The Influence of Hand Size on Touch Accuracy

Joachim Normann Larsen
University of Copenhagen
Copenhagen, Denmark
psf664@alumni.ku.dk

Tórur Højgaard Jacobsen
University of Copenhagen
Copenhagen, Denmark
rtv379@alumni.ku.dk

Sebastian Boring
University of Copenhagen
Copenhagen, Denmark
sebastian.boring@di.ku.dk

Joanna Bergström
University of Copenhagen
Copenhagen, Denmark
joanna@di.ku.dk

Henning Pohl
University of Copenhagen
Copenhagen, Denmark
henning@di.ku.dk

ABSTRACT

Touch accuracy is not just dependent on the performance of the touch sensor itself. Instead, aspects like phone grip or occlusion of the screen have been shown to also have an influence on accuracy. Yet, these are all dependent on one underlying factor: the size and proportions of the user's hand. To better understand touch input, we investigate how 11 hand features influence accuracy. We find that thumb length in particular correlates significantly with touch accuracy and accounts for about 12 % of touch error variance. Furthermore, we show that measures of some higher level interactions also correlate with hand size.

CCS CONCEPTS

• **Human-centered computing** → **Pointing**; *HCI theory, concepts and models*; *Empirical studies in HCI*; Mobile devices;

KEYWORDS

Touch input, pointing; mobile interaction

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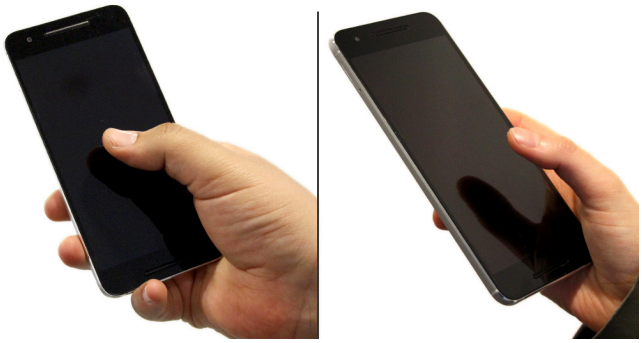

Figure 1: We investigate how touch error varies between users with different hand sizes. Seen here are a user with a large hand (left) and a smaller hand (right) holding the same phone. We find that thumb length in particular correlates significantly with touch error.

1 INTRODUCTION

Touch input is the dominant input method for many mobile devices, such as phones and smartwatches. As screen space on such devices is limited, the accuracy and fidelity of touch is an important consideration during design of touch-based user interfaces. Inaccuracies of touch impose restrictions on user interface design, such as necessitating larger controls.

A range of methods have been proposed to improve touch accuracy. For example, specifically-designed interaction techniques can help alleviate some issues of insufficient sensing precision [2]. But touch input itself can be made more accurate by modeling its inaccuracies. An example is work by Weir et al. [27] on using Gaussian process models to train offset functions for improved touch input. These models are generally data-driven and, while being able to improve touch accuracy, do not tell us much about *where* this error comes from in the first place. Furthermore, there likely are multiple factors that influence this error, yet *which* these are and *how much* they contribute to the overall error is also unclear.

Several factors influencing touch accuracy have been previously explored. For example, Holz and Baudisch have proposed that visual features on top of the touching finger determine the desired touch location [13]. Whether a target is in easy reach of the thumb [3], whether the thumb is curled or straight [22], as well as whether a user is multitasking [20] have all been shown to impact touch performance. An underlying factor in many cases is the user's grip—how the phone is held. Additionally, the dimensions of the user's hand (*anthropometrics*) are directly related to many of the factors above. For example, a larger hand necessitates a different grip than a smaller one (see Figure 1).

Some anthropometric factors have already been investigated. For instance: the effects of thumb length and breadth on touch input [17]; negative effects of larger thumb pad sizes on touch precision [2]; and the correlation between hand size and touch performance [24]. However, these works have focused on a particular task such as typing, a particular area of the screen, or a subset of hand measures. Thus, we still lack an overview of which measures most strongly correlate with touch accuracy across a touch screen.

