Thumb-In-Motion: Evaluating Thumb-to-Ring Microgestures for Athletic Activity

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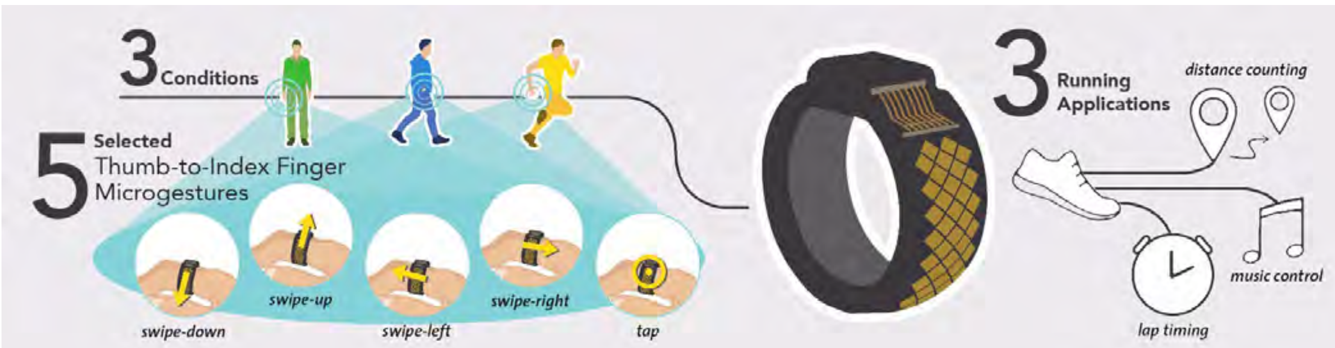

Figure 1: Using a touchpad ring, we focus on evaluating a low-fidelity thumb-to-index gesture set: *swipe-up/-down/-left/-right, and tap*. The accuracy and latency of these gestures, as well as the applicability in running applications was studied.

ABSTRACT

Spatial User Interfaces, such as wearable fitness trackers are widely used to monitor and improve athletic performance. However, most fitness tracker interfaces require bimanual interactions, which significantly impacts the user's gait and pace. This paper evaluated a one-handed thumb-to-ring gesture interface to quickly access information without interfering with physical activity, such as running. By a pilot study, the most minimal gesture set was selected, particularly those that could be executed reflexively to minimize distraction and cognitive load. The evaluation revealed that among the selected gestures, the tap, swipe-down, and swipe-left were the most 'easy to use'. Interestingly, motion does not have a significant effect on the ease of use or on the execution time. However, interacting in motion was subjectively rated as more demanding. Finally, the gesture set was evaluated in real-world applications, while the user performed a running exercise and simultaneously controlled a lap timer, a distance counter, and a music player.

CCS CONCEPTS

• **Human-centered computing → Interaction devices**;

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KEYWORDS

Thumb-finger gestures; Ring Interaction; Applicability Study; Running; Athletic Activities; Interaction in Motion; Spatial Interaction.

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1 INTRODUCTION

New emerging technology has increasingly impacted our daily lives, particularly within the realm of exercising. Over 80% of athletes use wearable technology to measure their performances [2]. Wearables track and quantify behavior, which we can utilize to support decisions, such as adjusting training sessions to meet daily goals [43]. Sport-watches are now being widely used to access real-time performance [26]. Typical sports-watch interfaces, such as the Garmin Vivosmart HR+'s [53], make use of a bimanual swipe and tap gestures on the screen. Although research has introduced alternative bimanual interactions [1, 29], particularly for running, these methods draw high attention and generate an increased cognitive load. This has a significant impact in changing the user's gait and speed [45]. Therefore, minimizing interference between the interaction and the athlete's physical activity is highly desirable, particularly for professional athletes [38].

To address this, we may establish a Reflexive Interaction [34] relying on simple input gestures that can be performed in milliseconds, without a substantial increase in cognitive effort. Unimanual thumb-to-fingers interfaces would enable microgestures [56] and thus can enable fast access without interfering with the physical activity. In particular, using taps and strokes from the thumb to the dominant index and middle finger has shown to be comfortable [18]. In research, a variety of wearable prototypes exist, which demonstrate thumb-and-index-finger-tip gestures even by using touchpads [14, 51]. While research has applied these techniques in walking conditions [52], knowledge of performances remain limited, particularly with task-loads. Comparisons of one-handed thumb-to-index interaction for walking and running in real scenarios are thus insufficient. Therefore, having a greater understanding of these interactions, will contribute to guide future human interaction with rings and wearable sport technologies.

In summary, this paper will contribute:

(1) The development of a small wearable ring-touchpad connected to a bracelet computer capable of recording and recognizing thumb to ring microgestures.
(2) A study to understand performance differences, in terms of *gesture completion time, ease of use,* and *workload,* of a low-fidelity thumb-to-index gesture set while standing, walking, and running.
(3) A follow up study that exhibits a real-time gesture recognizer based on training data from the previous study, in which we compare our ring-touch interaction with three different commonly used applications during athletic running.

