A Performance Comparison of On-Hand versus On-Phone Nonvisual Input by Blind and Sighted Users

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On-body interaction, in which the user employs one's own body as an input surface, has the potential to provide efficient mobile computing access for blind users. It offers increased tactile and proprioceptive feedback compared to a phone and, because it is always available, it should allow for quick audio output control without having to retrieve the phone from a pocket or bag. Despite this potential, there has been little investigation of on-body input for users with visual impairments. To assess blind users' performance with on-body input versus touchscreen input, we conducted a controlled lab study with 12 sighted and 11 blind participants. Study tasks included basic pointing and drawing more complex shape gestures. Our findings confirm past work with sighted users showing that the hand results in faster pointing than the phone. Most important, we also show that: (1) the performance gain of the hand applies to blind users as well, (2) the accuracy of where the pointing finger first lands is higher with the hand than the phone, (3) on-hand pointing performance is affected by the location of targets, and (4) shape gestures drawn on the hand result in higher gesture recognition rates than those on the phone. Our findings highlight the potential of on-body input to support accessible nonvisual mobile computing.

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Additional Key Words and Phrases: Blindness, nonvisual interaction, mobile computing, on-body interaction, user study

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1. INTRODUCTION

Touchscreen smartphones with screenreaders have expanded mobile computing access for blind users. With screenreading software, however, the device itself is effectively reduced to a gestural input surface with audio output. The visual display is unneeded. This creates an opportunity for alternative, lighter-weight methods to control the audio output, methods that could range from Bluetooth keyboards to emerging wearable devices [Ye et al. 2014]. We are exploring one possibility, *on-body input*, for which the user's own body acts as an input surface, either with or without visual feedback (e.g., Harrison et al. [2011] and Gustafson et al. [2011]).

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On-body input is a particularly attractive interaction approach for blind users who do not benefit from the visual display of the mobile device. It offers other benefits as well: it is always available, not requiring the user to pull out the phone, requires little or no instrumentation of the hands, provides increased tactile feedback compared to a touchscreen [Gustafson et al. 2013], and it may offer extra proprioceptive feedback. Despite this potential, there has been little investigation of accessible on-body input for users with visual impairments. Focusing on subjective feedback, Oh and Findlater [2014] found that blind and low-vision participants reacted positively to the idea of on-body input, in particular preferring the hand to a touchscreen phone for location-independent gestures when only one hand is free (e.g., when the other hand holds a cane or dog leash). The hand as an input surface was also considered to be more discreet and natural than other body locations.

In contrast, most studies of on-body interaction have included visual output [Harrison et al. 2011; Harrison et al. 2012; Harrison et al. 2010; Mistry et al. 2009; Tamaki et al. 2009], while a smaller number have investigated nonvisual use with sighted users [Gustafson et al. 2011; Lin et al. 2011; Gustafson et al. 2013]. Gustafson et al. [2013], for example, assessed nonvisual pointing performance and found that sighted users could point to targets more precisely on their hand than on a touchscreen phone. These on-body tactile benefits may be even stronger for users with visual impairments, for whom tactile acuity has been found to be greater than it is for sighted users [Gaunet et al. 2006; Goldreich and Kanics 2003; Stevens et al. 1996; Van Boven et al. 2000; Legge et al. 2008]. However, this performance question remains unexplored, as Gustafson et al. [2013] collected data from only one blind participant.

To assess the accessibility of on-body input with blind users, this article presents a study comparing nonvisual input on the hand versus on the phone with 12 sighted and 11 blind participants. Our study includes two nonvisual tasks. The first task builds on the work of Gustafson [2013] with sighted users by (1) including blind participants, and (2) examining a more thorough set of target locations per participant (20 vs. 5)—this latter difference allows for an analysis of input performance based on location. Our second task moved beyond pointing, by comparing input of more complex shape gestures on the hand and phone (e.g., a circle and a + sign). If on-body shape gestures are accessible for blind users, they could be used, for example, to quickly invoke a shortcut command to answer a phone call or control navigation directions.

Our results confirmed the conclusion of Gustafson et al. [2013] that the hand results in faster nonvisual pointing than the phone for sighted users, but also extends their pointing findings by showing: (1) that this result holds true for blind participants who have substantial nonvisual touchscreen experience, (2) that the accuracy of the first contact point upon touch down is higher on the hand, and (3) that different target locations on the hand result in different input performance. For shape gestures, the hand did not offer either a clear accuracy or consistency benefit over the phone, although it did result in significantly higher recognition rates when we classified drawn gestures with a shape-based gesture recognizer ($N [Anthony and Wobbrock 2010]). Although we hypothesized that the tactile and proprioceptive benefits of the hand would be even greater for blind participants than sighted participants, this hypothesis was not supported. We discuss potential reasons.

The contributions of this article are: (1) extension of previous findings on nonvisual touchscreen versus on-hand input to a new user group (blind persons) and another performance measure (accuracy), (2) investigation of how on-hand input performance differs based on target location, and (3) empirical evidence to show that shape gestures may be a feasible form of nonvisual input on the hand. Finally, we reflect on the implications of our results for nonvisual interaction and the potential benefits of on-body input to complement existing accessible mobile computing approaches.

2. RELATED WORK

Our research builds on work in on-body interaction and touchscreen accessibility. We also provide background on tactile acuity and proprioception.

2.1. Interaction on the Body

Interaction that employs the user's own body as an input surface is a subset of wearable interaction more generally. Various sensing techniques have been proposed to sense these on-body taps and gestures, including bio-acoustics [Harrison et al. 2010], an ultrasonic rangefinder [Lin et al. 2011; Liang et al. 2011], body-mounted color or depth cameras [Dezfuli et al. 2012; Gustafson et al. 2011; Oh and Findlater 2014; Harrison et al. 2012; Harrison et al. 2011; Tamaki et al. 2009; Mistry et al. 2009], infrared (IR) reflective sensors [Ogata et al. 2013; Kim et al. 2012; Nakatsuma et al. 2011; Laput et al. 2014], electromyography (EMG) [Saponas et al. 2009], and a touch-sensitive skin overlay (*iSkin*) [Weigel et al. 2015]. To support communication for deaf-blind users, Gollner et al. [2012] designed a glove that senses the Lorm alphabet and provides haptic feedback. One downside of this glove and others (e.g., Caporusso [2008] and Choudhary et al. [2015]), however, is that they cover much of the hand and thus reduce tactile perception.

