Nailz: Sensing Hand Input with Touch Sensitive Nails

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ABSTRACT
Touches between the fingers of an unencumbered hand represent a ready-to-use, eyes-free and expressive input space suitable for interacting with wearable devices such as smart glasses or watches. While prior work has focused on touches to the inner surface of the hand, touches to the nails, a practical site for mounting sensing hardware, have been comparatively overlooked. We extend prior implementations of single touch sensing nails to a full set of five and explore their potential for wearable input. We present design ideas and an input space of 144 touches (taps, flicks and swipes) derived from an ideation workshop. We complement this with data from two studies characterizing the subjective comfort and objective characteristics (task time, accuracy) of each touch. We conclude by synthesizing this material into a set of 29 viable nail touches, assessing their performance in a final study and illustrating how they could be used by presenting, and qualitatively evaluating, two example applications.

Author Keywords
Finger input; touch sensing fingernail; eyes-free; wearable

CCS Concepts
•**Human-centered computing** → **Touch screens;** *Pointing devices;*

INTRODUCTION
The increasing power and sophistication of wearable devices, such as smartwatches and smart glasses, is enabling new applications in areas such as health care [34], education/tutoring [15], maintenance [1], and transportation [26]. However, the diminutive size and on-body mounting of wearables mean they have very limited surfaces for traditional input techniques such as controlling a cursor or touching a screen [42]. Existing alternative approaches based on voice-commands or free-hand gestures compromise social acceptability [17] and may lead to fatigue [16] while hand-held controllers are awkward to carry and preclude device use during hands-busy tasks [32]. These problems mean that although wearables are now powerful computational tools, many input tasks remain slow, cumbersome and inexpressive.

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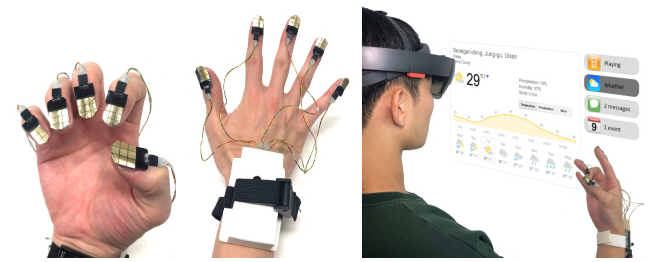


Figure 1. Nailz: five touch sensitive fingernails for wearable input. Left shows two close-ups of nail sensors on a hand, while right shows a user wearing the system during study tasks.

Worn devices that sense finger input [31] can offer a solution to these problems. It has been demonstrated that specific subsets of finger actions such as making poses [5], gestures [22] or touches [18] can be captured with systems worn on the wrist [21], finger [3], nail [20] or shoulder [33]. The input actions enabled by these systems are generally easily accessible [44], subtle or inconspicuous (e.g., via micro-gestures [4]) and expressive enough to support interaction via pointing, cursor control [20] and/or gestures [12].

While this work is diverse, limited attention has been devoted to input that takes place on the nails. We argue this is an omission as the nails are a highly appropriate site for input [9] – they are easily and comfortably accessible [40] and already commonly used as a site for body extension (e.g., with cosmetic artificial nails) [37]. Prior work reflecting these motivations has introduced touch-sensing thumbnails [20, 23] capable of capturing a small set of five gestures [20] or controlling a cursor [23]. We extend this work by studying how a full set of five touch sensing nails can be used to capture input relating to articulation of the hand as a whole. Due to the inherent complexity of the hand, we note the design space enabled by touches to all the nails will differ substantially from that discussed in prior work dealing with the touches to inner surfaces of the fingers [18, 39]. Furthermore, this space is inevitably larger than that possible on a single thumbnail [20], not least because it incorporates a novel set of designs based on the relationships between, or arrangement of, the different nails.

Building on these observations, the overarching contribution of this paper is the methodical exploration of the design space of single-handed multi-nail interaction. This took place in several stages. We first conducted a design workshop to generate interface, interaction and application concepts. We then assessed the viability of a large set of 144 of the basic input actions proposed in two user studies. In the first (N=16), we assessed the subjective comfort of each action. In the second (N=16), based on a fully functional prototype system re-implementing designs from prior nail systems [20, 23], we captured task time and the distinguishability of each input action using a simple threshold based classifier. We close by consolidating these outcomes into a final set of 29 viable actions, a revised personalized classifier (which achieves a mean accuracy of 94.3%) and a final evaluation (N=10) of both objective performance with the input actions and subjective opinions of demonstrators showcasing the system. We note that the data generated in each of these studies is novel and represents a valuable baseline for future work on single-handed nail and finger touch input techniques.

In sum, this work contributes to the design of new wearable input techniques by: 1) proposing the unexplored design space of a set of five touch sensitive nails and; 2) by documenting and instantiating the input actions and interface designs suitable for this system based on 3) a thorough and novel characterization of the comfort, time and accuracy of, and subjective response to, single-handed multi-nail touch input.

RELATED WORK

Wearable input systems based on touches between the fingers of the hand have been widely studied due to the fact they promise subtle socially acceptable input [17] that can be conveniently accessed [44] and operated eyes-free [18] while still retaining a large and expressive input space [33]. This is fundamentally due to the anatomical complexity of the hand: it is reported to have 27 separate Degrees of Freedom (DoFs) [10]. The thumb is especially adroit, accounting for five DoFs and positioned to access the rest of the hand with relative ease. Prior research has leveraged these properties to explore what both Whitmire *et al.* [39] and Soliman *et al.* [33] term “thumb-to-finger” input. This refers to systems in which the thumb taps [14], force-taps [24], swipes [35] or gestures over regions such as the side of the index finger [36] or the inner surfaces of all four fingers [18, 45] in order to support tasks such as providing a secondary input channel during touchscreen use [36], issuing commands, changing settings or typing [39]. A common approach is to treat each finger phalanx and/or joint as a different input region by, for example, placing a different command on each one [18]. Alternatively, with systems capable of sensing continuous input, a cursor can be controlled [31] or gestures such as letters or shapes can be drawn [45]. Finally, systems capable of detecting pose can capture full hand gestures, such as those involved in sign language [46].

There is also some data on human performance during thumb-to-finger input. For example, Huang *et al.* [18] capture comfort ratings for this type of input and show that while touches of the thumb to the inner surfaces of the index and middle finger are relatively easy to perform, touches to the ring and little fingers are more taxing. They also report selection accuracy for different numbers of targets distributed along the length of the fingers. These data are valuable baselines for our work.