2 RELATED WORK

2.1 Fitness Tracking Interfaces

Rooksby et. al stated that fitness tracking data is *"overwhelmingly for use in the short term"*, to set pace, to decide where to turn around, and to meet a daily goal [43]. Wearable technology used for jogging has been studied in the gym [41] and in the field [37, 49]. A study by Tholander et al. [50] showed that fitness trackers are becoming linked with athletic training, where athletes use biometric information to gain a better sense of their body. Throughout the workout, running athletes commonly track their pulse aiming to retain a certain heart-rate zone by calibrating their speed and exertion [50]. New fitness wearables have emerged providing real-time feedback, specific to the athletes' current activity performance and goals. Personal coaching devices like Moov [35], VI [31] and Bragi Dash [5] sense real-time biometric data and provide live audio feedback during training. While audio feedback may be preferred over visual feedback, haptic feedback may also be useful, particularly *"to inform the runner whether his/her knee moved too high"* [20]. These suggestions coincide with Nylander and Tholander's guidelines [38] in that feedback should allow the athlete to shift attention without interfering with their activity and improve the awareness of their movement.

2.1.1 *Rings as Fitness Trackers.*

The most compact fitness trackers to date are Oura [39] and Motiv [36]. Oura is one of the first rings able to track activity, sleep, temperature, and even suggest which days are more suitable for exertion based on the recovery index. While the Motiv Ring is slightly smaller, it is able to track activity, heart-rate, and sleep. However, these rings have yet to incorporate real-time input, and thus interaction design remains unclear.

2.2 Biomechanics of Thumb and Index

Thumb movement can be vertical (abduction/adduction) and horizontal (pronation/supination). Normal motion ranges have been investigated in prior work [30]. The thumb and finger range of movements (functional work spaces) were investigated and quantified, revealing that thumb-index (33.7%) and thumb-middle finger (27.1%) have the maximal functional work space [27].

2.3 Thumb-to-finger Interaction

Single-hand micro-gestures (SHMGs) [7] are proposed as being subtle and discreet finger gestures, which can be performed using one hand. In an elicitation study of SHMGs, 12 out of the 16 consensus gestures [7] use the thumb as the main finger. In DigitSpace [18], it has been found that using taps and strokes from the thumb to the dominant index and middle finger to be comfortable. While Tsai et al. [52] investigated thumb-to-finger tapping in two different physical conditions (sitting and walking), they did not see an effect, which may be due to the IMU sensor noises. Finger gesture recognition, such as pinches, has also been implemented through arm-mounted EMG sensors [44]. Alternatively, pinch gestures can be detected using a wrist mounted device equipped with an array of pressure sensors [10]. Moreover, finger pinching and sliding motions using the finger are detectable with a camera, such as those mounted on the upper body [32] or in a ring [8]. Recently, Google's Soli plus Leap Motion was used in a wearable setup [12]. However, the performance details concerning walking and running conditions remain unknown.

2.3.1 *Nail-mounted Devices.*

Nailo proposed using the nail of the thumb as an input surface enabling gestures such as *swipe-up/-down/-left/-right, and tap* [23]. FingerPad [9] is another nail mounted device that transforms the tip of the index finger into a touchpad. It investigates thumb and index interaction and flicking gestures by varying the target size over seated and walking conditions. For this interaction, the authors found a significant difference in completion time between walking and standing postures. Therefore, this paper will investigate if a similar effect occurs with 5 selected thumb-to-ring gestures, while the user is motion.

2.3.2 *Finger-worn Gesture Interfaces.*

A survey on finger augmentation devices [46] provides an overview of the body of work on finger-worn devices and provides a classification based on form factor, input, output, action, and domain. Since the 1990s, there have been attempts to use the ring's surface for cursor manipulation or as a chording keyboard [13, 42]. Tapping on the surface is frequently used to replace the mouse and keyboard [15, 17, 21, 22, 28, 40]; for controlling appliances and for detecting gestures of a novel vocabulary [24]. More recent projects include the MagicFinger [57], which demonstrates tap gesture input by sensing contact and movement with materials. FingerPing [58] is another project, which enables the detection of fine-grained hand poses using active acoustic on-body sensing, while eRing [55] enables the sensing of hand and finger postures by an electrical field sensing approach. Finally, LightRing [25] is able to sense the 2D location of a fingertip on any material surface. Among commercially available applications, SourceAudio [48] features a finger-wearable wireless gestural interface for adding effects to an electric guitar. Consequently, there is a growing interest in gestural interaction in the form of patents and products [11, 33]. Another product is Sony's Waterproof Walkman [47] that is equipped with a remote in form of a ring, allowing for music control.

