and supports subtle/discreet interaction, ii) suitable for virtual reality environments and iii) works while wearing gloves. Future work aims to validate these claims and explore how subtle and effortless such gestures can be.

9 CONCLUSION

In this paper, we presented a single-handed interaction technique which leverages a smartwatch and a smart ring to enable wrist gestures and pointing. Our work here has only explored the potential of WRIST and further studies are required. Among the four pointing techniques we studied, our result shows that WRIST macro-micro pointing appeared to be most accurate for the smallest width although the differences are not significant. As described, the gestures recognition is orientation invariant and can work when one hand is held up or resting down. Through technical and user evaluation, we show this technique is robust and participants can perform the gestures equally fast in the three postures we studied. Finally, demonstrated here and in our video figure, we show a range of applications in gaming, cursor and pointer control, gesture and hybrid input, map navigation, watch control and context-aware movements, which can take advantage of the WRIST watch-ring interaction and sensing technique.

ACKNOWLEDGMENTS

This research was partly supported by Next-Generation Information Computing Development Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT (NRF-2017M3C4A7066316) and Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No.2019-0-01270, WISE AR UI/UX Platform Development for Smartglasses).

REFERENCES

[1] Daniel Ashbrook, Patrick Baudisch, and Sean White. 2011. Nenya: Subtle and Eyes-free Mobile Input with a Magnetically-tracked Finger Ring. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 2043–2046. https://doi.org/10.1145/1978942.1979238

[2] Ravin Balakrishnan and I. Scott MacKenzie. 1997. Performance Differences in the Fingers, Wrist, and Forearm in Computer Input Control. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI '97)*. ACM, New York, NY, USA, 303–310. https://doi.org/10.1145/258549.258764

[3] Andrea Bianchi and Seungwoo Je. 2017. Disambiguating Touch with a Smart-ring. In *Proceedings of the 8th Augmented Human International Conference (AH '17)*. ACM, New York, NY, USA, Article 27, 5 pages. https://doi.org/10.1145/3041164.3041196

[4] Richard A. Bolt. 1980. &Ldquo;Put-that-there&Rdquo;: Voice and Gesture at the Graphics Interface. *SIGGRAPH Comput. Graph.* 14, 3 (July 1980), 262–270. https://doi.org/10.1145/965105.807503

[5] D. A. Bowman, C. A. Wingrave, J. M. Campbell, V. Q. Ly, and C. J. Rhoton. 2002. Novel Uses of Pinch Gloves™ for Virtual Environment Interaction Techniques. *Virtual Reality* 6, 3 (01 Oct 2002), 122–129. https://doi.org/10.1007/s100550200013

[6] Xiang Cao, Nicolas Villar, and Shahram Izadi. 2010. Comparing User Performance with Single-finger, Whole-hand, and Hybrid Pointing Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 1643–1646. https://doi.org/10.1145/1753326.1753571

[7] Géry Casiez, Nicolas Roussel, and Daniel Vogel. 2012. 1 € Filter: A Simple Speed-based Low-pass Filter for Noisy Input in Interactive Systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. ACM, New York, NY, USA, 2527–2530. https://doi.org/10.1145/2207676.2208639

[8] Edwin Chan, Teddy Seyed, Wolfgang Stuerzlinger, Xing-Dong Yang, and Frank Maurer. 2016. User Elicitation on Single-hand Microgestures. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 3403–3414. https://doi.org/10.1145/2858036.2858589

[9] Liwei Chan, Yi-Ling Chen, Chi-Hao Hsieh, Rong-Hao Liang, and Bing-Yu Chen. 2015. CyclopsRing: Enabling Whole-Hand and Context-Aware Interactions Through a Fisheye Ring. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. ACM, New York, NY, USA, 549–556. https://doi.org/10.1145/2807442.2807450

[10] Ishan Chatterjee, Robert Xiao, and Chris Harrison. 2015. Gaze+Gesture: Expressive, Precise and Targeted Free-Space Interactions. In *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction (ICMI '15)*. ACM, New York, NY, USA, 131–138. https://doi.org/10.1145/2818346.2820752