Input on Finger Nails

The nail is a convenient site for finger augmentation: it is rigid and has a cosmetic tradition of worn accessories that minimally interfere with use of the hands. However, in comparison to the wealth of literature on the fingers, it has attracted relatively little research attention. It has been previously proposed as a convenient site to mount tracking hardware for objects [37] or finger gestures that are independent [35] or that occur with respect to a sensor mounted on another finger [6] or an external device [7]. Typically such systems track in air movements of the thumb, the most articulate digit. Most relevant to the current paper is work that has placed touch sensors on nails – both Kao *et al.* [20] and Lee *et al.* [23] describe thumbnails covered with grids of capacitive electrodes capable of supporting input such as simple taps and swipes and controlling a cursor via a touch of another finger or by touching the thumbnail against the body. This paper extends this prior work by considering a full set of five nails, rather than a single thumbnail, by exploring inputs relating to full articulation of the hand (rather than cursor control) and by providing a thorough description of performance covering comfort, time and accuracy.

IDEATION WORKSHOP

To better understand the input and interaction space enabled by a set of touch sensitive nails we ran a design and ideation workshop with a group of five graduate students (three female, two male, mean age 27) engaged in either Industrial Design (four) or Human-Computer Interaction (one) programs. The goal was to generate diverse interaction ideas we could use to develop a set of concrete input actions. The workshop spanned three hours as follows:

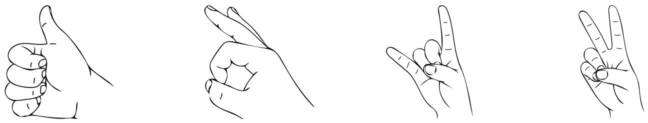
Ice-breaking/Priming (30 mins): Introductions and scene setting to establish the topic and input/use context – the workshop focused on using the nails as input for smart glasses. Accordingly, participants watched promotional videos from a set of existing smart glass products (Epson BT300, Google Glass, Microsoft Hololens, Vuzix Blade).

Brainstorming – Tasks (30 mins): Participants generated a set of useful services or tasks that could be performed by smart glasses, such as those relating to messaging, navigation or media applications. This took the form of a brainstorming session in which tasks were noted down on post-its, announced to the room and placed on the wall.

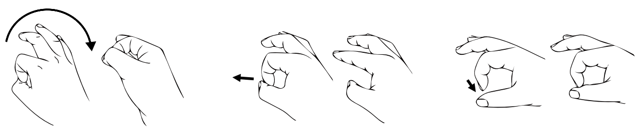
Brainstorming – Input (30 mins): Participants generated input actions, widgets and systems that a smart glass user could operate in order to access services and perform tasks on a device. This session followed the brainstorming format; ideas were kept distinct by using differently colored post-its.

Nail Input – Priming (30 mins): To provide context for the final task, we had each participant don a set of fake nails and showed them videos from a set of research papers [5, 11, 20, 35] and products (Nod [28] and Talon, www.talonring.com) dealing with finger augmentation and thumb-to-finger input. In addition to sensing touches, participants were informed the nail system could sense overall hand orientation and rotation.

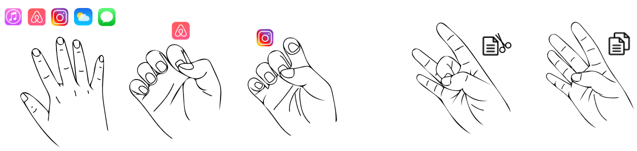
Brainstorming – Interaction Designs (30 mins): In the final brainstorming session, participants devised interaction concepts based on touching the nails they were wearing and using the input actions, widgets or techniques they had proposed to achieve the original set of tasks or services.



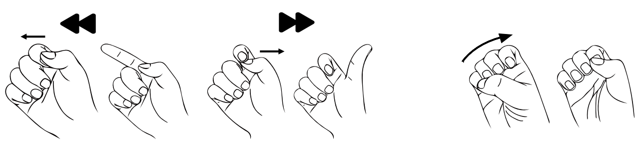
Symbolic/Pose: Hand poses proposed for like (nail tips touching hand), confirm (thumb touching index nail plate), play music and take photo.



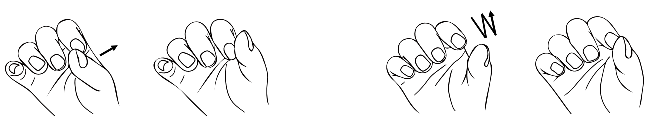
Movement metaphor: Touching a nail and twisting to control a setting, flicking the index to delete content and tapping a nail tip to select.



Spatial: Assigning apps or commands to specific nails.



Directional: Directional flicks or swipes for scrolling or navigation.



Primed/Abstract: Swipe nails to delete content, double tap tips to select.

Figure 2. Example designs proposed in the ideation workshop.

The session closed with debriefing. It generated 80 design concepts. These were diverse, but also subject to clear trends. Key variations occurred in the *nails* used, the touch *actions* employed and, to a lesser extent, the nail *regions* touched. In terms of the nails used, half the inputs relied on a single nail (mainly thumb and index) while another quarter used multiple nails either simultaneously (e.g. a two-finger tap), continuously (e.g. a swipe over two fingers), or as a discrete set (e.g., each nail as a short-cut button, but proposed as a group). In the discrete case, nail usage was evenly spread across all nails. In terms of actions, more than half the proposals used taps, while flicks and swipes were also common. Just three proposals featured other actions (circular swipes or rubbing). Finally, nail region was often not specified. When it cropped up, the tip was most frequently mentioned, and the edge or side were also used. The lack of specificity here may be due to the perception of a fingernail as a single location or "button".

Beyond this functional classification, we summarized the ideas through an affinity process: a single researcher clustered the full set of ideas based on the final descriptions, notes from the workshop and the summary statistics, ultimately deriving the following five themes (also illustrated in Figure 2).

Symbolic/Pose (21.25%): This collected ideas in which hand poses triggered applications or actions: a thumb-up (sustained contact by all four fingernails with the palm) for a social media like or favorite; an OK gesture of thumb covering index nail to signify approval; a "rock-on" hand gesture (middle and ring nails constrained by thumb) to open a music app; a "V" sign (ring and little covered by thumb) to take a photo.

Movement Metaphor (18.75%): Finger and hand motions were applied metaphorically. For example, flicking the index finger out from the thumb was proposed for sending a message, much as the same action might push a physical object away. Similarly tapping the finger was associated with real world button presses for activities such as taking a photo. Associating the same pose with a rotational hand movement was proposed for changing a setting – like gripping and turning a dial.

Spatial (17.5%): The fingers were also divided up spatially, so that different nails were associated with different functions such as launching a specific app, a concept that has appeared in prior work [18]. Additionally, these were qualified by the nail area or nail action being performed. For example, while tapping on the tip of a nail could open an app, holding the whole nail could copy content from it and flicking the finger away could paste into it.

Directional (20%): Proposals were also based on directional mappings. For example, flicking either the index (from the thumb) or the thumb (from the index) with the hand facing the user, actions which respectively involve predominantly leftward and rightward motion, were proposed to signify previous/next on an e-book app or media player. Similarly, moving the thumb over all fingernails when they were aligned vertically was proposed for scrolling.