2.3.3 Finger-worn Touchpads. More recently, FingerReader2.0 [4] utilized a touchpad attached to the index finger, which recognizes taps and simple thumb swipes. Ringteraction [14] proposes the thumb-index interaction using a more complex set of gestures (horizontal and vertical swipes, taps, and rotation) for the scenarios: parallel task completion, select+scroll, zoom+pan, focus+context. TouchRing [51] proposes using printed electrodes and capacitive sensing on a ring worn on the index finger to enable multi-touch gestures performed with the thumb, palm, and middle finger. These projects focus on the gesture recognition method for detecting horizontal and vertical swipes and tapping motions, concluding that vertical swipes yield greater accuracy in results than horizontal swipes. Neither FingerReader2.0 [4], Ringteraction [14], nor TouchRing [51] evaluate which gestures are the most simple to use or the usage of finger-worn touchpad while moving. Using a wearable interface, such as a finger-worn touchpad in form of a ring can allow for quick thumb-to-index gestures. This could potentially enable a Reflexive Interaction [34] and thus be highly useful for design interactions with low-interruption. We focus particularly on the context of sports, namely in walking and running scenarios. In these scenarios, interactions, such as changing a music track or switching a training program are required to be short without significantly disrupting the athlete.

3 PROTOTYPE

The prototype hardware consists of a touch-sensitive ring and wristband interconnected with a cable (*see Figure 2*).

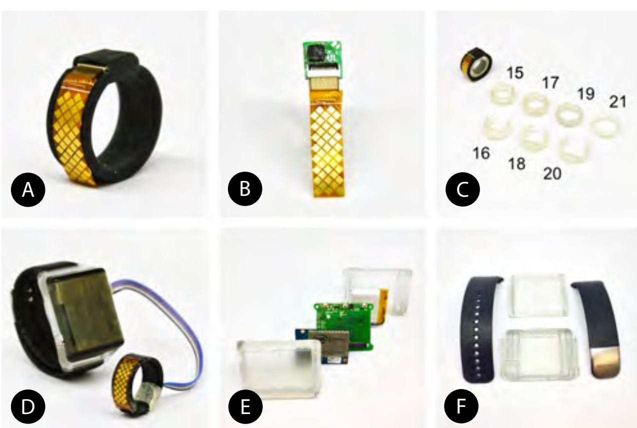

Figure 2: Prototype components: a) ring with touchpad, b) PCB of the touchpad, c) ring and 3D-printed fittings of different sizes & types, d) wristband connected to the ring, e) Intel Edison, PCB, battery, and wristband 3D-printed casing, and f) casing and straps.

3.1 Ring

3.1.1 Form Factor. The 3D printed ring has an external diameter of 27mm, a thickness of 3mm and width of 12mm. The internal diameter is 24mm and thus can fit those up to a size of 11 (20.6mm). To accommodate the fit to smaller fingers, we printed seven adapters. The inner diameters of the circular ring ranges from 15 to 19mm in .5mm steps (*see Figure 2c*).

3.1.2 Touchpad. A capacitive sensing touchpad in loading mode was designed and mounted on the left side of ring (see *Figure 2a, b*). The touchpad is implemented on a flexible double sided PCB, with surface dimensions of 24mm × 8mm. Underneath the surface, we placed 40 (2mm × 2mm) touch pads with a .1mm gap. Based on the capability of capacitive sensing able to detect a small distances from a nearing finger, we could interpolate a resolution of 320 × 192. In order to prevent the saturation of the electrodes, we used .5mm transparent tape to cover the touch pad. The calculations were completed using a MTCH6102 controller placed in a rigid PCB (*see Figure 2b*). The controller is able to output relative x,y coordinates, gesture decoding, and trigger an interruption at available data.

3.2 Wristband

3.2.1 Form Factor. The wristband has a similar form factor similar to Samsung Gear V1 watch. The casing is 3D printed with a multilateral 3D-Printer (Object 500) and has a size of 35mm x 25mm. The wristbands used are the originals from the Samsung Gear (*see Figure 2e*.)

3.2.2 Hardware. Our PCB designed incorporates an Intel Edison SOM (System On Module) with a Dual-core Intel Atom 500MHz processor, 1GB DDR3 RAM, 4GB eMMC flash, Bluetooth 4.0, Wifi, Wi-Fi Direct. The OS is an embedded Linux Yocto 1.1 (*see Figure 2e*). The ring and wristband are connected by a 5-wire cable, SDA and SCL, to communicate between the two devices using I2C protocol and the ring to be powered by the same battery located in the Wristband.

3.2.3 Autonomy. The system is powered by a 3.7V Lithium polymer battery with a capacity of 450mAh. The power consumption tests show that the device can last approximately 3.5 hours. While power efficiency was not one of our goals, it can be achieved by exploring strategies, such as standby modes or using more efficient programming languages such as C/C++. Since our prototype runs autonomously, we added the feature to run bash scripts to play sequences of audio commands. Also a Python application, based on the mraa library, is implemented in order to log all the touch information (id, x/y coordinates, time-stamps) locally.