[11] Ke-Yu Chen, Kent Lyons, Sean White, and Shwetak Patel. 2013. uTrack: 3D Input Using Two Magnetic Sensors. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology (UIST '13)*. ACM, New York, NY, USA, 237–244. https://doi.org/10.1145/2501988.2502035

[12] Ke-Yu Chen, Shwetak N. Patel, and Sean Keller. 2016. Finexus: Tracking Precise Motions of Multiple Fingertips Using Magnetic Sensing. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1504–1514. https://doi.org/10.1145/2858036.2858125

[13] Wei-Hung Chen. 2015. Blowatch: Blowable and Hands-free Interaction for Smartwatches. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '15)*. ACM, New York, NY, USA, 103–108. https://doi.org/10.1145/2702613.2726961

[14] Xiang 'Anthony' Chen, Tovi Grossman, Daniel J. Wigdor, and George Fitzmaurice. 2014. Duet: Exploring Joint Interactions on a Smart Phone and a Smart Watch. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 159–168. https://doi.org/10.1145/2556288.2556955

[15] Ashley Colley, Virve Inget, Inka Rantala, and Jonna Häkkilä. 2017. Investigating Interaction with a Ring Form Factor. In *Proceedings of the 16th International Conference on Mobile and Ubiquitous Multimedia (MUM '17)*. ACM, New York, NY, USA, 107–111. https://doi.org/10.1145/3152832.3152870

[16] Andrew Crossan, John Williamson, Stephen Brewster, and Rod Murray-Smith. 2008. Wrist Rotation for Interaction in Mobile Contexts. In *Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '08)*. ACM, New York, NY, USA, 435–438. https://doi.org/10.1145/1409240.1409307

[17] Artem Dementyev and Joseph A. Paradiso. 2014. WristFlex: Low-power Gesture Input with Wrist-worn Pressure Sensors. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology (UIST '14)*. ACM, New York, NY, USA, 161–166. https://doi.org/10.1145/2642918.2647396

[18] Clifton Forlines, Daniel Vogel, and Ravin Balakrishnan. 2006. HybridPointing: Fluid Switching Between Absolute and Relative Pointing with a Direct Input Device. In *Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology (UIST '06)*. ACM, New York, NY, USA, 211–220. https://doi.org/10.1145/1166253.1166286

[19] Jun Gong, Xing-Dong Yang, and Pourang Irani. 2016. WristWhirl: One-handed Continuous Smartwatch Input Using Wrist Gestures. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, New York, NY, USA, 861–872. https://doi.org/10.1145/2984511.2984563

[20] Anhong Guo and Tim Paek. 2016. Exploring Tilt for No-touch, Wrist-only Interactions on Smartwatches. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '16)*. ACM, New York, NY, USA, 17–28. https://doi.org/10.1145/2935334.2935345

[21] Aakar Gupta, Cheng Ji, Hui-Shyong Yeo, Aaron Quigley, and Daniel Vogel. 2019. RotoSwype: Word-Gesture Typing Using a Ring. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 14, 12 pages. https://doi.org/10.1145/3290605.3300244

[22] Faizan Haque, Mathieu Nancel, and Daniel Vogel. 2015. Myopoint: Pointing and Clicking Using Forearm Mounted Electromyography and Inertial Motion Sensors. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 3653–3656. https://doi.org/10.1145/2702123.2702133

[23] Da-Yuan Huang, Liwei Chan, Shuo Yang, Fan Wang, Rong-Hao Liang, De-Nian Yang, Yi-Ping Hung, and Bing-Yu Chen. 2016. DigitSpace: Designing Thumb-to-Fingers Touch Interfaces for One-Handed and Eyes-Free Interactions. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1526–1537. https://doi.org/10.1145/2858036.2858483

[24] Eleanor Jones, Jason Alexander, Andreas Andreou, Pourang Irani, and Sriram Subramanian. 2010. GesText: Accelerometer-based Gestural Text-entry Systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 2173–2182. https://doi.org/10.1145/1753326.1753655

[25] Ricardo Jota, Miguel A. Nacenta, Joaquim A. Jorge, Sheelagh Carpendale, and Saul Greenberg. 2010. A Comparison of Ray Pointing Techniques for Very Large Displays. In *Proceedings of Graphics Interface 2010 (GI '10)*. Canadian Information Processing Society, Toronto, Ont.,