Primed/Abstract (22.5%): Suggestions were also derived from current input technologies. Double tapping nail tips was proposed to select content while swiping across nail tips deleted it, in much the same way that secondary selection mechanisms and swipes are currently used on mobile devices. The use of nails for these basic interactions suggests that users may be able to generalize their existing knowledge about how to operate smart devices to a nail-based input system.

These design themes were frequently combined. For example, the *movement* of rotating a dial was merged with *spatial* mappings such that touching different fingers and rotating could control the volume, brightness, or play back position of media content with different nails. Similarly, the click *movement metaphor* for taking a photo was combined with *spatial* use of the different nails: the index for photo and middle for video.

INITIAL NAIL INPUT SET

We designed an initial set of nail inputs based on both prior work and key variations observed in the workshop: the different *nail(s)* used, *regions* touched and touch *actions*. To create a coherent and complete range of possibilities, we defined each dimension as follows:

Nail(s): Due to the diverse uses of both single and multiple fingers in the workshop, we included all five individual nails (*Single*) plus six nail combinations (*Mult*): all three adjacent finger pairs (e.g. index plus middle but not index plus ring), both contiguous finger triples and the quad of all four fingers

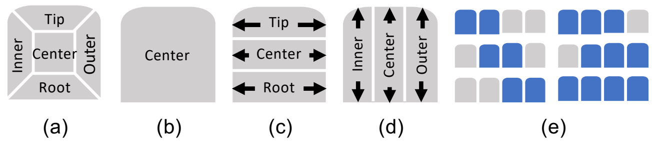


Figure 3. Nail Regions used in Single Tap (a), Flick (b) and bi-directional HSwipe (c) and VSwipe (d) input actions. (e) shows the six contiguous multiple (Mult) nail combinations highlighted in blue.

(see Figure 3 (e)). The thumbnail was not used in multiple nail inputs – it was inevitably the touching digit.

Nail Region: Although regions varied relatively infrequently in the workshop, touching different nail regions is the dominant way of interacting in prior work [20, 23]. As such, we opted to include five nail touch regions: *Tip*, the distal edge of the nail; *Center*, the plate of the nail; *Root*, the proximal edge of the nail over the lunula; *Inner* side, the lateral edge of the nail facing the first interdigital space (between thumb and index); and the *Outer* side, the opposite lateral edge of the nail that faces away from this space – see Figure 3 (a).

Action: Based on the actions proposed in the workshop, we included *Taps* of the nail, *Flicks* of the finger and swipes over the nail(s) either horizontally (*HSwipe*) or vertically (*VSwipe*) in both directions.

To instantiate these dimensions in a set of concrete input actions, we first differentiated between touches to single and multiple nails. For each action, we then defined the nails and regions on which it could be used. We excluded combinations if they were impossible (e.g., HSwipe on the Inner side of the nail), judged to be extremely challenging (e.g. VSwipe over multiple nails) or hard for a user to meaningfully distinguish (e.g., Flick from different nail regions). For single nail touches, we ultimately included all five nails for all actions. Taps could take place on all five nail regions (25 different inputs in total), Flicks on only the Center region (5 inputs), HSwipes on Tip, Center and Root regions in both left/right directions (30 inputs) and VSwipes on Inner, Center and Outer regions in both up/down directions (30 inputs). Single inputs are illustrated in Figure 3 (a) through (d). For multiple nail inputs, we include all six nail combinations (Figure 3 (e)) for Tap, Flick and HSwipe. *Mult-Taps* could take place on Tip and Center regions (12 inputs); *Mult-Flicks* on center regions (6 inputs) and *Mult-HSwipes* on Tip, Center and Root regions in left/right directions (36 actions). This process led to a comprehensive and intentionally inclusive set of 144 input actions that included the vast majority of single-handed input actions proposed in the workshop. Only seven input actions, involving either other body parts (e.g., the other hand or the face) or infrequently proposed motions (e.g., rubbing the nail), were excluded. The rest of the work in this paper sought to refine this set to a more practical and functional subset.

COMFORT STUDY

We first assessed the 144 input actions by capturing their perceived comfort, a metric previously used to make recommendations about viable finger input actions for use in interactive systems [25, 13]. In line with closely related prior work [18], the study was conducted with participants' unencumbered hands in order to capture comfort ratings in a natural situation, unbiased by the specifics of any prototype sensing system.

Figure 4. Example study instructions showing different actions and regions for single (top) and multiple (bottom) nails.

Participants and Method

Sixteen participants were recruited from the local student body via social media. All were right-handed, nine were female and seven male, and they had a mean age of 22.9 (SD 3.32). Using a one to five scale, they indicated they were fluent users of computers (4.6) and smartphones (4.8) but had little experience with wearables such as smartglasses (2.1). The experiment lasted approximately 30 minutes and the participants were compensated the local equivalent of five USD.

The study had participants try out and then rate the comfort of hand actions shown to them on a laptop screen. They were asked to use their right hands and find the most comfortable way to make each touch before assigning a rating – there was no prescribed method for making each touch. Each hand action was presented using both an image and textual description – see Figure 4 for examples. Ratings were captured using a five-point Likert-scale (1: very uncomfortable, 5: very comfortable, as in [18]). Each item in the set of hand actions appeared twice, once in each of two randomly ordered blocks composed of all actions. This arrangement led to logging 288 ratings per participant or 4608 ratings in total.

Results

We first performed a reliability check by calculating the mean per-user Pearson correlation between the two sets of ratings each generated [13]. This was 0.62 (SD: 0.12), indicating a moderate to strong relationship between the ratings assigned to repeated actions. This suggests participants were able to assess and report their comfort reliably and consistently and increases confidence that the data captured is valid. The overall mean rating reported in the study was 3.41/5.0, a figure prior work has suggested indicates high comfort [18]. Figures 5 and 6 present a summary of the comfort ratings for each nail, action and region and highlight that ratings varied considerably. Following prior work [25], we explored differences in these data statistically. We used the processes outlined by Wobbrock *et al.* [41] and applied the Aligned Rank Transform (ART) followed by factorial repeated measures ANOVA and pairwise *post-hoc* contrasts incorporating Bonferroni corrections. We calculated effect size using η_p^2 [8]. As our analysis

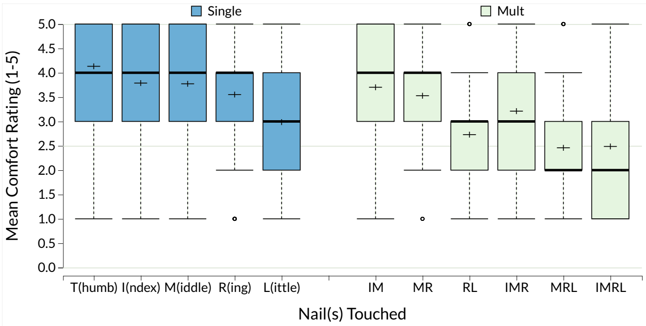


Figure 5. Comfort ratings for nail(s). Boxplots with bars, crosses, boxes, whiskers and dots indicating median, mean, interquartile range, min/max and outliers [27].