We extend previous work by including a large number of hand features, covering measures of hand and finger size. We examine the effects of those measures on touch accuracy over the entire screen of one smaller and one larger phone. Furthermore, we explore how one anthropometric measure—thumb size—correlates with five common touch interactions: swiping, scrolling, panning, typing, and selecting.

We find that thumb length in particular significantly decreases touch accuracy and overall accounts for about 12 % of the variance of touch error. Our findings show, however, that while thumb length accounts for a significant share of the error, individual differences in touch dominate. Hence, touch offset models trained on users with similarly sized thumbs are outperformed by per-user models.

2 RELATED WORK

We first review work on ways of improving touch input by either correcting for touch offsets or adapting target layouts. These techniques require models of touch performance, touch characteristics, or anatomical features of the hand, which we review as well. Finally, we discuss how knowledge of hand anatomy has been used for improving touch input.

Improving Touch Input

Touch input performance can be improved by sensor design, applying data or models of offsets on touch points, or by adapting touch target designs.

Sensors, like *Microchip's MXT336U* digitizer, allow for calibration to correct for background capacitance that could lead to distorted touch locations. However, such sensor corrections do not account for variation in touch accuracy induced by differences in grip or hand anatomy. For such user characteristics, software models (e.g., offset models) are needed to correct for individual differences.

As a finger usually covers more than one pixel of a touchscreen, this ambiguity needs to be resolved, for example, by picking the center of the touch ellipse as the touch location. Yet, this touch location does not necessarily align with where the user *intended* to touch [13]. This results in touch offsets (i.e., error), which can be corrected for if known and systematic. For example, Holz and Baudisch [12] showed that touch accuracy can be improved using fingerprint information.

Improving touch accuracy is simple once the offsets are modeled. However, fitting a good model to various users and use cases is challenging. Users' hands vary anatomically, and mobile devices can be grasped in many ways, with one or two hands, and with different hand postures and locations on a device. One way of using offsets is to predict those by applying machine learning to train offset models from raw touch data. For example, Weir et al. [27] used Gaussian processes to train user-specific touch offset models, and Mott and Wobbrock [19] combined user-independent and user-dependent offset models to compensate for motor and situational impairments. For each screen location such models can predict the most likely offset to apply to a touch event. Buschek et al. [5] also presented the *TouchML* toolkit to train such offset models.

The offset points can vary dramatically across a screen surface, particularly for single-handed input. The approaching angle of the thumb influences the touch profile on the screen because a slightly different part of the thumb pad touches the screen depending on the angle. For example, Roudaut et al. described how the slope of a touch surface influences touch accuracy [25].

In addition to offsets models, touch accuracy can be improved by compensating inaccuracies with touch target design. One approach is to adjust target sizes. When holding a phone and interacting with the same hand, touch input is often given with the thumb. Parhi et al. [21] modeled how large targets should be for accurate one-handed thumb input. Another approach is to adjust how the targets are laid out across the screen. For example, Karlson et al. [16] showed preferred regions for one-handed device use for four different device sizes, and Park and Han also investigated how target size and location influenced touch error [22, 23]. Trudeau et al. [26] further suggested that interface elements should be presented near the thumb's resting position instead of close to the limits of the functional area. And Goel et al. [9] demonstrated that phone grip can be inferred from device sensors, contributing to enabling adaptive layouts based on grip. However, like with offsets, understanding of users hand characteristics is a prerequisite for improving touch performance with target design.

The Thumb's Influence on Touch Performance

Unimanual touch performance is influenced by a complex interplay of user characteristics. For example, hand and finger size constrain the potential grip on the device, which in turn determines which parts of the screen are reachable.

Previous work has described many effects of motion-related factors on touch input with thumb. For example, Azenkot and Zhai [1] showed how text entry behavior changes as users switch hand postures, Bergstrom-Lehtovirta and Oulasvirta [3] modeled the reachable area on the screen for thumb, and Trudeau et al. [26] investigated a tapping task with a 12-key grid, showing that location significantly affects the user's grip in terms of joint positions in relation to the mobile device.

None of these studies, however, described the influence of thumb motion on touch accuracy. Accuracy is examined by Bergstrom-Lehtovirta et al. [4] and Goel et al. [8], but only as an indirect effect on hand movement through walking.