Canada, Canada, 269–276. http://dl.acm.org/citation.cfm?id=1839214.1839261

[26] Keiko Katsuragawa, Krzysztof Pietroszek, James R. Wallace, and Edward Lank. 2016. Watchpoint: Freehand Pointing with a Smartwatch in a Ubiquitous Display Environment. In *Proceedings of the International Working Conference on Advanced Visual Interfaces (AVI '16)*. ACM, New York, NY, USA, 128–135. https://doi.org/10.1145/2909132.2909263

[27] Daniel Kharlamov, Brandon Woodard, Liudmila Tahai, and Krzysztof Pietroszek. 2016. TickTockRay: Smartwatch-based 3D Pointing for Smartphone-based Virtual Reality. In *Proceedings of the 22Nd ACM Conference on Virtual Reality Software and Technology (VRST '16)*. ACM, New York, NY, USA, 365–366. https://doi.org/10.1145/2993369.2996311

[28] David Kim, Otmar Hilliges, Shahram Izadi, Alex D. Butler, Jiawen Chen, Iason Oikonomidis, and Patrick Olivier. 2012. Digits: Freehand 3D Interactions Anywhere Using a Wrist-worn Gloveless Sensor. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology (UIST '12)*. ACM, New York, NY, USA, 167–176. https://doi.org/10.1145/2380116.2380139

[29] Regis Kopper, Doug A. Bowman, Mara G. Silva, and Ryan P. McMahan. 2010. A Human Motor Behavior Model for Distal Pointing Tasks. *Int. J. Hum.-Comput. Stud.* 68, 10 (Oct. 2010), 603–615. https://doi.org/10.1016/j.ijhcs.2010.05.001

[30] Per-Ola Kristensson and Shumin Zhai. 2004. SHARK2: A Large Vocabulary Shorthand Writing System for Pen-based Computers. In *Proceedings of the 17th Annual ACM Symposium on User Interface Software and Technology (UIST '04)*. ACM, New York, NY, USA, 43–52. https://doi.org/10.1145/1029632.1029640

[31] Mikko Kytö, Barrett Ens, Thammathip Piumsomboon, Gun A. Lee, and Mark Billinghurst. 2018. Pinpointing: Precise Head- and Eye-Based Target Selection for Augmented Reality. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 81, 14 pages. https://doi.org/10.1145/3173574.3173655

[32] Gierad Laput, Robert Xiao, and Chris Harrison. 2016. ViBand: High-Fidelity Bio-Acoustic Sensing Using Commodity Smartwatch Accelerometers. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, New York, NY, USA, 321–333. https://doi.org/10.1145/2984511.2984582

[33] Huy Viet Le, Valentin Schwind, Philipp Göttlich, and Niels Henze. 2017. PredicTouch: A System to Reduce Touchscreen Latency Using Neural Networks and Inertial Measurement Units. In *Proceedings of the 2017 ACM International Conference on Interactive Surfaces and Spaces (ISS '17)*. ACM, New York, NY, USA, 230–239. https://doi.org/10.1145/3132272.3134138

[34] Jhe-Wei Lin, Chiuan Wang, Yi Yao Huang, Kuan-Ting Chou, Hsuan-Yu Chen, Wei-Luan Tseng, and Mike Y. Chen. 2015. BackHand: Sensing Hand Gestures via Back of the Hand. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. ACM, New York, NY, USA, 557–564. https://doi.org/10.1145/2807442.2807462

[35] Mingyu Liu, Mathieu Nancel, and Daniel Vogel. 2015. Gunslinger: Subtle Arms-down Mid-air Interaction. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. ACM, New York, NY, USA, 63–71. https://doi.org/10.1145/2807442.2807489

[36] Mbientlab. 2019. Wearables For Motion Tracking + Wireless Environment Monitoring. https://mbientlab.com/.