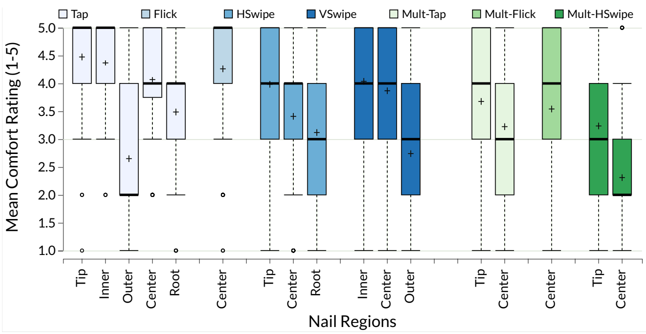


Figure 6. Comfort ratings for each action and region shown as boxplots.

involved eight separate ANOVAs, we applied a conservative alpha threshold of $p < 0.00625$ (0.05/8).

Seven ANOVAs examined all data from a particular input action involving either single or multiple fingers using both nail and nail region (except for flick actions, which did distinguish between regions) as independent variables. Table 1 summarizes the outcomes, omitting non-significant results and those with lower effect sizes ($\eta_p^2 <= 0.1$) for brevity. We note there were no significant interactions with effect sizes over 0.1, which suggests the *post-hoc* contrasts, which can be invalidated by interactions after ART procedures, remain valid. This analysis indicates that, in terms of the nail variable, single nail touches to the thumb were significantly more comfortable than to other fingers and touches to the little finger significantly less comfortable; comfort ratings for the other single fingers were similar and between these extremes. Multi-finger inputs involving the little finger were also rated as significantly less comfortable than those involving two or three of the other fingers. In line with prior work [18], these results indicate users feel reduced comfort when touching the little finger. In terms of the region variable, touches to the outer and root were significantly less comfortable than touches to the inner and tip, with touches to the center falling between these extremes for simple actions such as tap.

The final ANOVA compared data from each of the seven actions involving the Center region. We focused on this subset of data as Center is the only region present in all seven actions – we can therefore compare actions without confounds due to variations in region. Unsurprisingly, as the input actions were

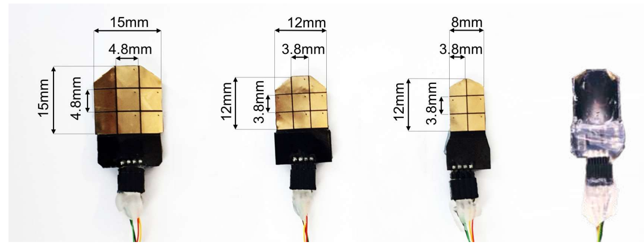


Figure 7. Nail touch sensors, showing electrode size and arrangement: thumb (left); index, middle and ring (center-left) and; little (center-right). The top corners of each board are rounded to mimic the shape of a human nail. The black sections sit behind the nail on the distal finger phalanx. Right image shows underside of thumb sensor mounted on a cosmetic artificial nail with thermoplastically insulated circuitry.

quite varied, it showed significant differences and the largest effect size in the study ($F(6, 90) = 26.5$, $p<0.001$, $\eta_p^2 = 0.64$). *Post-hoc* contrasts indicated single finger and simpler inputs were more comfortable. Specifically, Flicks were rated more comfortable than VSwipes ($p = 0.04$), HSwipes ($p < 0.001$) and all multi-finger actions (all $p < 0.001$). Similarly, Taps and VSwipes were more comfortable than HSwipe, Mult-Tap and Mult-HSwipe trials (all $p < 0.001$ bar VSwipe-HSwipe at $p = 0.03$). Additionally, Taps were more comfortable than Mult-Flick ($p = 0.011$) and Mult-HSwipe trials less comfortable than HSwipes ($p = 0.003$) and Mult-Flicks ($p < 0.001$).

Its worth informally contrasting the comfort data in this study with that reported by Huang [18] for the inner surfaces of the fingers. The most directly analogous data is for single taps on the dominant hand. Huang reports three ratings per finger ranging from 4.8/5 (left index distal phalanx) to 2.1/5 (right little proximal phalanx) and ultimately select seven finger regions due to their high comfort, defined as mean results over 3/5. In the current study, the mean ratings for the optimal three regions (tip, inner, center) on all nails all equal or exceed a mean rating of 4.07/5 – 15 tap locations in total. While this comparison is speculative, we suggest it indicates that simple nail touches may be both more comfortable and expressive than touches to the finger phalanxes. A candidate explanation for this is the relatively small scale of the movements involved in nail touches, compared to the stretching required to touch to areas such as the proximal phalanxes of the fingers. We note that while this comparison does not constitute formal proof, it does serve as supporting evidence that nail touches are a comfortable way to make input with the fingers.

NAIL SENSOR SYSTEM

Encouraged by these results, we developed a prototype that senses touches to all five fingernails. There are two approaches to this task in the literature. NailO [20], implements an impressively miniaturized 4mm thick standalone device featuring sensing, power, and communications all on the thumbnail. However, arguing that a device as thick as 4mm would interfere with use (and their empirical objectives), Lee *et al.* [23] designed a touch sensing nail system composed of a 0.3mm thick flexible PCB on the nail wired to a wrist mounted device with all other functionality. Our objectives align more closely with Lee *et al.*, so we opted for a similar implementation.

Action	*Variable(s)*	*F-Value*	*DOF*	*p*	η_p^2	*Post-hoc contrasts*
Tap	Nail	29.18	4, 360	0.001	0.24	All significant at p<=0.003 except I-M, I-R and M-R (non-significant)
	Region	111.38	4, 360	0.001	0.55	All significant at p<=0.01 except Tip-Inner (non-significant)
Flick	Nail	5.76	4, 60	0.001	0.28	I-L (p=0.03), M-R (p=0.01), M-L (p=0.003)
HSwipe	Nail	47.22	4, 435	0.001	0.3	All significant at p<0.001 except I-M, I-R and M-R (non-significant)
	Region	62.09	2, 435	0.001	0.22	All significant at p<0.001
VSwipe	Nail	30.99	4, 435	0.001	0.22	All significant at p<=0.005 except T-I (p=0.042) and I-M, I-R and M-R (non-significant)
	Region	191.22	2, 435	0.001	0.47	Both Outer-Inner and Outer-Center significant at p<0.001
Mult-Tap	Nail	16.64	5, 165	0.001	0.36	IM-MR not significantly different. IM and MR significantly different to all other combinations (p<=0.002)
	Region	24.8	1, 165	0.001	0.13	N/A
Mult-Flick	Nail	9.33	5, 75	0.001	0.38	IM different (p<=0.01) to all bar MR and IMR (non-sig.); MR sig. different to MRL and RL (p<=0.01)
Mult-HSwipe	Nail	76.46	5, 525	0.001	0.42	All significantly different (at p<=0.005) except IM-MR, IMR-MR, IMRL-MRL and MRL-RL
	Region	96.06	2, 525	0.001	0.27	All significantly different at p<0.001