Hand Anthropometrics

Touch accuracy is influenced by hand measures (e.g., finger lengths, finger pad sizes) and movement (e.g., the grip, fingers' ranges of motion). Hand measures influence how far the thumb can reach, and longer fingers with a similar range of motion reach further and wider. Therefore, the hand measures are in the root of touch performance. However, the influence of hand measures on touch accuracy has been examined only in subsets of measures or tasks previously.

Beyond studies that report some hand measures (e.g., [3, 21]), two studies using those in analyzing accuracy are worth mentioning here. One is by Kim et al., who investigated the influence of thumb length and breadth on touch input [17]. They used three different target grids (respectively three different target sizes), shown at the bottom of a phone, and measured task completion time as well as the number of errors. Participants with longer thumbs took more time, but there was no significant influence on the number of errors. We extend this work by measuring touch accuracy over the entire screen instead of selection errors in discrete grids on the lower screen.

Another recent study is by Prange et al., in which they explored correlations of four hand dimensions (total span, hand length, hand width, and zooming span) with several measures of touch interaction performance [24]. Their participants swiped, tapped, scrolled, and zoomed in a phone application. Prange et al. concentrated on correlations of hand size with interaction measures. In addition the hand size, we also cover measures of the fingers that have been suggested to influence touch (e.g., finger span [3], thumb pad [17], and thumb length [26]).

We find that thumb length has the greatest overall influence on touch and consequently use it in our investigation of interaction measure correlations. We also cover multiple tasks with an exploration of common touch input types.

3 DATA COLLECTION

Investigating whether hand size has an influence on touch performance requires a large amount of data. We hence collected touch data from participants with a wide range of hand sizes. The data collection was mainly focused on target acquisition, but also included higher level touch interactions. With this dataset we look for correlations between hand features and measures of touch performance.

Design

The data collection was split in two phases. Phase 1 consisted of tapping 1000 cross-hair targets which were presented subsequently at randomized locations across the entire screen. Phase 2 consisted of five interaction tasks with 10 repetitions each: swiping, scrolling, panning, typing, and selection. To allow for some familiarization, participants were always presented with one of each task type in the first round. Afterwards, participants went through a fully randomized sequence of another 9 repetitions of each task type. Parameters for each task were also chosen randomly. The participants completed the process on two different phones, and phone order was counterbalanced. We asked participants to hold the phone in their dominant hand and use only that hand's thumb for input. Participants were seated in a quiet room during the whole study.

Participants

We recruited 27 participants (16 male, 10 female, 1 transman; age 19–68, M=29.0, SD=9.4) from around our institution. All participants owned a touch-enabled phone. The majority (23) of the participants were right-handed, four were left-handed. We mirrored left-handed participants' data and thus did not control for handedness.

From each participant we collected a set of hand measures (see Figure 2), following a consistent procedure that controlled hand posture. The measures were: (1) thumb pad width (which may as such influence touch size [13]), (2) index finger length from the base of the thumb (which influences thumb reach), (3) finger span between the thumb and the index finger (which also influences thumb reach [3] and the aiming angle of the thumb), (4) finger span between the thumb and the little finger and (5) palm width (both of which influence the breadth of the grip and thus may influence phone's vertical stability), (6) palm length, (which influences the length of the grip and thus may influence horizontal stability), and (7–11) the lengths of each of the five fingers. See Table 1 for an overview of ranges of the different measures.

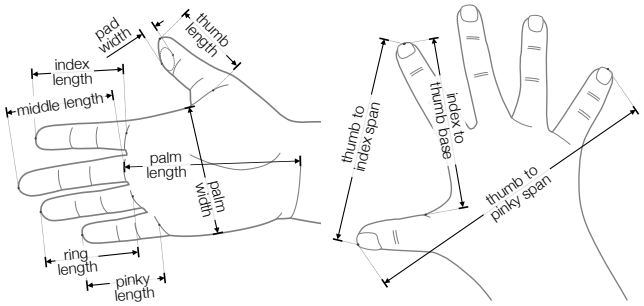

Figure 2: We collected 11 measures of each participant's hand: the lengths of all fingers down to the base, the distance between the tip of the index finger and the base of the thumb, the width and length of the palm, the width of the thumb pad, and the spans between the thumb and the index and pinky fingers.