[37] Jess McIntosh, Asier Marzo, and Mike Fraser. 2017. SensIR: Detecting Hand Gestures with a Wearable Bracelet Using Infrared Transmission and Reflection. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology (UIST '17)*. ACM, New York, NY, USA, 593–597. https://doi.org/10.1145/3126594.3126604

[38] Scott D. McPhee. 1987. Functional Hand Evaluations: A Review. *American Journal of Occupational Therapy* 41, 3 (1987), 158–163. https://doi.org/10.5014/ajot.41.3.158

[39] David E Meyer, Richard A Abrams, Sylvan Kornblum, Charles E Wright, and JE Keith Smith. 1988. Optimality in human motor performance: ideal control of rapid aimed movements. *Psychological review* 95, 3 (1988), 340.

[40] Alessandra Moschetti, Laura Fiorini, Dario Esposito, Paolo Dario, and Filippo Cavallo. 2016. Recognition of Daily Gestures with Wearable Inertial Rings and Bracelets. *Sensors* 16, 8 (2016). https://doi.org/10.3390/s16081341

[41] Motiv. 2019. 24/7 WEAR. FITNESS. ONLINE SECURITY. Motiv Ring. https://mymotiv.com.

[42] Mathieu Nancel, Emmanuel Pietriga, Olivier Chapuis, and Michel Beaudouin-Lafon. 2015. Mid-Air Pointing on Ultra-Walls. *ACM Trans. Comput.-Hum. Interact.* 22, 5, Article 21 (Aug. 2015), 62 pages. https://doi.org/10.1145/2766448

[43] Dan R. Olsen, Jr. and Travis Nielsen. 2001. Laser Pointer Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '01)*. ACM, New York, NY, USA, 17–22. https://doi.org/10.1145/365024.365030

[44] Oura. 2019. Introducing Moment, Understand meditation like never before. https://ouraring.com.

[45] Kurt Partridge, Saurav Chatterjee, Vibha Sazawal, Gaetano Borriello, and Roy Want. 2002. TiltType: Accelerometer-supported Text Entry for Very Small Devices. In *Proceedings of the 15th Annual ACM Symposium on User Interface Software and Technology (UIST '02)*. ACM, New York, NY, USA, 201–204. https://doi.org/10.1145/571985.572013

[46] Mahfuz Rahman, Sean Gustafson, Pourang Irani, and Sriram Subramanian. 2009. Tilt Techniques: Investigating the Dexterity of Wrist-based Input. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 1943–1952. https://doi.org/10.1145/1518701.1518997

[47] Umar Rashid, Jarmo Kauko, Jonna Häkkilä, and Aaron Quigley. 2011. Proximal and Distal Selection of Widgets: Designing Distributed UI for Mobile Interaction with Large Display. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. ACM, New York, NY, USA, 495–498. https://doi.org/10.1145/2037373.2037446

[48] Jun Rekimoto. 2001. GestureWrist and GesturePad: Unobtrusive Wearable Interaction Devices. In *Proceedings of the 5th IEEE International Symposium on Wearable Computers (ISWC '01)*. IEEE Computer Society, Washington, DC, USA, 21–. http://dl.acm.org/citation.cfm?id=580581.856565

[49] Gabriel Reyes, Jason Wu, Nikita Juneja, Maxim Goldshtein, W. Keith Edwards, Gregory D. Abowd, and Thad Starner. 2018. SynchroWatch: One-Handed Synchronous Smartwatch Gestures Using Correlation and Magnetic Sensing. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4, Article 158 (Jan. 2018), 26 pages. https://doi.org/10.1145/3161162

[50] Gabriel Reyes, Dingtian Zhang, Sarthak Ghosh, Pratik Shah, Jason Wu, Aman Parnami, Bailey Bercik, Thad Starner, Gregory D. Abowd, and W. Keith Edwards. 2016. Whoosh: Non-voice Acoustics for Low-cost, Hands-free, and Rapid Input on Smartwatches. In *Proceedings of the 2016 ACM International Symposium on Wearable Computers (ISWC '16)*. ACM, New York, NY, USA, 120–127. https://doi.org/10.1145/2971763.2971765

[51] T. Scott Saponas, Desney S. Tan, Dan Morris, Ravin Balakrishnan, Jim Turner, and James A. Landay. 2009. Enabling Always-available Input with Muscle-computer Interfaces. In *Proceedings of the 22Nd Annual ACM Symposium on User Interface Software and Technology (UIST '09)*. ACM, New York, NY, USA, 167–176. https://doi.org/10.1145/1622176.