Most projects combine on-body input with visual output using a wrist-worn display [Loclair et al. 2010] or small, body-worn projectors [Tamaki et al. 2009; Harrison et al. 2010, 2011, 2012; Mistry et al. 2009]. Others [Lin et al. 2011; Dezfuli et al. 2012; Gustafson et al. 2011, 2013], such as Gustafson et al.'s *Imaginary Interfaces* [Gustafson et al. 2011, 2013], are more applicable to users with visual impairments in that they provide spatial, screenless interaction—for example, mimicking the familiar layout of a smartphone screen on the user's hand [Gustafson et al. 2011]. In terms of user preference for on-body input design, Weigel et al. [2014] asked sighted users to create their own on-body gestures, and found the forearm and hand to be preferred locations over the upper arm.

A few studies have investigated on-body input performance under nonvisual conditions [Lin et al. 2011; Dezfuli et al. 2012; Gustafson et al. 2011, 2013]. Lin et al. [2011] studied sighted participants' accuracy and speed in pointing to nonvisual locations on the forearm. They segmented the forearm into 5 to 9 sections, and found that pointing accuracy degraded with more than six segments; no differences in speed were found. As mentioned in the Introduction, Gustafson et al. [2013] instead focused on the hand, comparing input on the palm versus a touchscreen phone. Their findings showed that participants were faster at pointing to targets on the hand than on the phone when visual cues were absent. While that paper also reports on an exploratory evaluation of the same tasks with one blind participant, to our knowledge, no larger performance study with visually impaired participants has been conducted. As such, the first task in our study replicates and extends the phone-to-hand comparison with both blind and sighted participants by Gustafson et al. [2013].

2.2. Accessible Touchscreen Interaction for Blind Users

Through a diary study and interviews, Kane et al. [2009] showed that mobile technology allows visually impaired users to gain independence. Modern touchscreen devices, however, rely heavily on visual cues and provide little tactile feedback. To improve the accessibility of touchscreen-based mobile phones for blind users, proposed solutions have included enhancing tactile feedback through external hardware devices [Vanderheiden 1996; Landau and Wells 2003], physical overlays [Kane et al. 2011, 2013], or the use of location-insensitive gestures [Bonner et al. 2010; Frey et al. 2011; Guerreiro et al. 2008; Kane et al. 2008; McGookin et al. 2008]. *Slide Rule* [Kane et al.

2008], for example, adapted multitouch gestures to support more accessible navigation. Commercial products also offer screenreading software for users with visual impairments. Apple iOS's VoiceOver,[1] for example, speaks each item aloud as the user touches it, and provides discrete navigation through items with location-insensitive flick gestures.

To better understand the accessibility of touchscreen gestures for users with visual impairments—relevant to our second task—Kane et al. [2011] conducted two studies on gesture creation and articulation with sighted and blind participants. They found that gestures drawn by blind participants were less consistent than those drawn by sighted participants. However, unlike in our study, their sighted participants received visual feedback. In a later study, Oh et al. [2013] proposed and evaluated two techniques for providing feedback to visually impaired users as they learn unfamiliar touchscreen gestures (sonification and corrective verbal feedback). These techniques could potentially be applied for learning gestures on the hand, and could be useful to explore in future work.

2.3. Tactile and Proprioceptive Senses for Supporting Nonvisual Interaction

With nonvisual interaction, tactile and proprioceptive senses play important roles. Gustafson et al. [2013] showed that, for sighted users, while visual feedback is the dominant sense when it is available, tactile feedback is important for fast nonvisual input. The utility of this tactile feedback may be even greater for blind users. A number of studies on passive touch (i.e., sense of being touched) have shown that blind people, both congenitally blind and those who became blind later in life, have superior tactile acuity to sighted people [Van Boven et al. 2000; Gaunet et al. 2006; Goldreich and Kanics 2003; Legge et al. 2008; Stevens et al. 1996; Goldreich and Kanics 2006; Alary et al. 2008]. Goldreich and Kanics [2003], for example, showed that blind participants were able to distinguish thinner grooves on a flat surface than sighted peers, although the difference in acuity was only 0.33mm. Stevens et al. [1996] also showed that blind participants outperformed a sighted group in discriminating a gap between two points. The minimum size that was distinguishable for the blind and sighted groups was 1.94mm and 2.31mm, respectively. Practically speaking, these differences are small, but suggest that blind users may disproportionately benefit from increased tactile feedback compared to sighted users under nonvisual conditions.

Proprioception, the ability to move and locate body parts without visual cues, has been used for mid-air, eyes-free interaction (e.g., Li et al. [2010], Morelli and Folmer [2012], and Folmer and Morelli [2012]). Li et al. [2010] examined eyes-free mid-air pointing accuracy for controlling mobile applications, comparing performance of sighted versus visually impaired participants. Their results showed that participants with visual impairments were less accurate and slower than sighted participants. However, the sighted participant group had visual feedback and was younger than the visually impaired group, and proprioception degrades with age [Adamo et al. 2009]. Other research with age-matched groups has yielded conflicting results. Some studies have shown that blind participants have better proprioceptive acuity than their sighted peers (e.g., Ozdemir et al. [2013], Jones [1972], and Gaunet et al. [2006]), for example, in pointing more accurately under nonvisual conditions [Gaunet et al. 2006]. Other studies have found no difference between blind and sighted groups (e.g., Petkova et al. [2012] and Gosselin-Kessiby et al. [2009]), for example, in localizing the right hand in space with no visual cues. Fiehler et al. [2009] have also shown that proprioceptive spatial acuity of blind adults depends on their spatial experience, such as orientation and mobility training at an early development stage. Despite this contradictory evidence

[1] https://www.apple.com/accessibility/ios/voiceover/.

comparing blind and sighted participant groups, proprioception is likely a benefit for all users of nonvisual on-body interaction compared to a touchscreen phone.

3. METHOD

To assess the performance of nonvisual on-body input compared to input on a flat surface for blind and sighted users, we designed and conducted a single-session study with 23 participants. Compared to the simple location-independent gestures (e.g., press-and-hold, swipe right) that we previously studied [Oh and Findlater 2014], here, we focus on absolute pointing and more complex gestures involving two hands. Absolute pointing, that is, pointing to a specific location on the hand or phone, could result in highly efficient interaction if it is accurate. This study included two tasks, the first of which was a controlled *pointing task* with 20 target locations on the hand or phone, based on Gustafson et al. [2013]. The second task assessed performance and subjective feedback with more complex *shape gestures*. In designing the study tasks, our goal was to make each condition as realistic as possible while still conducting a controlled performance experiment. This motivation underlies many of our study decisions, such as using the hand's natural landmarks to configure pointing targets rather than having targets of uniform size.