4 STUDY 1: COMPARING WALKING, STANDING, RUNNING

The purpose of the study is to understand the performance of thumb-to-index finger gestures at different levels of physical engagement, such as standing, walking, and running. The overarching aim was to create an interaction that can be quickly performed and impose low cognitive demands. The gesture completion time, ease of use, and the task-load were the core focus.

4.1 Pilot Study

In order to determine a suitable gesture set, a small pilot study was conducted with 5 participants (2 females) aged between 24 and 29yrs (M = 26.2yrs; SD = 2.28yrs). All participants were provided with a set of 3D printed rings. The participants were asked to wear one and creatively perform any kind of one-handed finger-gestures that came into their minds. Based on the observations, wearing the ring on the index finger resulted in a higher number of gestures. These observations coincide with previous works, which found thumb-to-index finger gestures as most preferable [7, 18] and has greater precision [54]. While a variety of zick-zack and circular gestures have been performed, all participants also suggested rather simple gestures, which were: *swipe-up/-down/-left/-right, and tap*. Since these gestures can be executed quickly and appeared natural to the participants, they were selected for further evaluation.

4.2 Study Design

4.2.1 Participants. We recruited twelve right-handed participants (6 females; age range, 19-26 years; M = 22.6 years; SD = 1.8 years). Six of them reported to have never worn rings, while two reported to wear rings daily, two more than once a week, and two on a monthly basis. We measured finger dimensions, as they may have been a factor in influencing participants' subjective ratings and performances. The users' index finger had a mean width of M = 1.79cm (SD = .21) and a mean length of M = 8.98cm (SD = 1.29). Their thumb had a width M = 1.9cm (SD = .16), thumb length M = 6.89cm (SD = 1.43).

4.2.2 Procedure. The procedure started with signing the consent form, collecting demographic data, measuring hand dimensions (thumb and index) with a caliper, and taking a picture with the hand on a ruler mat. An appropriate ring size was then found for the participant by trying different sizes (*see figure 2-c*). The participant was asked to wear headphones and after ensuring that the volume was audible, we played an audio clip explaining the task and instructed them to perform the gestures on the touchpad.

4.2.3 Task. The participants were asked to perform the five gestures (*swipe-up/-down/-left/-right, and tap*) on the ring touchpad once they were heard in the headphones. The experiment was a within-subjects comparative study evaluating the gestures over the three balanced conditions; standing, walking, and running. A standard circular outdoor running track was used for walking and running. Participants were asked to run at a normal pace they felt comfortable with. The audio instructions for gesture execution were played at different frequencies: regular (frequency of 4s, 3s, and 2s), fast (frequency of 1s), and random (frequency varying between 1s and 3s). The same sequence of gestures were given in all three different conditions. After each condition a NASA TLX [16] questionnaire was filled out, followed by a questionnaire rating ease of use and precision. After the last condition, they were asked to choose a combination of gestures to control an applications menu and suggest suitable applications for this type of interaction.

4.2.4 Data Gathering. Data on completion time was autonomously collected by the prototype. For each condition, there was a number of 120 gestures distributed equally between the five types of gestures (24×5). Overall, we gathered 360 trials per subject, which is a total of 4320 trials. The ease of use and the perceived precision is rated on a 5-point Likert scale ranging from 1 (*Very Easy*) to 5 (*Very Difficult*). The NASA TLX is rated on a scale ranging from 1 to 20. Distractions can easily occur when the participant is in motion. Therefore, prior to processing, the data was cleaned and checked for any accidental touches, incorrect gestures that mismatched the audio instruction, and multiple gestures which were performed accidentally.

4.3 Results

4.3.1 Completion Times. The completion time is defined as the time between when the touchpad is initially touched and when the finger is lifted off. The mean completion times for the gestures across all conditions differ slightly (*see Figure 3*): tap= 165ms (SD= 87ms), right= 200ms (SD= 110ms), down= 180ms (SD= 68ms), left= 201ms (SD = 100ms), up= 221ms (SD= 107ms). A one-way ANOVA for correlated samples (repeated measures) could *not* reveal any significant effect on condition type or on completion time. This indicates that no gestures were performed significantly quicker or slower when standing ($F_{4,44}$=1.11; p=.3), walking ($F_{4,44}$=3.44; p=.16), or running ($F_{4,44}$=.32; p=.33). Also, our evaluation could not indicate performance differences when performing a swipe-up ($F_{2,22}$=1.2; p=.32), swipe-down ($F_{2,22}$=.12; p=.9), swipe-left ($F_{2,22}$=1.1; p=.4, swipe-right ($F_{2,22}$=2.2; p=.13), tap ($F_{2,22}$=.74; p=.5) gesture while being engaged in physical activity (standing -> walking -> running).