1622208

[52] Roy Shilkrot, Jochen Huber, Jürgen Steimle, Suranga Nanayakkara, and Pattie Maes. 2015. Digital Digits: A Comprehensive Survey of Finger Augmentation Devices. *ACM Comput. Surv.* 48, 2, Article 30 (Nov. 2015), 29 pages. https://doi.org/10.1145/2828993

[53] Garth Shoemaker, Leah Findlater, Jessica Q. Dawson, and Kellogg S. Booth. 2009. Mid-air Text Input Techniques for Very Large Wall Displays. In *Proceedings of Graphics Interface 2009 (GI '09)*. Canadian Information Processing Society, Toronto, Ont., Canada, Canada, 231–238. http://dl.acm.org/citation.cfm?id=1555880.1555931

[54] Shaishav Siddhpuria, Keiko Katsuragawa, James R. Wallace, and Edward Lank. 2017. Exploring At-Your-Side Gestural Interaction for Ubiquitous Environments. In *Proceedings of the 2017 Conference on Designing Interactive Systems (DIS '17)*. ACM, New York, NY, USA, 1111–1122. https://doi.org/10.1145/3064663.3064695

[55] Shaishav Siddhpuria, Sylvain Malacria, Mathieu Nancel, and Edward Lank. 2018. Pointing at a Distance with Everyday Smart Devices. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 173, 11 pages. https://doi.org/10.1145/3173574.3173747

[56] Lee Stearns, Uran Oh, Leah Findlater, and Jon E. Froehlich. 2018. TouchCam: Realtime Recognition of Location-Specific On-Body Gestures to Support Users with Visual Impairments. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4, Article 164 (Jan. 2018), 23 pages. https://doi.org/10.1145/3161416

[57] Paul Strohmeier, Roel Vertegaal, and Audrey Girouard. 2012. With a Flick of the Wrist: Stretch Sensors As Lightweight Input for Mobile Devices. In *Proceedings of the Sixth International Conference on Tangible, Embedded and Embodied Interaction (TEI '12)*. ACM, New York, NY, USA, 307–308. https://doi.org/10.1145/2148131.2148195

[58] Talon. 2019. Meet Talon, the Smart Ring. https://www.talonring.com.

[59] Lucia Terrenghi, Aaron Quigley, and Alan Dix. 2009. A Taxonomy for and Analysis of Multi-person-display Ecosystems. *Personal Ubiquitous Comput.* 13, 8 (Nov. 2009), 583–598. https://doi.org/10.1007/s00779-009-0244-5

[60] Hsin-Ruey Tsai, Cheng-Yuan Wu, Lee-Ting Huang, and Yi-Ping Hung. 2016. ThumbRing: Private Interactions Using One-handed Thumb Motion Input on Finger Segments. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '16)*. ACM, New York, NY, USA, 791–798. https://doi.org/10.1145/2957265.2961859

[61] Theophanis Tsandilas, Emmanuel Dubois, and Mathieu Raynal. 2013. Modeless Pointing with Low-Precision Wrist Movements. In *Human-Computer Interaction – INTERACT 2013*, Paula Kotzé, Gary Marsden, Gitte Lindgaard, Janet Wesson, and Marco Winckler (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 494–511.

[62] Valve. 2019. Use the World's Best Virtual Reality Technology, Royalty Free. https://partner.steamgames.com/vrlicensing.