3.1. Participants

Participants were recruited via campus e-mail lists and local organizations that serve people with visual impairments. In recruiting participants, we addressed two limitations commonly seen in studies comparing visually impaired and sighted users: variation in vision levels of the visually impaired group and an age discrepancy between the two groups. Twelve sighted (7 female, 11 right-handed) and 11 totally blind (5 female, 8 right-handed) individuals participated in this study.[2] We roughly age-matched the two groups, such that sighted participants were, on average, 51.8 years old ($SD = 11.9$, range 26–67) versus 52.4 years old ($SD = 10.8$, range 33–67) for blind participants. Six of the blind participants had become blind later in life (years post-onset: $M = 31.0$, $SD = 16.7$), while five were born blind. All participants had touchscreen phone experience, and were compensated for their time.

3.2. Apparatus

The custom experimental system consisted of a Logitech 1080p HD webcam C930e, touch sensors connected to an Arduino Leonardo board, and tracking software running on a laptop with an Intel Core i5 processor and OSX 10.9.4. To ensure data consistency across the hand and phone conditions, we used this tracking setup for both interfaces rather than using the native touchscreen sensing on the phone. Hands are typically bigger than today's smartphones, thus we selected a relatively large phone (Google Nexus) to limit the disparity. The main software was written in C++ and used the OpenCV library for image processing. The system: (1) tracked the pointing finger, (2) detected touch on the phone or hand, (3) automatically generated pointing targets, (4) provided audio feedback upon touch, and (5) included a conductive touchpad for participants to tap at the start of each trial. This *starting touchpad* was 6.35×6.35cm and placed 15cm away from the phone or nondominant hand.

3.2.1. Stabilizing the Phone and Hand. We affixed the phone or nondominant hand to a stand to ensure that it did not move and the camera angle remained steady during study tasks. The stand itself was angled for comfort, based on feedback from pilot

[2] Four more participants (1 sighted) were initially recruited but excluded from analysis because they were unable to learn the target-naming scheme in the pointing task even after training.

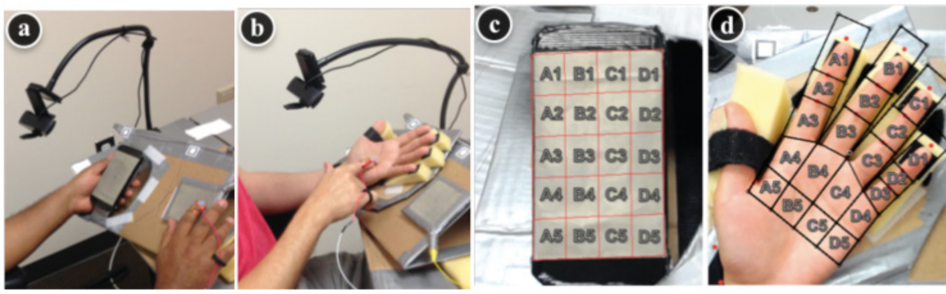


Fig. 1. Experimental setup showing the camera and approach used to stabilize (a) the phone or (b) nondominant hand during tasks, and corresponding target locations (c, d). At the start of each trial, participants tapped on the square touchpad on the right side of the stand. The entire setup was reversible for left-handed participants.

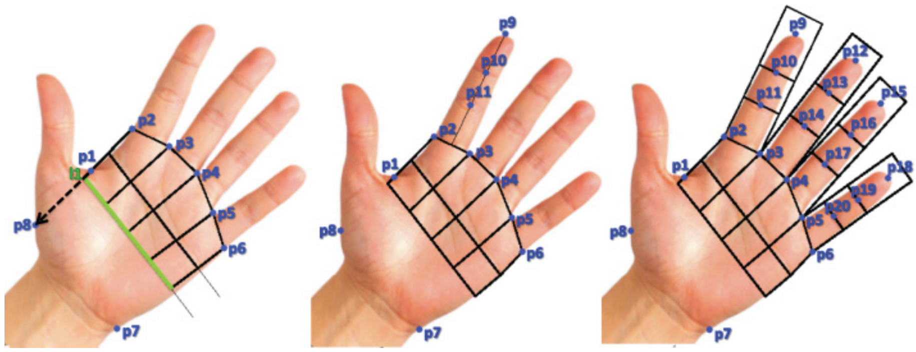
(a) Top view. (b) Bottom view.

Fig. 2. Finger-worn touch sensor.

participants. Cutouts in the stand allowed the participant to hold the phone, which was attached to the stand by Velcro (Figure 1(a)). For the hand, Velcro straps fastened the wrist and thumb to the stand. To prevent curling of the fingers—which would impact the size and shape of targets—the fingers rested on slightly angled foam wedges and the fingernails were secured to the foam using small pieces of Velcro tape (Figure 1(b)). This allowed the upper (input) side of the hand to be completely bare, so as not to hinder tactile feedback. The rotation of the phone or hand could be adjusted to be comfortable for each participant during an initialization step. Finally, the entire setup was reversible, to support both left- and right-handed participants.

3.2.2. Finger Tracking and Touch Detection. Unlike previous studies that used depth information alone to track the fingertip and detect touch (e.g., Dezfuli et al. [2012], Gustafson et al. [2011], and Harrison et al. [2011, 2012]), we found such an approach to be insufficient for precise measurements. Instead, we combined a color marker for x, y tracking with a separate lightweight touch sensor on the pointing finger (Figure 2). The color marker was placed 5mm down from the tip of the participant's finger. The x, y coordinates of the touched point were determined by image moments of the camera frame after filtering colors and removing noise. The touch sensor consisted of conductive thread that was shielded from the user's skin with 3mm-wide nonconductive tape. It connected to an Arduino Leonardo board running software that used the *CapSense* library to detect changes in capacitance from touching the pointing finger to the user's nondominant hand. For the phone condition, conductive fabric covered the screen, allowing for the same touch detection approach.

3.2.3. Pointing Task Target Configuration. For the pointing task, 20 targets are used for each condition. The targets are named by column (A–D) and row (1–5), as shown in



(a) Targets on the palm. (b) Targets on the fingers. (c) After configuration.

Fig. 3. Configuring targets for the hand condition for a right-handed user. See main text for detail.

Figures 1(c) and 1(d). Configuration of the targets is done per user on the laptop once the phone or hand is affixed to the stand.