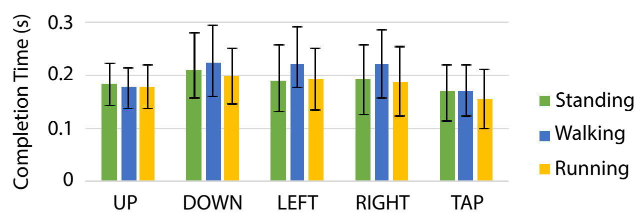

Figure 3: The completion times, with 95% confidence intervals, of the 5 gestures under the standing, walking, and running conditions for all participants (*n*=13).

4.3.2 Ease of Use. For the ease of use, a one-way ANOVA correlated sample was followed. None of the five gestures were found as easier or harder to execute when standing ($F_{2,22}$=2.43; p=.06) or when walking ($F_{2,22}$=2.05; p=.1). However, with increasing speed, the ease of use slightly decreases (*see Figure 4*). Thus, in the running condition, the tap was perceived to be significantly easier to perform than swipe-right ($F_{4,44}$=3.88; p<.01, HSD[.05=1.09]). Moreover, an ANOVA ($F_{2,8}$=6.16; p=.02) could evidence another effect, which is confirmed by a Tukey HSD post hoc analysis (HSD[.05]=.32), revealing that thumb-to-index gestures are easier to perform when standing compared to running (p<.01).

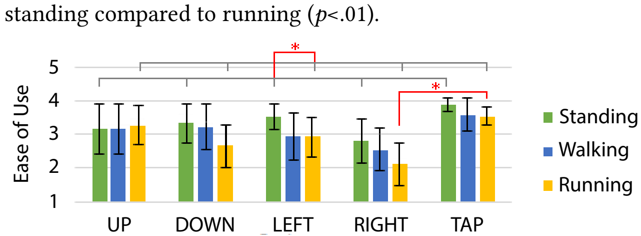

Figure 4: The mean 'ease of use' for the 5 gestures, with 95% confidence intervals, under the standing, walking, and running conditions were rated by all participants (*n*=12) on a 5-point Likert scale ranging from 1 (Very Easy) to 5 (Very Difficult).

4.3.3 Perceived Precision. A one-way ANOVA for correlated samples did not reveal significant differences for the gestures: swipe-up ($F_{2,22}$=1.94; p=.17), swipe-down ($F_{2,22}$=2.27; p=.12), swipe-left ($F_{2,22}$=.63; p=.54), and tap ($F_{2,22}$=.76; p=.48) as being perceived differently with changing walking speeds. However, significance from an ANOVA ($F_{2,22}$=5.81; p<.01) is being confirmed by a Tukey HSD test (HSD[.05=.75]) at the swipe-right gesture (p<.01), which is perceived as having greater imprecision while running compared to walking (*Figure 5*).

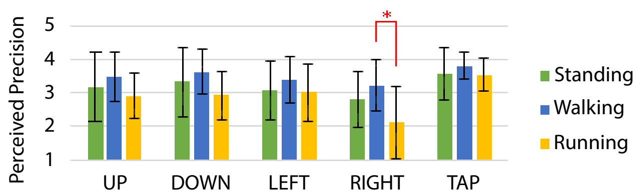

Figure 5: The Perceived Precision of the 5 gestures, with 95% confidence intervals, under the standing, walking, and running conditions rated by all participants (*n*=12). 5-point Likert scale ranging from 1 (Very Easy) to 5 (Very Difficult).

The perceived reduction of precision when running is supported by the actual correctly executed gestures based on our sensor data. However, the user did not substantially recognize this imprecision. The numbers amounts as follows: standing M = 80.3% (SD = 10.9%), walking SD = 80.8% (SD = 11.2%), and running SD = 77.8% (SD = 9.8%).

4.3.4 Task Load. The NASA TLX features six attributes that provide insights on the created load for the user. Again, we utilized a one-way ANOVA for correlated sample to analyze the gathered data. The following attributes did not significantly differ at varying physical activity across all three conditions: Mental Demand - MD ($F_{2,22}$=2.62; p=.09), Temporal Demand - TD ($F_{2,22}$=.5; p=.61), and the level of Frustration - F ($F_{2,22}$=2.1; p=.15).

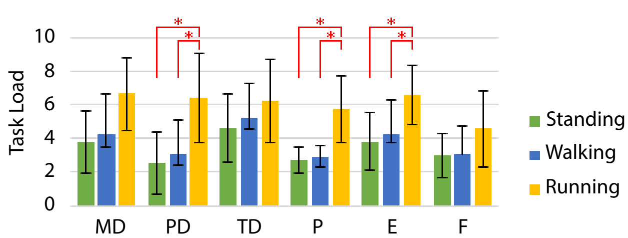

Figure 6: NASA TLX raw value means for the 5 gestures, with 95% confidence intervals, under the standing, walking, and running conditions rated by all participants (*n*=12). A significant difference is identified at Physical Demand and Effort.