To confirm that our set of participants is representative, we compared their hands with reported hand measurements from the literature. Specifically, we used reported hand anthropometry of US army personnel (1003 females and 1304 males) [11], Koreans (154 females and 167 males) [15], and people from Western Australia (110 females and 91 males) [14]. We compared the length of the thumb and index finger and checked males and females separately. To check whether our sample differs from the reported means, we ran two-sided one-sample t-tests (Bonferroni corrected). The only significant difference we found is that our male participants' thumbs and index fingers were significantly larger than those of male Koreans. While our results thus likely generalize to Western populations, further studies might be required for populations with different average hand sizes.

We also calculated correlations between our participants' features using Pearson's correlation coefficients. As shown in Figure 3, most pairs of features are highly correlated. This is not surprising, as hand features usually remain proportional over the range of hand sizes. Yet, there remains variability and while the highest correlation was 0.96 (lengths of middle and ring fingers) the mean correlation was 0.64. Hence, it is important to examine the hand features separately, instead of an aggregate "hand size" measure.

Table 1: We measured the length of 11 hand features of our participants.

Feature name	Range	Mean	Std-dev
Thumb length (TL)	5.4–7.8 cm	6.5 cm	0.5 cm
Index finger length (IL)	6.4–8.5 cm	7.3 cm	0.6 cm
Middle finger length (ML)	7.1–9.2 cm	8.0 cm	0.6 cm
Ring finger length (RL)	6.5–8.5 cm	7.4 cm	0.6 cm
Pinky finger length (PL)	5.2–7.4 cm	6.1 cm	0.5 cm
Thumb pad width (TPW)	1.4–2.7 cm	2.0 cm	0.3 cm
Palm width (PaW)	7.3–10.2 cm	8.5 cm	0.8 cm
Palm length (PaL)	9.0–12.0 cm	10.7 cm	0.8 cm
Index tip to thumb base (ITL)	8.5–13.8 cm	11.1 cm	1.2 cm
Thumb to index span (TIS)	9.0–18.8 cm	11.9 cm	2.1 cm
Thumb to pinky span (TPS)	14.1–23.8 cm	18.3 cm	2.5 cm

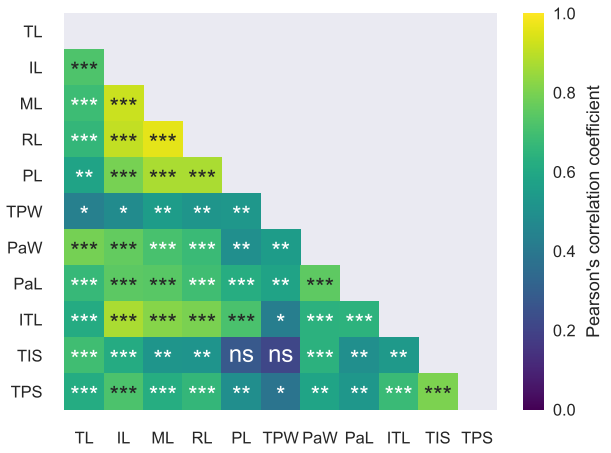

Figure 3: Pearson's correlation coefficients and significance levels for all pairs of hand features. Except for two pairs, all features are significantly correlated.

Apparatus

We used two different phones for the evaluation: an *iPhone 6* and a *Nexus 6P*. While the former is 13.8 × 6.7 × 0.7 cm small (5.7 in screen diagonal), the latter measures 15.9 × 7.8 × 0.7 cm (4.7 in screen diagonal). In the current device landscape, the Nexus 6P is of average size, while the iPhone 6 is representative of a class of smaller phones.

We developed the study software using the Xamarin platform so that both devices could share most of the code. However, we used native GUI elements on both Android and iOS. We also collected touch input data via the native APIs. We scaled targets and UI elements to be of equal physical size on both phones. The application ran in fullscreen mode.