For the phone, a researcher clicks the corners of the input area, which is then split evenly into columns and rows. For the hand, we laid out 20 targets where the five rows start at the fingertips and do not cover the bottom half of the palm. The choice to include 20 targets (5 rows $\times$ 4 columns) on both the phone and the hand follows Gustafson et al. [2013], and is based on smartphone home screens that typically lay out icons in 5 or 6 rows $\times$ 4 columns. A set of reference points is used to maximize the use of natural landmarks by aligning targets with fingertips, phalanges of the fingers, thumb versus palm, webs between fingers, and border with the wrist. As shown in Figure 3, points from $p1$ to $p6$ segment the palm from the fingers and thumb; $p7$ is the outer join between palm and wrist. For the thumb, this segmentation also requires extending $\overleftrightarrow{p2p1}$ and demarcating its intersection with the edge of the palm ($p8$). To automatically generate palm targets, $\overline{p2p8}$ and $\overline{p6p7}$ are each divided into four equal segments, the top two of which delineate the two rows of the palm. These rows are in turn divided into columns based on the finger webs, but with equal widths at the bottom; the outside two cells are also adjusted to reach the edge of the hand (compare Figure 3(a) to Figure 3(b)).

Finally, to generate finger targets, the researcher selects the fingertips (e.g., $p9$) and, on the line segment from the midpoint of the finger base (e.g., $\overline{p2p3}$) to the tip, selects the natural divisions between phalanges (e.g., $p10$ and $p11$). The targets are then automatically generated as shown in Figure 3(c). In pilot studies, participants regularly pointed to the very top of the finger, which meant that the pointing finger would be touching, yet *above* the nondominant hand's finger. To support this common interaction, we extended the height of the top row targets on the hand by 50% of the width of the target.

3.3. Procedure

Participants completed a single 2-hour study session. It began with a background questionnaire, after which participants completed both the pointing and shape-drawing tasks for one interface condition (hand or phone), followed by the other interface condition. The order of presentation for hand versus phone was fully counterbalanced within each participant group; the pointing task always preceded the shape-drawing task. To ensure nonvisual performance, sighted participants were blindfolded during the tasks. The touch sensor was placed on the index finger of the participant's dominant hand, and the hand and phone were affixed to the stand as described earlier (see Figures 1(a), 1(b)).

3.3.1. Pointing Task. Participants first explored the names and locations of targets by running their pointing finger over the hand or phone. Based on touch-and-explore interfaces, the system read each target aloud as it was touched. Selection of a target occurred on finger lift-up. For each trial, participants tapped on the starting touchpad to reposition their hand, and to initiate timing and cause the instruction to be read aloud. Upon a correct selection, a chime sound played from the laptop; no audio feedback was provided for incorrect selection. For example, if a participant makes a contact, the name of the touched location will be read aloud. Then participants can either lift up their finger to confirm the location or keep browsing for the correct target location depending on the current target. As brief practice, participants performed one random practice trial before beginning the main task.

Participants then performed 3 blocks of 20 trials as a *learning* phase and another 3 blocks as a *trained* performance phase (120 trials in total). Each block included the 20 locations in Figures 1(c) and 1(d), presented in random order. Participants were asked to find the target location as quickly and accurately as possible. They were allowed to retry the trial if they realized that they had misunderstood where the location was after hearing the target name, for example, pointing to D1 instead of A1, or if they needed to have the target name to be repeated. After the task, participants provided subjective feedback on ease, accuracy, and speed.

3.3.2. Shape-Drawing Task. Participants drew five shape gestures: circle, equilateral triangle, square, plus sign (+), and equal sign (=). This set was chosen to cover a variety of characteristics such as curviness/straightness of lines, length of lines, shape closure, and angle between two strokes (e.g., parallel, perpendicular). Before starting the task, a brief verbal description of each gesture was given and participants were allowed to explore a raised physical guide for each shape (geometric shapes or mathematical symbols may not be familiar to all blind participants [Amirabdollahian et al. 2002; Jackson 2002]). Participants then completed six blocks of trials, including one practice and five test blocks, in which each block consisted of the five shapes presented in random order (25 trials in total). As with the pointing task, participants tapped on the starting touchpad to begin each trial. Participants were asked to take as much time as they needed to draw the shape accurately and consistently on their palm. For feedback, a brief, high-pitched sound played at every touch down or up.

3.4. Experiment Design and Hypotheses

For the pointing task, the study used a $2 \times 2 \times 2$ mixed factorial design, with user *Group* as a between-subjects factor (levels: sighted vs. blind), *Interface* as a within-subjects factor (levels: hand vs. phone), and *Phase* as a within-subjects factor (levels: learning vs. trained). For the shape-drawing task, the study used a 2×2 mixed factorial design, with *Group* as a between-subjects factor and *Interface* as a within-subjects factor.

Based on the finding by Gustafson et al. [2013] that sighted users were faster at pointing nonvisual on their hand than on a phone, and on studies that show blind individuals have higher tactile acuity than sighted individuals [Van Boven et al. 2000; Gaunet et al. 2006; Goldreich and Kanics 2003, 2006; Legge et al. 2008; Stevens et al. 1996], we derived the following hypotheses:

—H1: The hand is faster for pointing than the phone.
—H2: The hand is more accurate for pointing than the phone.
—H3: The pointing performance benefits (speed and accuracy) of the hand are greater for blind participants than for sighted participants.

—H4: The hand results in more accurate shape gestures than the phone (compared to an ideal reference shape).
—H5: The hand results in more consistent shape gestures than the phone when gestures are redrawn repeatedly.
—H6: The shape-drawing benefits (accuracy and consistency) of the hand are greater for blind participants than for sighted participants.

3.5. Data and Analysis

For both tasks, the system continuously logged timestamped x, y coordinates and touch status for the index finger. For the target-pointing task, we collected data from six blocks of 20 trials from 23 participants for both phone and hand conditions. To reduce the influence of outlier trials, we removed 58 trials that were three standard deviations above and below the mean per participant. There were 16 misrecorded trials, leaving a total of: $6\times20\times23\times2-58-16 = 5446$ trials. For the shape-drawing task, 5 blocks of 5 trials for two interfaces were collected from 23 participants, for a total of: $5\times5\times2\times23 = 1150$ trials.

We specify which statistical tests were used throughout the results. In general, we apply paired t-tests and repeated-measures ANOVAs for pointing accuracy and speed. Wilcoxon signed-rank tests and repeated-measures ANOVAs with Aligned Rank Transform (ART) [Wobbrock et al. 2011] were used for subjective ratings, and for shape accuracy and consistency, which violated the normality assumption of the parametric tests. For posthoc pairwise comparisons (t-tests or Wilcoxon signed-rank tests), Holm's sequential Bonferroni adjustments were used to protect against Type I error [Holm 1979]. Finally, the audio recordings were analyzed to thematically group participants' comments and open-ended responses.

4. RESULTS

For both the pointing and shape-drawing tasks, we cover performance and subjective data, examining the difference between two user groups both on phone and the hand.