Table 1. Aligned Rank Transformed ANOVA and post-hoc test results from the comfort study. Data from non-significant tests and tests with low effect sizes ($\eta_p^2 <= 0.1$) are not presented. Nails denoted by initials: T(humb), I(ndex), M(iddle), R(ing) and L(ittle)

We created three different flexible PCBs based on mean nail sizes [19] for the thumb, index/middle/ring and little fingers. Figure 7 shows the sizing, spacing, electrode count and arrangement for each PCB. In each board, capacitive sensing was handled by an MPR121 micro-controller mounted on the bottom of the PCB and designed to be positioned behind the nail on the distal phalanx of the finger. The nail portion of each PCB was glued to a standard cosmetic artificial nail. To improve robustness, the front tips of the PCB were curled around the nail pad, preventing the PCB from detaching during use and ensuring the tip of the nail was touch sensitive. A layer of thermoplastic adhesive was applied to the area containing the micro-controller to create a smooth, comfortable and insulated bottom surface to the whole PCB. Each nail prototype was approximately 1mm thick and flexible enough to fit snugly on a wide range of nail shapes. We firmly adhered it to participants' nails using commercial adhesive gel pads.

All five nails in a set were wired to a single Arduino MKR1010 mounted on the wrist with lightweight AWG32 wires that did not restrict finger motions. The wrist unit also featured an IMU (BNO080) configured to measure raw accelerometer data from wrist/hand motions. All data was captured and transmitted over USB to a host PC at a rate of 100Hz. In terms of the specific data captured, we followed numerous prior implementations [30] and sampled raw and baseline capacitive sensor readings from each electrode to derive a grayscale touch image representing the location and intensity of contact with each nail. On the host PC we processed each image using a typical process: we up-scaled it by a factor of three, used flood fill to segment separate contacts, selected the largest as the dominant touch area and, finally, calculated image moments to summarize this contact as an ellipse with the properties of location, size (major/minor axis length), angle and eccentricity [43]. We also retained all raw touch images to support subsequent analysis.

PERFORMANCE STUDY

This study used the full set of 144 inputs actions and the nail prototype system. All visuals were presented on a PC screen. It sought to complement the comfort study by collecting objective performance data: the time it took to perform each input action; the raw touch sensor data, and; accuracy based on a threshold based input classifier we developed (see below). The goal was to use this data to help select a final set of viable input actions that can be performed rapidly and that are readily distinguishable from each other.

Participants, Procedure and Design

Sixteen undergraduate students participated in the study (mean age of 22.9 (SD 1.65), 9 males, all right-handed). They were fluent computer (4.6/5) and smart-phone (4.8/5 users) and screened for average or larger nail size [19]. The experiment took 40 minutes with each participant compensated with 10 USD. To encourage good performance, an additional 20 USD was awarded to the two top performing participants (determined using a normalized weighting of time and accuracy).

Throughout the study, participants were seated at a desk in front of a laptop computer. The study began with participants donning the nail sensor and wrist processor unit on their dominant hand. The study task and input actions were then explained and participants completed a familiarization session (max two minutes) where they could freely ask questions, try input actions and see a visualization of their inputs on the laptop. After ensuring all actions and study instructions were understood, the main trials began. To start each trial, participants needed to press the space bar on the laptop with their dominant hand – the one wearing the prototype. This ensured all input actions started from a similar "hands-occupied" pose. A depiction of one of the input actions was then shown (see Figure 4) on the laptop and participants were asked to perform this action rapidly and accurately. After an initial nail touch, the instructions changed to show a circular cursor and a grey highlight illustrating the nail regions that they needed to touch to successfully complete the trial. Trials terminated on release of all nails, or timed out after ten seconds. Trial duration was defined as the period between the initial key press and final release of the nails. Breaks between successive nail touches of 200ms were allowed, as pilot testing indicated small gaps in multiple nail touches occurred frequently. After each trial, participants received feedback as to its correctness.

Trials were presented in 144 randomly ordered blocks, each containing four repetitions of the same input action. Trials resulting in touches to incorrect nails (e.g., index when middle was requested) were considered invalid and repeated. Furthermore, the first trial in each block was discarded as practice. We therefore retained a total of 432 trials involving touches to correct fingers per user (6912 in total). The goal of this structure was to screen out clear errors (wrong fingers) and to reduce the impact of examining and interpreting the study instructions on the measured performance: for each input action, we captured data from a standard hand pose (pressing a key) but only immediately after participants had practiced it.

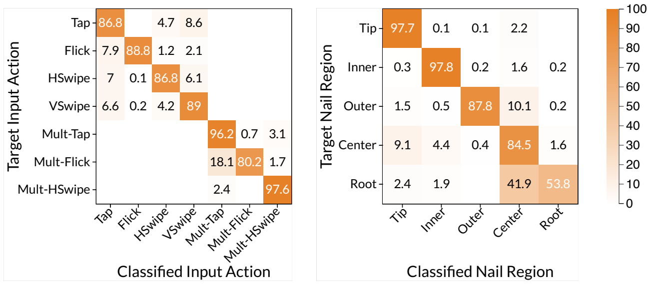


Figure 8. Confusion matrices for classifying input action (left) and nail region (right). Data shown in percentages so rows sum to 100.

Nail Input Recognizer

We created a simple decision tree to classify nail touches from the five sensors to one of the 144 nail inputs. We first omitted data from the first and last 50ms of each touch, effectively ignoring touches less than 100ms in duration. This was because the initial and final stages of a touch could vary strongly in position and velocity as different finger regions came into contact with the sensors [38]. Furthermore, we observed very short touches may represent inadvertent contact with the nails. In cases where the resultant set of touches spanned multiple nails, we tested for invalid sets (e.g., use of the thumb or non-contiguous fingernails such as index and little) and screened the results to create valid combinations by removing the thumb or the temporally shortest touch.