A main effect was found at the following attributes (*see also Figure 6*): Physical Demand - PD ($F_{2,22}$=6.74; p=.005) - a Tukey HSD test ([.05]=2.89) suggests that thumb-to-index gestures create a higher PD when running compared to standing (p<.01) and to walking (p<.05). Performance - P ($F_{2,22}$=7.2; p=.004) - a Tukey HSD post hoc ([.05]=2.24) indicates the user to perceive having a rather negative performance level when running in comparison to standing (p<.01) and to walking (p<.05). Effort - E ($F_{2,22}$=6.5; p=.006) - a Tukey HSD test ([.05]=2.-07) reveals users to have a greater effort when running in comparison to standing (p<.01) and to walking (p<.05).

4.3.5 Qualitative Feedback . The participants suggested a variety of different scenarios, although we found a strong preference for controlling music players and fitness trackers (10 participants mentioned at least one of these, 5 participants mentioned both). Other scenarios included controlling the phone (4), while driving (4), manipulating a navigation system (3), replacing a computer joystick (2), or using the ring for authentication, such as for unlocking a device or opening a door (1). As a context of use, swimming and cycling were also suggested.

In addition, we asked all subjects for their preferences in controlling a menu. Their preferences clearly favoured up and down swiping (58.3%) motions. Also combinations of taps (25%), left and right swipes together with taps (8.3%), left and right swipes together with up and down (8.3%) were also preferred. Participants suggested gestures they considered suitable for controlling applications, such as: long press (3 participants), drawing shapes, rubbing, double tap, rhythmic tapping, and variations of tapping. Participants observed that some thumb gestures were more comfortable than others: *«It felt unnatural to perform the up gesture.»* or *«Left is easier than right.»* One subject felt *«Up and down is slightly uncomfortable»*. Another participant noted: *«Up and down is more seamless than left and right as there is little space to swipe to the right. More intuitive compared to a sequence of taps»*.

4.4 Summarizing the Findings

This study revealed that the physical activity level does not heavily affect the users' thumb-to-index gesture execution. This finding, however, was contrary to the users' initial impression. Furthermore, gesture completion time remained the same. The subjectively perceived level of precision also did not differ with increasing walking speed, except when executing the swipe-right gesture. Although swipe-right tends to be the most complicated gesture to perform, users did not perceive this gesture as being more difficult to perform compared to other gestures, such as a simple tap for the conditions of standing and walking. Generally, however, users perceived executing thumb-to-index gestures as easier while standing in contrast to running. Also, the physical demand and the needed effort was rated to be poorer when running. Our sensor data, however, does *not* confirm the execution accuracy (M=86.9; SD=4.7) of gestures as substantially different when running (*details: see 5.1.1 Apparatus. Condition 3 - T*). Overall, the qualitative feedback supported our assumption that the tap may be the preferred gesture. Other gestures, such as swipe left and swipe-down were noted as being natural, and thus may also be preferable. Nevertheless, individual preference will always dominate.

5 STUDY 2: COMPARING INTERACTION TECHNIQUES

The purpose of this study is to compare our thumb-to-index finger ring technique with commonly used interaction techniques. Therefore, we evaluated three proof-of-concept applications typically used while running: (1) the control of a music player, (2) the control of a distance tracking application, (3) and the control of a stop watch.

5.1 Study Design

The study was designed to compared three interaction techniques (*see Figure 7*)

- Condition 1: bimanual interaction with an unmodified sports-watch using visual feedback on the screen (SO).
- Condition 2: bimanual interaction with a modified sports-watch app using custom-added audio feedback (SA).
- Condition 3: unimanual thumb-to-index interaction using our prototype with audio feedback (T).

All 3 applications are controlled by swipe and tap gestures using the watch's touchscreen (SO, SA) or using the ring's touchpad (T).

Figure 7: Study setup showing the participant running while using the third condition: Ring-Touch (T). The other conditions include using the Sports-watch Original (SO) and Sports-watch Audio (SA).

5.1.1 Apparatus.
Condition 1 - SO: All three applications were running on a sports watch *Garmin Vivoactive HR.* We developed a Garmin smart watch application presenting a GUI with touch gestures. The watch was problematic as it lacked a music player and created difficulties in logging the user's interaction, including the distance, time, and pace. Consequently, we used the Garmin Connect IQ SDK 2.3.4 to access the device via a smart phone. To communicate with the Garmin watch, we implemented an Android application (on a phone, worn at the user's arm) using Android API 24 (Android 7.0: Nougat) and Connect IQ Mobile SDK 1.4 for Android. Communication between the Garmin watch Audio Interface and Android application was achieved via Bluetooth. Controlling these apps were accomplished by finger-touch input from the opposite hand at the watch's screen.