Phase 1: Touch Accuracy

In Phase 1 we collected speed and accuracy data to determine how anthropometric hand features influence touch accuracy across the screen estate. The task was to use the thumb to tap 1 cm large crosshair targets (see Figure 4) appearing on the screen. The participants were instructed to tap the targets as accurately and as fast as possible. In total, Phase 1 consisted of tapping 1000 targets. The targets appeared immediately after the previous one was tapped, and the target locations were randomized across the entire screen.

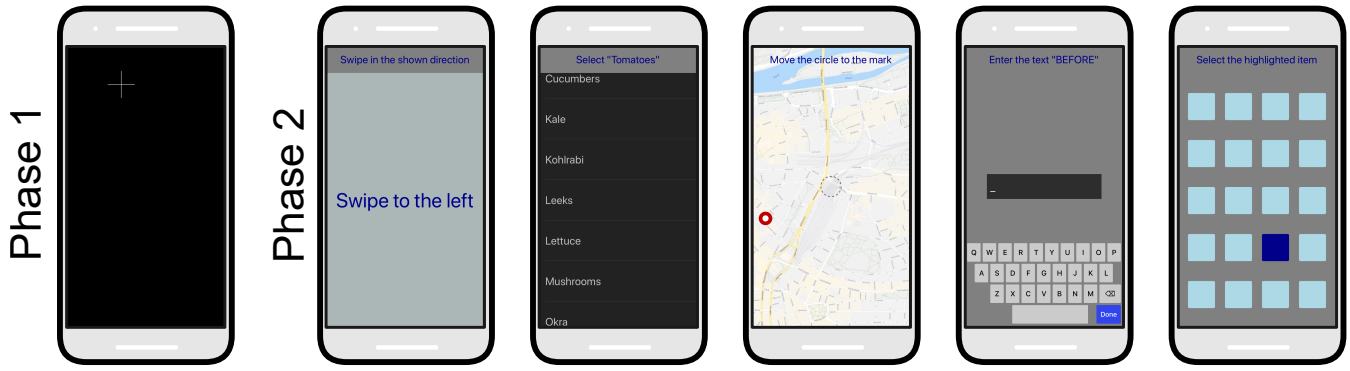

Figure 4: Screenshots of the Android study interface. The leftmost screen shows phase 1's touch accuracy task. The other five show screens from phase 2's: swiping task, scrolling task, panning task, typing task, and selection task.

Phase 2: Recording Touch Patterns

In Phase 2 we collected touch pattern data to explore potential relationships of anthropometrics to higher level interactions. We collected data in five types of tasks representing common interactions with mobile phones (see Figure 4). In addition to the touch data, we also logged device motion data (such as accelerometer readings).

Swiping. In this task, participants needed to swipe left or right. This is equivalent to interactions like moving to the next picture, or liking someone in a dating app. The target direction was shown in the middle of the screen. Participants could freely choose the gesture location.

Scrolling. In this task, the participants located an item in an alphabetical list by scrolling up or down. The list contained 33 vegetables and the initial view was always centered on the middle. Target items were randomly chosen from the top/bottom 25 % respectively. This represents a common task with menus and indexed lists, such as a phone's contact book. Similar to swiping, but in the vertical axis, this task did not restrict the gesture's location.

Panning. In this task, the participants positioned a pin on a map into a target circle displayed at the middle of the screen. This represents panning input which is common in such map applications, as well as when browsing or viewing large images. The path, the location, and the number of the panning gestures were not restricted.

Typing. In this task, the participants entered words, which were displayed on the screen. Instead of the native keyboards, we provided a simple shared keyboard for both phones. Each trial, we sampled from the 100 most common English words with 5–7 characters from the Brown Corpus. All words were uppercased so no case switching was necessary.

Selection. In this task, the participants selected a highlighted target in a grid of squares. The squares were laid out on a 4×5 grid, similar to, for example, a common mobile phone home menu (e.g., on the iPhone 6). This interaction is similar to the task in phase 1, but with buttons in a familiar layout instead of crosshair targets.

Post-Processing

Overall, we captured 54000 touches in the first phase and 2700 interactions in the second phase. We first mirrored all data from left handed participants along the x-axis. This allows for a unified further analysis and all figures show the data for right-handed use. All touch data was transformed from device-dependent pixel coordinates to device-independent measurements in millimeters.