Based on the touched nails, we then determined the touch action. We differentiated flicks from other events by examining IMU data in the 100ms immediately after release of the nails – we used a threshold on the peak summed magnitude of accelerations along x and y axes (i.e., those capturing information from finger/wrist flexion movements and omitting deviation). Touches not classified as flicks were checked for movement on the nail. Specifically we examined the SD of both x and y motion and, in the case of multi-finger taps, the temporal order of touches to different nails (sequential/simultaneous). Sequential touches, or those exceeding a specific movement SD threshold were used as criteria to classify touches as either horizontal or vertical swipes in both directions. Any remaining unclassified touches were considered taps. Finally, we classified nail regions by calculating mean touch position and dividing each nail into five equally sized areas, as illustrated in Figure 3 (a). The two thresholds used in this initial recognizer were established via iterative testing during system development. They were intended to support empirical study, and we do not expect them to be optimal. We considered peak acceleration over 0.41g to signify a Flick and SD of x or y motion during a touch over 0.26 sensor units (1.25mm on the thumb and 0.99mm on the fingers) to signify a swipe.

Results: Distinguishing Nail Inputs

We analyzed classification errors in order to better understand how people make input, and errors, on touch sensing nails.

Nail(s). We recorded 574 inputs (7.67%) to wrong nails, with most (5.93%) occurring in multiple nail touches. These problems fell into three categories: *missing* (omitted nail(s) 4.37%); *excess* (extra nail(s), 1.95%) and; *mistakes* (wrong nail(s), 1.34%). Missing errors predominantly occurred with Mult-HSwipe (84.0%) and/or on touches to three or four fingers (74.5%). Excess touches also occurred, for the most part, in multiple nail touches, particularly those involving ring and little fingers (84.7%).

Actions. The mean classification rate for actions was 90.5%. Flicks were frequently misclassified as Taps and there was also confusion between Tap, HSwipe and VSwipe – see Figure 8 (left) for full details.

Regions. The mean classification rate for regions was 80.8%. Tip and Inner showed good performance, with Center, Root and Outer more substantially overlapped – see Figure 8 (right).

We note numerous factors contributed to these misclassifications including: *cognitive errors* such as misinterpretation of the study instructions; *performative errors* such as slipping onto an adjacent nail during input, or using the nail, rather than the pad, of the touching digit to make contact; *system errors* resulting from non-optimal acceleration/movement thresholds for Flick and Swipe detection and; *fundamental limitations* relating to the small size of the nails – there is simply little space to distinguish between regions or to make swiping motions. In the trials we retained for analysis, the mean accuracy among all 144 input actions was 74.2% (or 68.5% if nail touches to wrong fingers are included). The uneven distribution of these errors provides clear directions for simplification of the gesture set and improvement of the system. These include: minimizing touches to multiple nails; designing swipes to be more readily distinguishable from taps; avoiding challenging nail regions (Root, Outer) and; refining system input thresholds.

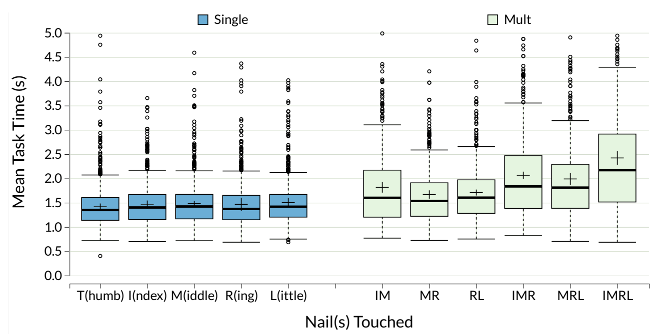


Figure 9. Task completion time for each single and multiple nail input shown as boxplots. Outliers greater than 5 seconds not shown.

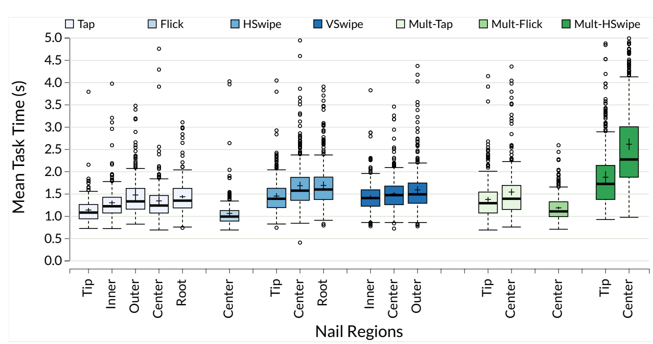


Figure 10. Task completion time for each action and region shown as boxplots. Outliers greater than 5 seconds not shown.

Results: Time Performance

Figures 9 and 10 show task completion time for each nail, region and action. We analyzed this data following procedures from the comfort study: eight repeated measures ANOVAs; Greenhouse-Geisser sphericity corrections applied when indicated; a conservative alpha threshold of $p < 0.00625$; and followed up with Bonferroni corrected *post-hoc* t-tests. Table 2 summarizes the significant results, omitting non-significant results for brevity. Due to the comparatively low effect sizes, we did not conduct follow up testing on the HSwipe interactions.

In general the results in Table 2 show fewer differences than the comfort data. This is in line with prior suggestions that users can tolerate a range of comfort levels before their objective performance will be impacted [13] and highlights the importance of rigorously gathering this type of qualitative data. The Tip nail region offers significantly faster performance than other regions in three of the four of the input actions it features in (Tap, HSwipe and Mult-HSwipe). Similarly, the Inner and Center regions also enable faster performance in a more limited set of circumstances. These results suggest these regions should be prioritized. We also note the effect of the nail variable in Mult-HSwipe reflects the increased distance traveled when more nails are involved in a touch; it is inevitable.

We conducted a final RM-ANOVA on time data from each of the seven actions involving the shared Center region. As with the comfort study, we opted to focus on this region as it is the only one that is used in all seven actions, therefore avoiding potential confounds in the analysis due to the different regions used with each action. This test revealed significant differences ($F(2.78, 41.76) = 47.34$, $p < .001$, $\eta_p^2 = 0.759$). Flicks were performed rapidly, with single Flicks significantly faster than all other actions bar Mult-Flicks ($p < 0.037$), which were in turn faster than all other actions bar single Taps ($p < 0.008$). In contrast, HSwipes were performed slowly, with single HSwipes significantly slower than single VSwipes ($p = 0.04$) and Taps ($p = 0.009$) and Mult-HSwipes inevitably slower than all other actions (all $p < 0.001$) – in contrast to other inputs this action involved a sustained and time consuming movement across two to four fingers. Based on this limited set of differences, we conclude that objective performance with a wide range of different input actions on the nails is viable: while some actions may be particularly readily executed (e.g., Flicks), most basic actions such as Taps and VSwipes can be performed with quite consistent speed.