Condition 2 - SA: For the second condition, the screen of the Garmin sportswatch is blacked out without any information shown. However, the app runs in the background to capture the user's finger-touch gestures from the opposite hand at the sportwatch's screen. This transmits the gestures to the Android application to trigger relevant actions, such as skipping the song or opening the audio menu. The audio menu did not contain more than two options (e.g., select between *fitness* by swipe-up and *music* by swipe-down. Swiping left would return to the previous menu. The menu's labels are read aloud, only once a valid gesture has been identified.

Condition 3 - T: In order to recognize gestures with our prototype, we built a gesture recognizer using a supervised machine learning approach. For this, we used the data set collected from our previous user study, which contains 2919 pre-processed gestures collected from 12 participants (swipe-up: 612, swipe-right 599, swipe-down 486, swipe-left 582, tap 640). They were randomly split into a training (80%) and test (20%). We utilized a simple feature extraction method which provided 3 relevant features (sum of point-to-point displacements in X,Y direction and time frame). Subsequently, two classifications models were trained using SVM and Multi Layer Perception (MLP) classifiers. Since there were not much of non-linear boundaries, performance of the both models were almost similar. We decided to implement SVM classifier on the ring since it is much simpler than MLP classifier. The average f1-score of 11 participants is 86.9% (*SD*=4.7%) and the average recall is 89% (*SD*=11%), see also the confusion matrix (Figure 8). Our prototype also connects to the android phone via Bluetooth and controls the music player, lap timer, and distance counter via the audio menu.

a	b	c	d	e	< classified as
0.74	0.07	0	0.09	0.1	**a** TAP
0.01	**0.97**	0.01	0	0.01	**b** SWIPE-DOWN
0.01	0.01	**0.98**	0	0	**c** SWIPE-LEFT
0.01	0.04	0.02	**0.77**	0.16	**d** SWIPE-RIGHT
0.01	0.01	0.03	0.06	**0.89**	**e** SWIPE-UP

Figure 8: Confusion matrix generated out of 2919 pre-processed gestures collected from 12 participants from the first study.

5.1.2 Procedure. The procedure started with signing the consent form, collecting demographic data. As we designed a balanced within-subjects comparative study, each condition (SO, SA, T) was tested with the user in a different order. Depending on the condition, the devices (headset, smartphone, smartwatch/ring) were attached to the participant. The sportswatch was placed at the wrist of the non-dominant hand (left). The ring-touchpad-bracelet (T) was mounted on the dominant hand (right). We spent time with the participants to properly introduce them to the devices, to the proposed running task, and to increase their familiarity with the applications. After task completion of each condition (SO, SA, T), the participants were asked to fill out a questionnaire with the System Usability Scale (SUS) [6] followed by a number of other questions and an open-ended interview.

5.1.3 Participants & Task. We recruited 18 healthy and right-handed participants (8 females; age range, 19-28 years; M = 22.3; SD = 2.4 years). The instructions given to participants were to run a total of 800m at a constant speed, while having to control any one of the three applications every 100m, which was indicated by a landmark on the tartan running track. The participant could access 1) the tracked time, distance, and speed, 2) set a timer, and 3) control the music player (play, pause, next) as desired. Depending on the condition, the interaction with the interface was either bimanually with visual output (SO), bimanually with audio output (SA), or unimanually with audio output (T).

5.1.4 Data Gathering. In order to compare different interaction techniques, we made use of an SUS, which features 10 attributes. Additionally, we asked 11 more questions, which we found to be an interesting point of comparison. These questions and the SUS were rated on a 5pnt Likert-scale, ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). More qualitative data was gathered by an open-ended questionnaire afterwards. While a variety of sensor data was also gathered, such as interaction time etc., the findings were obvious and therefore not analyzed. (1) Audio-interfaces yield longer interaction times and (2) bimanual interactions create greater physical and time effort than unimanual interactions.

5.2 Results

5.2.1 Usability. The SUS scores for each conditions are: SO (*M*= 63.06, *SD*= 17.4), SA (*M*= 67.7, *SD*= 10.2), T (*M*= 70.0, *SD*= 16.54). Following the general interpretation of SUS, allows us to comment that only condition 3 (T) is considered as being usable (*M*>= 68) in a running scenario. Based on figure 9, it is clear that users tend to prefer using condition 3 (T) more frequently, while they have a high confidence in the system. Also, T tends to be perceived as less complex, easier to use, and less cumbersome. Moreover, the ring prototype was rated to have higher inconsistency, which is due to the lower gesture recognition accuracy. However, these described affects are not statistically different to our limited sample size (*n=18*) suggested by a single-factor ANOVA ($F_{2,34}$=.75; *p*>.05).