We further processed the touch data from phase 1 to remove outliers, based on timing and error. If touches occurred faster than normal reaction times, we removed those. This drops 298 trials with reaction times below 160 ms[1], which make up 1.6 % of our data. We also removed trials that took much longer than average (indicating participants were likely distracted during the trial), removing 77 trials that took more than 2.9 s (i.e., 5 standard deviations above the mean), which equals another 0.4 % of the data. Finally, we removed trials where the touch error (measured in device-independent millimeters) is much larger than average. Over both phones and all trials, the average error was 4.0 mm with a standard deviation of 8.1 mm. We remove all trials where the error is exceeding 3 standard deviations above the mean (i.e., touches off more than 28.7 mm). These were another 213 trials (1.2 % of the data), and resulted in a total number of 3.2 % of the trials being outliers.

We keep all but participant 4 and 5's trials from phase 2. These two participants erroneously used their other hand in that phase, instead of performing the interactions with the thumb. Furthermore, due to technical issues, participants 2 and 3 only completed some of the trials in phase 2.

4 THE INFLUENCE OF HAND ANATOMY ON TOUCH ACCURACY

We first report on the results for Phase 1: touch performance, influence of hand features, and error correction based on such features.

[1]Outliers per https://www.humanbenchmark.com/tests/reactiontime/statistics

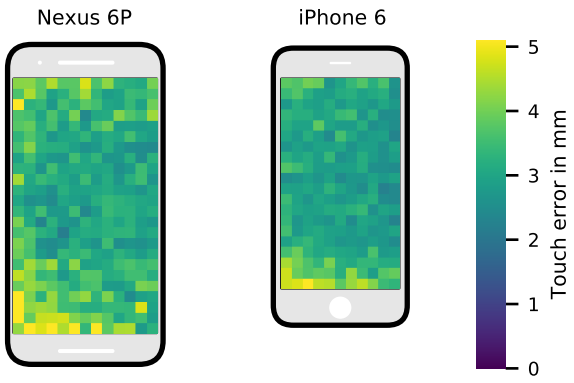

Figure 5: Magnitude of touch error after normalizing for handedness. The error varied over each phone's screen with the largest errors occurring away from the center. Error was larger along the edge opposite the one where the phone was held. This effect is more pronounced in the larger Nexus 6P.

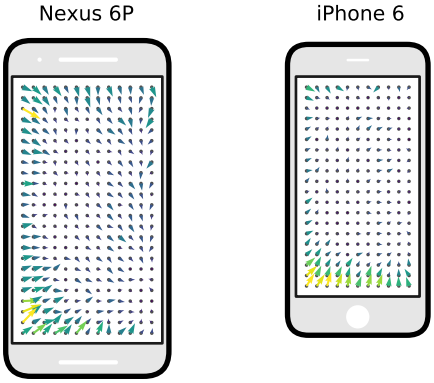

Figure 6: Plotting the direction of the touch error shows that participants tended to touch more inwards than the target's location when the target was close to the screens' extremes. This hints that the reaching motion often required for those targets introduced an additional source of error.

Overall Touch Performance

Before investigating how hand anatomy influences touch accuracy, we first report on overall touch performance. The average touch error on the Nexus 6P and iPhone 6 were 3.4 mm and 3.1 mm respectively. A paired sample t-test showed a significant effect of phone type on touch error: $t(26) = 2.65, p < 0.05$. Hence, we retained phone as a factor in the subsequent analyses. The overall average touch error was 3.2 mm.

The touch error is not distributed equally over the screens. As shown in Figure 5, error is lowest in the middle of the phones and along the right side (i.e., where the phones were held,). Towards the far corners, error increases—an effect larger in the Nexus 6P, likely due to the bigger device size. The direction of the touch error further highlights how users tended to touch further inwards than the targets along the corners (see Figure 6). A reason for this effect might be required reaching motions for those targets and a subsequent increase in error.

Table 2: Correlation of hand features and touch error.