It is also worth contextualizing the numerical results. Task times in the study capture performance of an input action from a "hands-busy" pose of pressing a key to start the trial: given this constraint, we believe the mean per trial task time for the whole study of 1.64s (including 0.93s of reaction time) represents strong performance and reflects the ready physical availability of the nails as a site for thumb-to-finger [31] and finger-to-thumb touch input. We note there is no directly comparable task performance time data from prior nail based input systems: Kao *et al.* [20] report only classification accuracy while Lee *et al.* [23] report data for touches of the thumbnail to the face, a quite different scenario. Regardless, we note their data for tap inputs ranges from 1.48 seconds for an error-prone "land-on" selection method to 2.52s for a more reliable "lift-off" technique. Our mean data, drawn from a wide range of different input actions, lies towards at the bottom end of this range – touches between the fingers can in general, be performed more rapidly than touches to the face, most likely due to their familiarity. While further data and comparative studies are required, we believe our results are sufficient to support the idea that a wide range of thumb-to-finger and finger-to-thumb nail touches can be performed rapidly by users.

Finally, we also highlight how individual differences, such as in hand/finger size or flexibility, varied the performance of the input actions. For example, although the thumb-to-finger pattern was constant, some participants readily touched their thumb tips to distant targets (e.g., the little fingernail) while others appeared to stretch more, which tended to result in larger touches with the whole thumb pad. Similarly, 19% of participants touched their nails against their palms to achieve multiple nail inputs. These variations suggest that creating a universal nail touch input system that can be reliably used by all people will be challenging; personalization may be needed.

REVISED SYSTEM DESIGN

Based on both study results, we revised the system design in terms of the input actions it supports and the recognizer it uses to classify them. To demonstrate the revised system is both expressive and useful, we created several example applications to showcase its functionality. We describe this work below.

Final Input Set

We refined the input set to 29 actions, 20.1% of the original size. We included actions based on the following criteria and goals. Actions in the set should be:

Comfortable, defined as actions that score over the mean (3.41) comfort score. We discarded most multiple nail inputs and the less comfortable finger regions of Root and Outer.

Distinguishable, via selecting actions that were more reliably recognized and by providing redundancy. This was achieved by assigning different actions to different regions (e.g., Center for Mult-Tap and Tip for Mult-HSwipe)

Diverse, achieved by retaining examples from the majority of input actions and all five of the themes identified in the ideation workshop (see Figure 3).

Consistent, achieved by making exceptions to prior heuristics to create a coherent set. For example, including a set of input actions on the little nail that match those on the other nails, even though its comfort and performance results were reduced.

The final input actions included 25 Single nail inputs: ten Taps (on each nail Tip and Center); ten VSwipes (on each nail Inner region in both up and down directions); five Flicks (on each finger). Multiple inputs were restricted to the pair of index and middle fingers. There were four in total: Mult-Tap on the Center region; Mult-HSwipe on the Tip in left and right directions) and Mult-Flick on the Center Region. This set of actions is rich enough to enable designs derived from all five of the themes identified in the ideation workshop.

Action	*Variable(s)*	*F-Value*	*DOF*	*p*	η_p^2	*Post-hoc test results*
Tap	Region	10.57	4, 60	0.001	0.413	Tip significantly faster than Inner, Outer, Root (all p<=0.002); Inner significant faster than Outer ($p = 0.033$)
HSwipe	Region	15.03	1.36, 20.44	0.001	0.501	Tip significantly faster than Center ($p = 0.0076$) and Root ($p = 0.0001$)
	Nail:Direction	4.46	4, 60	0.003	0.229	N/A
	Nail:Region	2.89	8, 120	0.006	0.162	N/A
VSwipe	Region	7.57	2, 30	0.002	0.335	Inner significantly faster than Outer ($p <= 0.0085$)
Mult-HSwipe	Nail	29.94	3.07, 45.98	0.001	0.666	Touches to fewer fingers significantly faster (all $p < 0.0017$) except IM-IMR and IM-MRL (both non-significant)
	Region	28.99	1.41, 21.15	0.001	0.659	Tip significantly faster than Center ($p < 0.001$) and Root ($p < 0.001$). Center faster than Root ($p = 0.002$)

Table 2. ANOVA and post-hoc test results on time data from performance study. Data from non-significant tests are not presented. Fingers denoted by initials: T(humb), I(ndex), M(iddle), R(ing) and L(ittle).

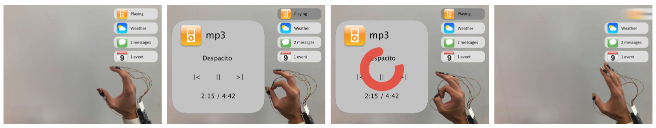


Figure 11. Notification sample application showing how nail touches can access multiple functions (e.g. open, delete) seamlessly.

Revised recognizer

We revised the recognizer based on study data and the reduced input set. Firstly, we merged Center region with Root and Outer for Tap and ignored touches to ring and little fingers during multiple nail input. Secondly, we optimized thresholds using a brute force search to minimize misclassifications in the initial study. We set new thresholds as 0.38g for peak acceleration and 0.13 sensor units (0.625mm for thumb and 0.5mm for fingers) for movement SD. Finally, we leveraged the redundancy of regions to actions by modifying thresholds according to the region touched. Specifically, for touches on the Inner region we halved the threshold for VSwipe detection while for touches to the Tip or Center, we doubled it. This made the system more sensitive to and resilient against small movements, depending on whether or not they were expected for a given region. Together, this boosted accuracy to 88.7%.

Sample applications

To showcase how the final set of input actions could be used to control a wearable device, we developed sample information management applications for a typical wearable: smart glasses. These embody and express key qualities of input via finger augmentation – movements are small in scale (i.e., composed of mirco-gestures [4]) and performable eyes-free [2]. We describe two examples in detail below, and developed other applications (e.g., calendar, weather) using similar designs.

Notifications. We developed a system to manage notifications through nail touches. When a notification arrives, it can be peaked at by tapping the nail tip; transitioning to holding the center provides an expanded view. When finished, the notification can be left on the stack by simply removing the touching finger, or deleted by flicking the nail - see Figure 11 If there are multiple notifications, the top four can be assigned to each of the fingers in vertical order, providing immediate access to each without scrolling.

Media. We explored metaphors in the context of a media playback application. Users can play/pause content through tapping on the index and middle nails, a configuration in which the pair of fingers resembles a pause icon (||). Similarly, a thumbs-up hand pose (all fingertips in contact with palm) marks favorite items while horizontal swipes left/right signify previous/next song operations. For continuous input, nail touches can be combined with motion data: tap and hold the index tip while rotating the hand to control the playback position. Finally, vertical swipes up/down on the thumbnail adjust the volume higher or lower.

VERIFICATION STUDY

A final study evaluated the use of the revised 29 item input action set, recognizer and example applications. We sought to: assess classification accuracy; explore the impact of threshold personalization; capture performance in a more realistic task and; solicit qualitative comments, reactions and feedback.