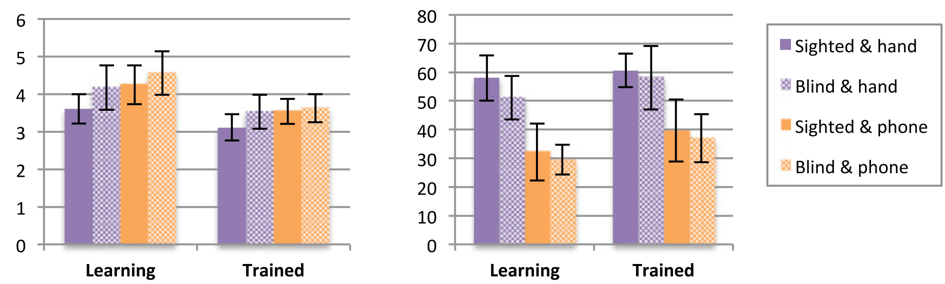
4.1. Pointing Task

We report on the primary performance measure of selection time, which encompasses both speed and accuracy, and a secondary measure of the accuracy of only the first point of contact. We also examine performance based on target size and location.

4.1.1. Selection Time. *Selection time* per trial was defined as a comprehensive performance measure that includes an implicit time penalty for errors. It was calculated from the starting signal (when the participant tapped the start touchpad) until a finger-up event occurred on the *correct* target location (Figure 4(a)). This measure is impacted both by proprioception, as the participant moves one's pointing finger through the air, and by tactile feedback, after the finger touches down and moves on the surface of the opposite hand.

Supporting H1, the average selection time on the hand was 3.59s ($SD = 0.77$), which was faster than the 3.98s for the phone ($SD = 0.72$). A $2\times2\times2$ ($Group, Interface, Phase$) repeated-measures ANOVA found that the difference was statistically significant, by main effect of *Interface* ($F_{1,21} = 7.17$, $p = 0.014$, $\eta^2 = 0.25$).

Participants also improved significantly between the learning and trained phases (main effect of *Phase*: $F_{1,21} = 102.18$, $p < 0.001$, $\eta^2 = .83$). As shown in Figure 4(a), the average time in the learning phase was 4.13s per target ($SD = 0.75$), compared to only 3.45s per target in the trained phase ($SD = 0.60$). No other main or interaction effects were significant. Although we had expected to see greater performance advantages on



(a) Selection time (sec.) (b) First contact success rate (%)

Fig. 4. Average selection time (a), and average first-contact success rate (b) for the learning and trained phases of the pointing task ($N_{sighted} = 12$; $N_{blind} = 11$). Error bars indicate 95% confidence intervals.

the hand for blind participants than for sighted participants, no support was found for H3.

4.1.2. First Contact Success Rate. While selection time, provided earlier, encompassed both speed and overall pointing accuracy, we also isolated *first contact success rate* as the percentage of trials in which the participant's first touch point landed within the bounds of the target (see Figure 4(b)). This secondary measure of accuracy relies solely on proprioception. Because selection occurs on lift up, these rates are not comparable to standard error measures, but do provide insight into one aspect of performance efficiency. Supporting H2, the hand was more accurate than the phone, with an average accuracy of 57.0% ($SD = 12.8$) across groups, compared to 34.8% for the phone ($SD = 14.4$). A 2×2×2 repeated-measures ANOVA (*Group* × *Interface* × *Phase*) revealed that this difference was significant, by a main effect of *Interface* ($F_{1,21} = 57.6$, $p < 0.001$, $\eta^2 = 0.73$). Accuracy also improved significantly from the learning phase to the trained phase, jumping from 42.8% ($SD = 11.9$) to 48.9% ($SD = 12.9$) by main effect of *Phase* ($F_{1,21} = 12.38$, $p = 0.002$, $\eta^2 = 0.37$). Finally, although we had hypothesized that the performance advantages of the hand would be greater for blind participants than for sighted participants (H3), no other main or interaction effects were significant.

4.1.3. Impact of Target Location and Size. As a secondary analysis, we computed selection time and first-contact success rate for each target on the hand and phone. To reflect more experienced use, this analysis includes only the trained phase data. As well, because of the lack of performance differences between the blind and sighted user groups described earlier, we combined data from the two.

As Figure 5 shows, while performance was generally better on the hand than on the phone, there was also a greater range in results across targets. The fingertips, for example, appear to be particularly fast and accurate. To broadly compare the impact of different target locations on selection time and first-contact success rate, we grouped the targets by row and column, and conducted one-way repeated-measures ANOVAs with the following single factors for each device (hand and phone): *Rows* (5 levels: from fingertip to palm) and *Columns* (4 levels: left to right/index to baby finger). We report only posthoc pairwise comparisons that were significant at $p < 0.05$ after a Holm-Bonferroni adjustment.

Compared to the phone, the performance of each target on the hand could be affected more by its location because some locations might have more distinctive landmarks than other locations (e.g., fingertip vs. palm).

For the hand, rows and columns both significantly impacted speed (*Rows:* $F_{4,88} = 7.396$, $p < 0.001$, $\eta^2 = 0.252$; *Columns*: $F_{3,66} = 4.359$, $p = 0.007$, $\eta^2 = 0.165$). For

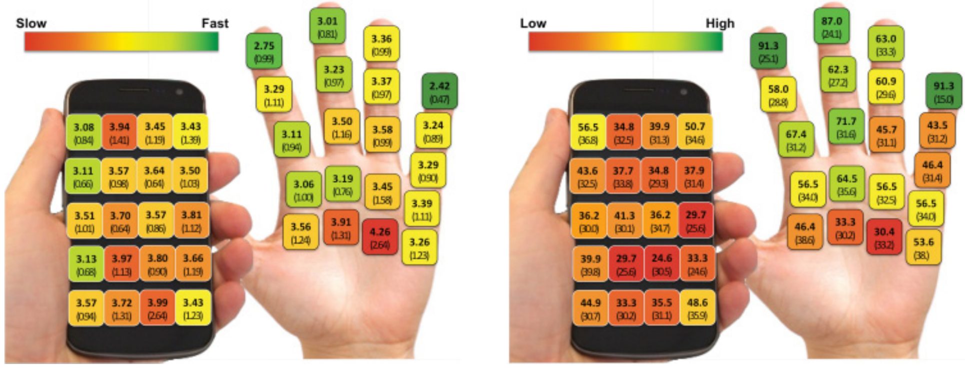


Fig. 5. Heat maps for average selection time (left, sec.), and first-contact point accuracy (right, %) per target in the pointing task, averaged across participants (with *SD* in parentheses) ($N = 23$). The fingertips resulted in particularly strong performance results.

rows, the fingertips and the top row on the palm (fourth row overall) offered a speed advantage. Pairwise comparisons showed that participants were significantly faster pointing to the fingertips than to the second, third, and fifth rows, and were faster with the fourth row than the fifth row. For columns, the third column was slower than the rightmost column. Similarly, rows and columns both significantly impacted first-contact success rate (*Rows*: $F_{4,88} = 21.13$, $p < 0.001$, $\eta^2 = 0.490$; *Columns*: $F_{3,66} = 4.037$, $p = 0.011$, $\eta^2 = 0.155$). Similar to the selection-time results, pairwise comparisons showed that the fingertips (top row) were more accurate than all other rows, and the fifth row was less accurate than all other rows. For columns, the third column was less accurate than the first two.