Hand feature	Pearson r	Pearson r
Thumb length	0.35	0.39
Index finger length	0.26	0.23
Middle finger length	0.20	0.20
Ring finger length	0.22	0.19
Pinky finger length	0.10	0.08
Thumb pad width	0.19	0.02
Palm width	0.18	0.15
Palm length	0.13	0.09
Index tip to thumb base	0.10	0.11
Thumb to index span	0.16	0.23
Thumb to pinky span	0.15	0.21

Hand Features' Impact on Touch Error

The unequal distribution of touch errors suggests that there may be influences on touch error other than just sensor noise. For example, the higher error at the extremes could be due to users having a harder time reaching those locations. Such reaching would be influenced by finger size, but also the overall hand size of a user.

Figure 7 shows the relationship between hand features and touch error for each of the collected hand measurements, while Table 2 shows the corresponding correlations. Overall, the 11 features show a similar influence on error. This is explained by the generally large correlation of any two hand feature measurements, as described earlier. Particularly relevant to touch input are the length of the thumb and the size of the thumb pad. Both show strong correlations with other hand features (e.g., thumb length is most strongly correlated with the width of the palm; Pearson's $r(25) = 0.8, p < 0.001$). The two themselves are also correlated; Pearson's $r(25) = 0.4, p < 0.05$.

Yet, while there is strong correlation of features overall, there could still be differences in how heavily they each influence the accuracy of touch. We used a multiple regression approach to further investigate the influence of individual features. For this we aggregated the data to per-participant error averages with their hand features as initial factors to regress on. In addition to these fixed effects, we added phone and participant as random effects. To focus on the main factors influencing touch error, we then performed model selection using AIC. Table 3 shows the final model features as well as their coefficients and p-values. The fitted model explains about a quarter of the variance of touch errors; multiple R-squared = 0.35, adjusted R-squared value = 0.25.

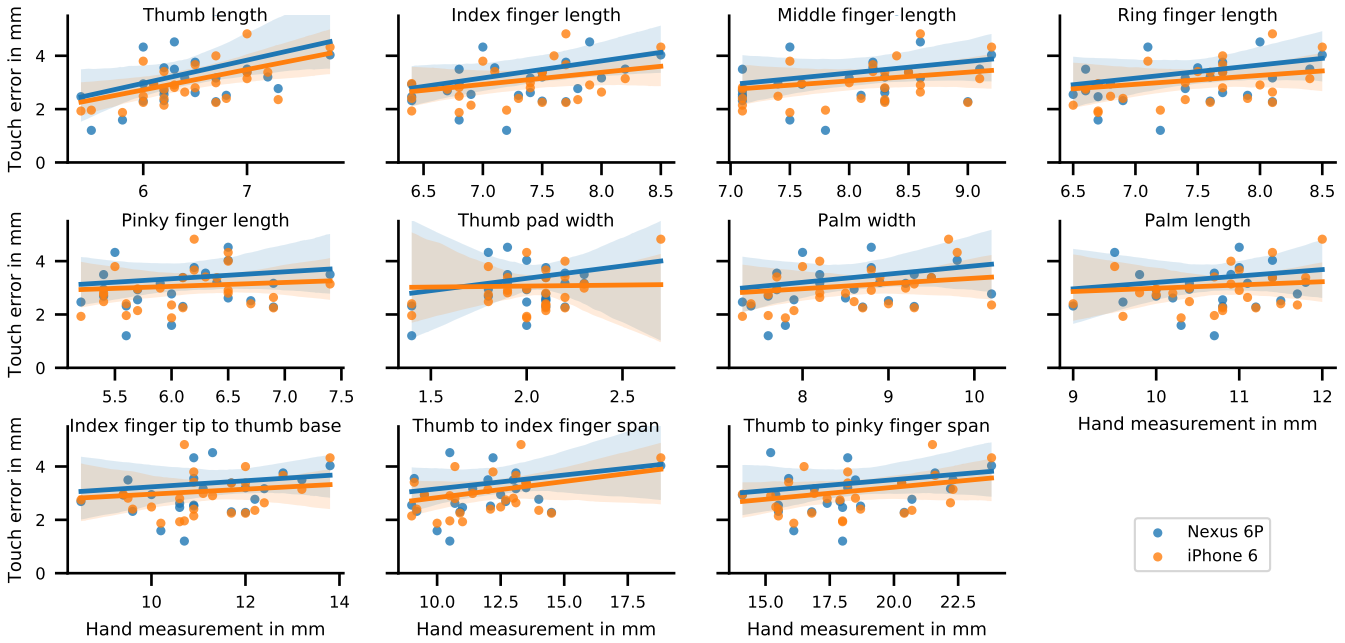

Figure 7: Regression plot of the influence of each of the collected hand size measurements on touch error.