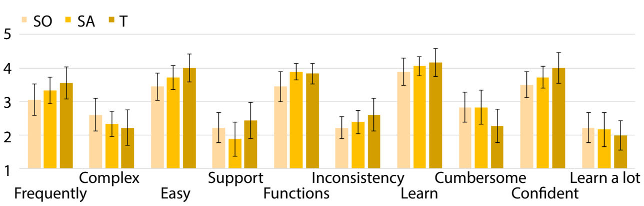

Figure 9: Average ratings for SUS questions comparing three conditions: Sports-watch Original (SO), Sportswatch Audio feedback (SA), and Ring-Touchpad (T).

5.2.2 Custom Questionnaire. We asked the participants to rate 11 more questions, such as if the system is satisfying, helpful, mentally stimulating, attractive, etc. However, a one-way ANOVA for correlated samples only found two questions to be significantly different. *Q7: Using this device is frustrating* - was significantly higher ($F_{2,34}$=6.75; *p*=.003) for the ring prototype T (*M*=3.6; *SD*=.78) in comparison to SO (*M*=2.6; *SD*=1.1) and SA (*M*=2.66; (*SD*=.8), which was confirmed by a Tukey HSD test ([.05]=.75). The reason for this is the accuracy of the gesture recognition, which is substantially lower with our ring prototype in contrast to a commercial smartwatch product. However, *Q9: Using this system is fun* - was significantly higher ($F_{2,34}$=3.32; *p*<.05) for the ring interaction T (*M*=3.8; *SD*=.8) in comparison to SO (*M*=3.2; *SD*=1) and SA (*M*=3.3; *SD*=.9).

5.2.3 Qualitative Feedback. For the final step, we conducted an open ended interview, which was audio-taped. The main difficulties the participant encountered was of particular interest. This was similar to P5: *«Having to glance once to see all the information is more convenient than listening to the information audio [...]. Also, having a physical button makes me very sure that my input goes through»*. For improvements, the subjects agreed on increasing the gesture recognition or incorporating an instant feedback function.

On our last question; *Which apparatus may be preferred and why?*, achieved the following result: SO (4 participants), SA (4 participants), T (10 participants). The majority preferred the ring for different reasons, such as: *«Easier to use while running»* (P15), *«It does not interfere with my running speed and requires very little motion to use»* (P13), *«Minimal effort, did not disrupt my running form, least cluncky UI»* (P15), *«Easy to learn, does not interfere with sport, lightweight; functions good enough for running»* (P16), *«Interaction with the ring is extremely convenient because it only requires one hand and audio feedback helps with the situation»* (P18).

5.3 Summarizing the Findings

Although, *«Audio is more convenient than visual [feedback], especially when running faster/trail running [...], visual [interfaces] allow more options like volume control.»* (P12). Therefore, thumb-to-index gestures may not be the most optimum option to manipulate complex information interfaces. For the proposed applications, it became clear that the ring prototype did not perform worse than other conditions. Instead, a higher usability score was achieved during athletic running. Ultimately, comparing a new prototypical input strategy with highly accurate consumer devices is never a fair comparison. Accuracy rates for hand-crafted prototypes are generally lower, which increases the level of frustration. Nevertheless, most users preferred the thumb-to-index interaction, as it is unimanual and created less interference.

6 CONCLUSION

A touchpad ring prototype was developed and demonstrated how unimanual thumb-to-index interaction allows the user to interact with a wearable device during athletic running. Our observations coupled with the users' experience, reveal that this technique did not interfere with athletic running activity. Therefore, this solves an important interaction problem in the domain of athletic sports applications [38]. For gestures, tapping motions, as well as the swipe-left and swipe-down, were the most preferred, since they appeared natural to the user. While this technique may not be preferable for manipulating complex information interfaces, it is highly suitable for a short and subtle interactions such as for skipping a song or rejecting a phone call [34].

7 FUTURE WORK

Thumb-to-index interaction has increasingly been considered as an input for wearable devices, such as smartglasses [18]. With the advent of fitness trackers, the wearables market can increase their consumer reach. This potentially extends wearables to the human body through smart clothing and on-body sensing [19]. The insights developed from researching ring-touchpad usage in motion, can thus inform future sports wearables designs, athletic interaction, and improve the accessibility of information for athletes. However, it was discovered that athletic activities also yield specific challenges. When being involved in considerable motion, accidental touches (false-positives) may increase. As athletic activities generally accelerate sweat accumulation, the surface of the ring gets covered by moisture, making capacitive sensing over-sensitive and thus increasing true-negatives.

Besides sports applications, this can be applied in everyday scenarios, particularly when an individual is preoccupied with a primary task and is required to micromanage an emerging secondary task. Moreover, the thumb-to-index interaction can provide an increased interaction space in the Peripheral Interaction [3] domain, which has great potential for enabling a Reflexive Interaction [34].

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