For the phone, different rows did not significantly impact speed, but columns did ($F_{3,66} = 5.431$, $p = 0.002$, $\eta^2 = 0.198$). Posthoc pairwise comparisons showed that the outer edges were the fastest—the leftmost column was significantly faster than the middle two columns. No significant effects were found for first-contact success rate.

The more marked performance differences across locations for the hand could be due at least partly to variation in target size across location, a decision that we had purposely made to ensure that the hand condition was realistic and made use of physical landmarks. Hands also varied from one participant to the next in size and shape. To investigate the relationship between target size on the hand and the measures of selection time and first-contact success rate, we computed Pearson's correlation coefficients for each measure. Although statistically significant due to the large sample size (23 participants $\times$ 20 targets), the correlation between target size and speed was negligible in magnitude ($r = -0.026$, $n = 460$, $p < 0.001$). However, a moderate positive correlation was found between target size and first-contact success rate ($r = 0.424$, $n = 460$, $p < 0.001$). While our study design does not allow us to isolate the impact of target size on the performance measures, these results suggest that size may play some role.

4.1.4. Subjective Feedback. In terms of overall preference, 9 out of 12 sighted participants preferred the hand to the phone, while blind participants were more evenly split, with 6 votes for hand and 5 for phone. This trend could be due to blind participants' familiarity with nonvisual interaction with a touchscreen phone, since all of them had a smartphone. For example, one blind participant, B7, said: "I'm more familiar with the phone, I've been an iPhone user for almost two years." Participants also rated the hand and the phone in terms of subjective ease, accuracy, and speed using 5-point scales (5 is best); see Figure 6. For each measure, we ran a 2×2 repeated-measures ANOVA with

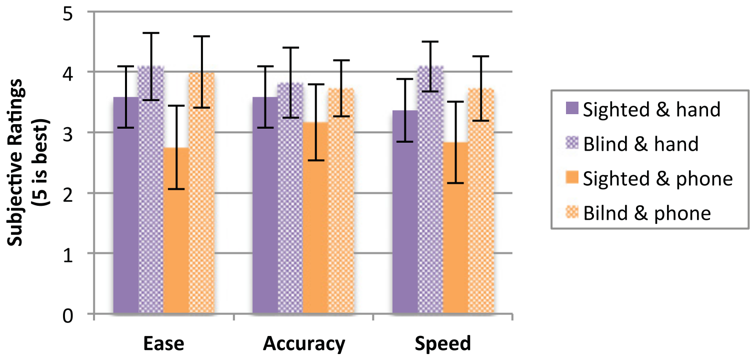


Fig. 6. Average subjective ratings for ease, accuracy, and speed for the pointing task ($N_{sighted} = 12$; $N_{blind} = 11$). Error bars indicate 95% confidence intervals.

ART. Blind participants reported generally higher ease and speed ratings compared to sighted participants, perhaps due to their comfort level with nonvisual interaction. Significant main effects of *Group* on ease ($F_{1,21} = 8.57$, $p = 0.008$, $\eta^2 = 0.29$) and speed ($F_{1,21} = 5.80$, $p = 0.025$, $\eta^2 = 0.22$) were observed. No other main or interaction effects were significant.

4.1.5. Summary. The speed results support H1 and confirm the conclusion of Gustafson et al. [2013] that the hand allows faster target pointing than the phone for nonvisual use. Furthermore, we extended this result to show that it applies to blind users who already have experience with nonvisual interaction. We also found support for H2, which provides new insight on first-touch location accuracy, showing that it is higher on the hand than the phone (likely due to proprioceptive differences). No support was found for H3 that the performance benefit is greater for the blind group than the sighted group. Per-target analysis revealed that target location impacted pointing performance, particularly on the hand (e.g., fingertips vs. palm). Finally, though not conclusive, sighted users may have a stronger preference than blind users for the hand compared to the phone for nonvisual pointing input.

4.2. Shape-Drawing Task

To explore the feasibility of supporting eyes-free gestural input, we computed gesture recognition rates based on the drawn shape gestures. We also assessed geometry-based accuracy and consistency measures of the gestures.

4.2.1. Recognition Rate. To assess the practicality of shape gestures on the hand versus phone, we applied the $N multistroke recognizer, which is size, rotation, and location invariant, and does not require many training examples [Anthony and Wobbrock 2010]. Recognition rates were calculated twice: (1) 5-fold cross-validation within a single participant by training on four gesture examples and testing on the remaining one, and (2) across participants in the same user group by testing on each participant after training on the rest. The results are summarized in Figure 7.

For the recognition rates, we ran a 2×2×2 (*Group*, *Interface*, *Training Set*). Overall, the hand resulted in significantly higher recognition rates than the phone ($F_{1,21} = 13.61$, $p = 0.001$, $\eta^2 = 0.39$), and sighted participants' gestures were more accurately recognized than blind participants' gestures ($F_{1,21} = 7.09$, $p = 0.015$, $\eta^2 = 0.25$). As one would expect, for *Training Set*, rates were significantly higher if training was personalized within each participant as compared to the user group as a whole ($F_{1,21} = 150.00$, $p < 0.001$, $\eta^2 = 0.88$). No other main or interaction effects were significant.

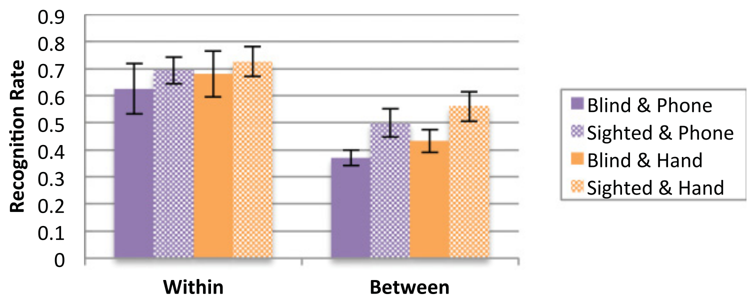


Fig. 7. Average recognition rate for the shape-drawing task for both within and between participants ($N_{sighted} = 12$; $N_{blind} = 11$). Error bars indicate 95% confidence intervals.