Participants and Method

We recruited ten participants from the local student body via social media channels. All were right-handed, five were female and they had a mean age of 24.1 (SD 3.14). They indicated they were fluent users of computers (4.2/5) and smartphones (4.5/5) but had little experience with wearables such as smartglasses (1.8). The experiment lasted approximately 45 minutes and the participants were compensated 10 USD. The experiment contained three stages, each separated by a short break. The goal of the first stage was to compare performance results with the previous study and provide data to optimize personalized per-user thresholds. The procedure followed the performance study but used the reduced set of 29 input actions. In the second stage there were four trial blocks (the first treated as practice), each containing all 29 actions presented in a random order. The goal of this stage was to explore performance when users were not aware of the input action they would need to make. Furthermore, it enabled us to validate the personalized thresholds from the first stage on a fully independent test set. In the final stage, we showed the two applications described in the prior section to participants, had them try out and experience these for 10 minutes and then conducted a semi-structured interview to capture their reactions and opinions. The interviews were audio-recorded and transcribed. For this stage of the study, participants wore the Microsoft HoloLens and all UI content was shown on this device. In total, this study retained 870 trials in the first stage, 870 trials in the second stage and approximately 60 minutes of transcribed interview contents.

Results

The mean per trial duration and accuracy of the first and second stages was (1.43s / 1.61s) and (89.7% / 88%), modest improvements over the prior study. Reaction times showed similar trends (0.83s / 0.95s). This suggests users benefited from the smaller number of actions and had little difficulty with the more challenging task in the second stage. Wrong finger errors were also low throughout: 1.1% in both stages. This indicates reducing multiple finger inputs was an effective

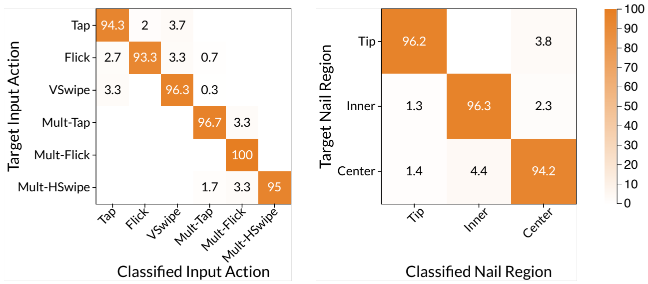


Figure 12. Confusion matrices for classifying input action (left) and nail region (right) using personalized recognizers on trials from the second stage in the verification study. Data shown as percentages, so rows sum to 100.

strategy. Despite the data derived thresholds used in the first stage, single finger Flick remained prone to misclassification with Tap (11.3%) and VSwipe (2%) and Tap and VSwipe were also often confused (5.7% and 14.7%). This suggests user performance of these actions is diverse: fixed thresholds are not ideal. Accordingly, we used a brute force search to find per-user thresholds that minimize classification errors in the first stage of the study. We applied these thresholds to the second study of the study, leading to an improved mean classification accuracy of 94.3%. Figure 12 shows confusion matrices for personalized action and region classification thresholds. This result indicates that personalization is effective and, likely, necessary to produce an effective nail input system.

Comments from the third stage of the study were transcribed and analyzed using affinity diagramming to identify clusters and themes. Participants highlighted qualities including: "convenient" (P0, P1, P5, P6); expressive, "various operations are easily done" (P8, P9) and; ease of access (P2, P6), or as both P7 and P8 noted "no other equipment is needed". Nailz was favorably compared to mid-air gestures by P3 and P8 noted using nail touches was "less tiring, simpler and socially acceptable". Participants also felt many of the input actions were readily learnable. P0 remarked: "play/pause and next/prev songs are well matched with Nailz action" and changing playback position with rotations was just "like rotating a knob". P3 and P4 valued familiar actions, referring to uses of flicking to delete and long tap to open notifications as "intuitive". Similarly, P1, P2, and P9 appreciated the use of directional mappings between finger/hand movements and interface contents – they were "well matched each other". There were worries about "unfamiliar mappings" (P2, P4, P5, P6), but also a consensus that "it becomes easier after some time" (P4, P5, P6). The comfort and utility of some of the input actions were questioned, particularly by three participants who stressed "input on the little nail is frustrating" (P0, P5, P7), possible due to Midas touches as the "little finger is curved, so little nail was touched unintentionally" (P9). Consequently "real world use will involve more wrong touches" (P5). Some of the input actions were felt as designed to mitigate this problem: P0 suggested long tap to open "can prevent mistakes". Overall, we conclude participants were positive on Nailz as a viable, always available, eye-free and socially acceptable input system for wearable computing.

DISCUSSION AND CONCLUSION

This paper characterizes how a set of touch sensitive nails can be used to control other wearables such as smart glasses. The data provides a useful complement to prior nail touch [20, 23] and finger articulation systems [18, 33] and can also serve as a baseline for future work. One key point of comparison is recognition accuracy. In a system based on a single thumbnail, Kao *et al.* [20] report accuracy among five input actions – cardinal swipes and a long tap – to be 92.3% [20]. The data in this paper, covering all nails and a more diverse 29 item final input set, achieves an improved accuracy of 94.3% using personalized recognizers – this is a strategy that should be further pursued in the future. This accuracy figure also compares well to prior work on camera tracked finger augmentation – Soliman *et al.* [33] report finger identification rates of 90.2% (vs the 98.9% reported here) and can recognize one of eight action types with an accuracy of 91.06%. We suggest the direct sensing paradigm we use may be inherently more accurate than camera tracking systems. We also extend prior work by reporting additional metrics. Specifically, we add to the limited prior reports of task times (of thumbnail touches to the face [23]) and comfort (of touches to the inner finger phalanxes [18]) with comprehensive data on thumb-to-finger [39] and finger-to-thumb nail touches. These show that nail touches can be performed rapidly – in a mean of 1.61s in the second stage of the verification study, a figure at the lower end of the 1.32s to 2.448s range reported for taps triggered by land-on and lift-off actions by Lee *et al.* [23]. In addition, nail touches are comfortable – the 144 touches we studied were rated with a mean of 3.41/5 which compares well to the mean of 3.34/5 for 12 touches to the inner fingers in Huang *et al.* [18]).

In conclusion, this paper explores finger input for wearable computing via the novel form factor of a set of five touch sensitive fingernails. It explores the design space of this system, presenting a large set of 144 possible inputs and characterizes the comfort, distinguishability and time taken to perform each of these actions using a fully functional prototype. We close by evaluating a final input set refined by data from the earlier studies and capturing qualitative comments about example applications. We show that touch inputs on the nails are expressive, can be comfortable and efficiently performed and are readily recognized using simple criteria. We believe that the range of small scale inputs supported, the simple classification scheme and the speed with which participants performed all testify to the viability of this approach. Future work should improve sensor hardware (e.g., via on-skin films [29]), integrate the system with signal propagation approaches to finger input for improved flick classification [22], consider aesthetics (e.g. decorative covers [20, 37]), examine more sophisticated recognition schemes, explore solutions to Midas touches (e.g., activation gestures such as a multi-nail swipe), investigate personalization processes (e.g., unsupervised learning) and study nail touch input in the field.

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