[63] Daniel Vogel and Ravin Balakrishnan. 2005. Distant Freehand Pointing and Clicking on Very Large, High Resolution Displays. In *Proceedings of the 18th Annual ACM Symposium on User Interface Software and Technology (UIST '05)*. ACM, New York, NY, USA, 33–42. https://doi.org/10.1145/1095034.1095041

[64] Andrew M. Webb, Michel Pahud, Ken Hinckley, and Bill Buxton. 2016. Wearables As Context for Guiard-abiding Bimanual Touch. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, New York, NY, USA, 287–300. https://doi.org/10.1145/2984511.2984564

[65] Martin Weigel and Jürgen Steimle. 2017. DeformWear: Deformation Input on Tiny Wearable Devices. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 2, Article 28 (June 2017), 23 pages. https://doi.org/10.1145/3090093

[66] Hongyi Wen, Julian Ramos Rojas, and Anind K. Dey. 2016. Serendipity: Finger Gesture Recognition Using an Off-the-Shelf Smartwatch. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 3847–3851. https://doi.org/10.1145/2858036.2858466

[67] Daniel Wigdor and Ravin Balakrishnan. 2003. TiltText: Using Tilt for Text Input to Mobile Phones. In *Proceedings of the 16th Annual ACM Symposium on User Interface Software and Technology (UIST '03)*. ACM, New York, NY, USA, 81–90. https://doi.org/10.1145/964696.964705

[68] Gerard Wilkinson, Ahmed Kharrufa, Jonathan Hook, Bradley Pursglove, Gavin Wood, Hendrik Haeuser, Nils Y. Hammerla, Steve Hodges, and Patrick Olivier. 2016. Expressy: Using a Wrist-worn Inertial Measurement Unit to Add Expressiveness to Touch-based Interactions. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 2832–2844. https://doi.org/10.1145/2858036.2858223

[69] Jacob O. Wobbrock, Andrew D. Wilson, and Yang Li. 2007. Gestures Without Libraries, Toolkits or Training: A $1 Recognizer for User Interface Prototypes. In *Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology (UIST '07)*. ACM, New York, NY, USA, 159–168. https://doi.org/10.1145/1294211.1294238

[70] Xing-Dong Yang, Tovi Grossman, Daniel Wigdor, and George Fitzmaurice. 2012. Magic Finger: Always-available Input Through Finger Instrumentation. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology (UIST '12)*. ACM, New York, NY, USA, 147–156. https://doi.org/10.1145/2380116.2380137

[71] Hui-Shyong Yeo, Xiao-Shen Phang, Steven J. Castellucci, Per Ola Kristensson, and Aaron Quigley. 2017. Investigating Tilt-based Gesture Keyboard Entry for Single-Handed Text Entry on Large Devices. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 4194–4202. https://doi.org/10.1145/3025453.3025520

[72] Shumin Zhai, Carlos Morimoto, and Steven Ihde. 1999. Manual and Gaze Input Cascaded (MAGIC) Pointing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '99)*. ACM, New York, NY, USA, 246–253. https://doi.org/10.1145/302979.303053

[73] Cheng Zhang, Anandghan Waghmare, Pranav Kundra, Yiming Pu, Scott Gilliland, Thomas Ploetz, Thad E. Starner, Omer T. Inan, and Gregory D. Abowd. 2017. FingerSound: Recognizing Unistroke Thumb Gestures Using a Ring. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 120 (Sept. 2017), 19 pages. https://doi.org/10.1145/3130985

[74] Cheng Zhang, Xiaoxuan Wang, Anandghan Waghmare, Sumeet Jain, Thomas Ploetz, Omer T. Inan, Thad E. Starner, and Gregory D. Abowd. 2017. FingOrbits: Interaction with Wearables Using Synchronized Thumb Movements. In *Proceedings of the 2017 ACM International Symposium on Wearable Computers (ISWC '17)*. ACM, New York, NY, USA, 62–65. https://doi.org/10.1145/3123021.3123041

[75] Cheng Zhang, Qiuyue Xue, Anandghan Waghmare, Ruichen Meng, Sumeet Jain, Yizeng Han, Xinyu Li, Kenneth Cunefare, Thomas Ploetz, Thad Starner, Omer Inan, and Gregory D. Abowd. 2018. FingerPing: Recognizing Fine-grained Hand Poses Using Active Acoustic On-body Sensing. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 437, 10 pages. https://doi.org/10.1145/3173574.3174011

[76] Yang Zhang and Chris Harrison. 2015. Tomo: Wearable, Low-Cost Electrical Impedance Tomography for Hand Gesture Recognition. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. ACM, New York, NY, USA, 167–173. https://doi.org/10.1145/2807442.2807480