Table I. Accuracy and Consistency Measures for Task 2

		Blind		Sighted	
		Phone: *M* (*SD*)	Hand: *M* (*SD*)	Phone: *M* (*SD*)	Hand: *M* (*SD*)
Accuracy	Aspect ratio[a]	0.36 (0.22)	0.39 (0.33)	0.28 (0.11)	0.30 (0.08)
	Closure[a] (px)	30.17 (15.59)	34.84 (18.60)	25.95 (12.75)	28.96 (14.60)
	Angle[b] (°)	7.77 (3.37)	11.29 (5.66)	8.11 (4.90)	10.81 (5.57)
	Length ratio[b]	0.20 (0.11)	0.25 (0.17)	0.14 (0.08)	0.16 (0.04)
Consistency	Aspect ratio[a]	0.17 (0.07)	0.14 (0.05)	0.24 (0.20)	0.27 (0.25)
	Closure[a] (px)	11.26 (12.14)	7.02 (8.12)	6.58 (3.92)	8.43 (6.74)
	Angle[b] (°)	4.59 (3.49)	4.18 (3.28)	2.81 (2.01)	6.70 (6.43)
	Length ratio[b]	0.10 (0.07)	0.12 (0.13)	0.07 (0.06)	0.08 (0.04)
	Size[a,b] (px^2)	3751 (7838)	3407 (5536)	1000 (1178)	2157 (1216)

[a]Used for circle, triangle, and square.
[b]Used for plus and equal signs.
Note: Accuracy is computed as the *absolute difference* between the raw measure and an ideal shape, and consistency is the *standard deviation* across each participant's five test trials per shape. Smaller numbers are better ($N_{sighted} = 12$; $N_{blind} = 11$).

4.2.2. Geometry-Based Accuracy and Consistency Measures. While the recognition rate analysis indirectly requires that gestures be accurate and consistent, we also explicitly examined geometry-based accuracy and consistency of the shapes collected. Accuracy was defined as the *absolute difference* between the drawn shape and an ideal shape (e.g., a perfect square). For the circle, equilateral triangle, and square, we calculated this difference for *aspect ratio*, the ratio of width to height (ideally 1), and *closure* [Kane et al. 2011], the Euclidian distance between the start and end points of the gesture (ideally 0). For the plus and equal signs, we calculated the *angle* between the two strokes (ideally 90° for + and 0° for =) and the *length ratio* of the shortest stroke to the longest stroke (ideally 1, which represents equal length). Consistency for each of these measures was defined as the standard deviation across the five test trials that each participant drew per shape. Finally, we looked at the area of the minimum bounding box and consistency of that size.

The results are inconclusive regarding these accuracy and consistency measures. Examining the raw means for accuracy measures shown in Table I, all measures are closer to the ideal shape on the phone than on the hand if compared within the blind group or the sighted group. This trend is contrary to H4 and H6, although 2×2 (*Group* × *Interface*) repeated-measures ANOVAs with ART for each measure revealed no significant main or interaction effects. For the consistency measures, the same analyses revealed a few significant effects, although no clear picture emerged. The significant effects were: main effect of *Interface* on consistency of size ($F_{1,21} = 9.89$,

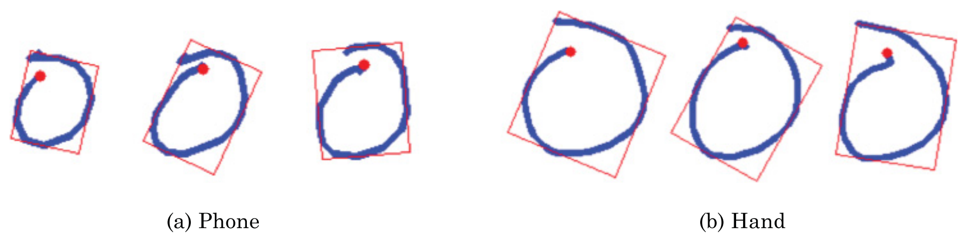


Fig. 8. Examples of circles on the phone and on the hand by blind participant B5. The red rectangles show the minimum bounding box for each shape and the dots indicate the starting point of each stroke. The sizes of the shapes are larger on the hand.

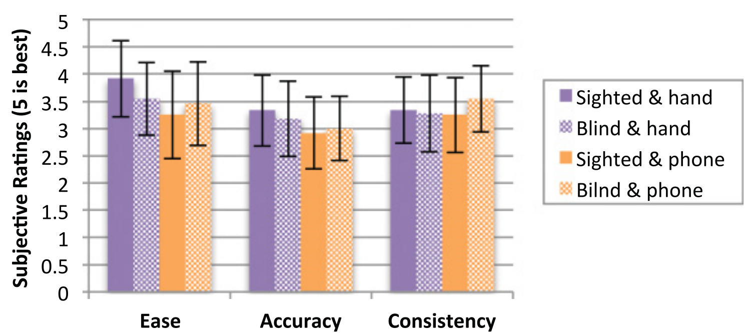


Fig. 9. Subjective ratings for ease, accuracy, and consistency for shape-drawing task ($N_{sighted} = 12$; $N_{blind} = 11$). Error bars indicate 95% confidence intervals.

$p = 0.005$, $\eta^2 = 0.32$), interaction effect between *Group* and *Interface* on consistency of size ($F_{1,21} = 5.85$, $p = 0.025$, $\eta^2 = 0.22$), and interaction between *Group* and *Interface* on shape closure ($F_{1,21} = 5.56$, $p = 0.028$, $\eta^2 = 0.21$). It is unclear whether the results would change with a larger sample size.

Finally, participants created bigger gestures on their hand than on the phone (e.g., Figure 8). A 2×2 repeated-measures ANOVA with ART revealed a significant main effect of *Interface* on size ($F_{1,21} = 19.15$, $p < 0.001$, $\eta^2 = 0.48$). No other main or interaction effects were significant.

4.2.3. Subjective Feedback. In terms of overall preference for shape gestures, 7 out of 12 sighted participants preferred the hand to the phone, compared with only 4 out of 11 blind participants. These trends are similar to the first task. Participants who preferred the hand valued its tactile feedback. For example, B7 said: “You can feel where you started and where you ended. You may have more control to draw the shape.” In contrast, the flatness of the phone was the most popular reason for favoring it over the hand, mentioned by 4 sighted and 7 blind participants. For example B2 said: “phone is sort of drawing on a paper, because it’s flat. [Because of the] valleys and peaks, I never know if the square on the hand was really a square.”

Participants also rated the two interfaces on ease, accuracy, and consistency using 5-point scales (5 is best), as shown in Figure 9. For each rating, we ran a 2×2 repeated-measures ANOVA with ART but no main or interaction effects were significant.

4.2.4. Summary. While the geometric analyses were inconclusive (no support for H4 through H6), the gesture recognition rates were significantly higher on the hand than on the phone. These recognition-rate findings thus provide secondary support that gestures drawn on the hand are more accurate and consistent than on the phone (H4 and H5). Subjective preference trends were similar to the pointing task, with more sighted than blind participants preferring the hand.

5. DISCUSSION

Our findings both confirm the study by Gustafson et al. [2013] of nonvisual pointing performance by sighted users on the hand versus a phone, and broaden those findings to include gestural input. More important, we extend these findings to blind users, showing that on-body input offers an alternative to the touchscreen phone as a means of accessible mobile interaction. Our results also show that the location of the first touch down on the hand is more likely to be within the intended target's bounds than it is on the phone. This finding suggests that proprioception even before the hands touch is partly responsible for the performance advantage of the hand.

For the shape-drawing task, the hand resulted in higher gesture recognition rates than the phone, indirectly indicating that shapes drawn on the hand were more consistent than on the phone. Blind users had lower recognition rates than sighted users, which may be due to differences in spatial cognition ability (e.g., Thinus-Blanc and Gaunet [1997] and Pasqualotto and Proulx [2012]) or even simply due to lower familiarity with the shapes that were used [Jackson 2002; Amirabdollahian et al. 2002]. The comparison of blind versus sighted shape gestures is also consistent with the study by Kane et al. [2011] on touchscreens, although their sighted participants received visual feedback. It is important to note, however, that overall recognition rates were relatively low and would need to be improved upon for practical use (e.g., through more training examples or a different recognizer).

Because blind individuals have higher tactile acuity than sighted individuals [Goldreich and Kanics 2003; Van Boven et al. 2000; Stevens et al. 1996; Legge et al. 2008], we had expected that the performance benefits of the hand would be particularly noticeable for the blind participant group. No support was found for this hypothesis in either task. This null result could be because, in practical terms, the difference between sighted and blind individuals' tactile acuity is simply too small to matter. The tactile grating detection and 2-point gap discrimination studies [Goldreich and Kanics 2003; Stevens et al. 1996], for example, showed differences of only 0.33mm and 0.37mm, respectively. Proprioception may also be playing a larger role than tactile acuity. Another somewhat contrary trend, though not statistically significant, suggests that sighted participants were more likely than blind participants to prefer the hand to the phone. This could be due to blind participants having more experience and familiarity with nonvisual interaction on touchscreen devices, since all blind participants owned a smartphone. Further work is needed, however, to confirm whether these preferences would remain unchanged with more realistic or longer-term use of on-body interaction.

Despite perhaps not being *more* beneficial for blind users than sighted users, our findings suggest that pointing to targets on the hand is a viable and efficient input technique for accessible mobile computing. In designing future on-hand interfaces, the fingertips, which are known for high acuity (e.g., Stevens and Choo [1996] and Craig and Lyle [2001]), would be good locations for frequently needed shortcut commands as participants were faster and more likely to touch down immediately within a target's bounds in these regions than in other areas. In addition, pointing performance differs depending on which finger the target is located (e.g., index or ring finger), and should be taken into account when placing targets. As with the advantage of the fingertips, these differences across fingers may be at least partly due to known acuity differences (e.g., Vega-Bermudez and Johnson [2001] and Legge et al. [2008]). Last, while most blind participants preferred drawing shape gestures on the phone, the hand may offer better gesture recognition accuracy. As such, future work should explore the potential for accessible shape-based gestural shortcuts.

In terms of practical implications, 0.4s of performance gain per target for on-hand pointing should offer a perceptible improvement over the phone, especially for tasks that include successive pointing (e.g., unlocking a passcode, dialing a 10-digit phone number). Fast access to functionality may also be offered with gestural shortcuts [Ouyang and Li 2012; Li 2010], and the hand shows promise in terms of improving recognition rates for such nonvisual gestures. Finally, although our lab-based study setup did not reflect a real-world sensing setup, emerging wearable technologies may allow for on-body input to move beyond the lab (e.g., Ogata et al. [2013], Weigel et al. [2015], and Laput et al. [2014]). Still, building unobtrusive, lightweight, and robust sensing is a nontrivial challenge for future work.

6. LIMITATIONS AND FUTURE WORK

When designing the target layout for the pointing task, our focus was to maximize the role of natural landmarks of the hand. We thus adapted the target layout to each participant's hand to provide a more realistic, ecologically valid assessment of on-hand input performance than could be achieved by replicating the rectangular shape of a phone on the hand. As a result, and as must have also been the case in Gustafson et al. [2013], the average target size on the hand was bigger than the phone: 6.31cm^2 ($SD = 2.19$) on average compared to 4.03cm^2. Although we attempted to mitigate this difference by using a relatively large phone, further work is needed to clearly separate the impacts of size and other layout factors from tactile and proprioceptive feedback.

Another limitation is that we may have found different results had we provided more training for each task, considering that on-hand input was new to participants. It may also be useful to examine potential differences between *early-blind* (who became blind at birth or a young age) and *late-blind* individuals, to control visual experience in assessing performance on spatial tasks [Gaunet et al. 2006; Lehtinen-Railo and Juurmaa 1994]. Tactile acuity is also affected by factors such as age [Goldreich and Kanics 2003], thus a matched-pair design that takes age into account could offer more experimental power in future work.

To reduce input variability and facilitate accurate sensing, we stabilized the hand and phone during data collection. A more realistic scenario would allow both hands to move freely and could uncover additional issues, such as the need to keep the hands within the camera's field of view. As future work, we plan to investigate other more wearable sensing techniques that show promise, such as infrared reflective [Ogata et al. 2013] or flexible skin overlay sensors [Weigel et al. 2015].

7. CONCLUSION

We confirmed that a user's own hand allows for faster nonvisual pointing than a touchscreen phone, and extended this finding to blind users. Furthermore, the hand offers better first-touch location accuracy and results in higher shape gesture recognition rates than the phone. While we had expected that the higher tactile acuity of blind users would provide an even greater benefit for on-hand input compared to sighted users, it could be that, practically speaking, these differences between the two user groups are too small to matter. As future work, we plan to revisit prior studies of on-hand interaction and apply their findings to real-world situations with improved sensing technology.

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