These results show that touch error is not just influenced by any one hand feature. However, the size of the hand does feature into what results in touch errors. The model also showed that the length of the thumb is the most influential feature from our set. Intuitively, this makes sense as thumb length has a direct impact on what parts of the screen are reachable. We thus decided to focus on thumb length as an influence on touch error for the remaining analysis.

To quantify the influence of thumb length on touch error, we used a second mixed effect model with thumb length as the only fixed effect and the same random effects as in the first model. The conditional R_GLMM^2 of this model is 0.895 (i.e., 89.5 % of the variance is explained by the model). However, much of the error is due to the random effects, such as individual performance. The marginal R_GLMM^2 hence is only 0.122, meaning that about 12.2 % of the variance of touch error is explained by thumb length.

Table 3: Touch error model with seven features after model selection. All F-values for F(1, 46).

Hand feature	Coefficient		F	p
Pinky finger length	−2.1	SE=0.70	8.65	< 0.01
Palm width	−1.0	SE=0.37	7.82	< 0.01
Index tip to thumb base	−0.4	SE=0.25	2.50	0.12
Thumb to index span	−0.2	SE=0.12	3.89	0.05
Ring finger length	1.0	SE=0.77	1.81	0.18
Thumb length	2.1	SE=0.55	14.44	< 0.001
Index finger length	2.1	SE=0.90	5.37	< 0.05

A Closer Look at the Influence of Thumb Length. As we saw in Figure 7 and in the analysis above, thumb length overall positively correlates with error. For example, the average touch error of the three participants with the shortest thumbs was only 1.8 mm. On the other hand, the average error for the three participants with the longest thumbs was 3.3 mm. Yet, there remains an influence of individual differences and there is variation within people with similarly-sized thumbs. For example, the standard deviation of the two groups mentioned above is 0.3 mm and 0.8 mm respectively.

As we saw earlier, error is unevenly distributed over the phones' screens. We hypothesize that this is possibly due to reaching behavior introducing a source of error. If that is the case, we would expect different thumb sizes to increase errors only at *certain areas* of a screen. For example, there is a part of the screen (the shape of an annulus sector) that the thumb pad can touch without a need to change finger posture or grip, simply by rotating the thumb at the base. On the other hand, a target closer to the corner the phone is held at requires the thumb to curl up to reach it. Similarly, targets further away require stretching the thumb and often a grip change to facilitate that reaching motion.

Figure 8 shows where on the screen thumb length had the largest influence. For this we compute the slope of the *touch error ~ thumb length* regression over the surface of the phones. As shown, there is no area where a smaller thumb resulted in less error. Instead, over much of the phone surfaces, larger thumbs fared slightly worse. Yet, towards the lower edge of the phone, larger thumbs resulted in a more marked increase in touch error.

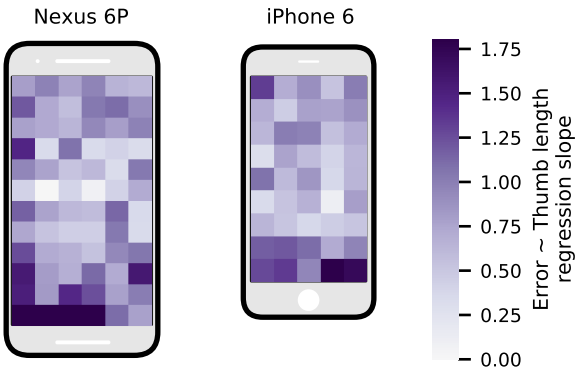

Figure 8: We computed local linear regression models to estimate the strength of the relationship between thumb length and error. For much of each phone's screen, longer thumbs only resulted in slight error increases. However, towards the bottom, longer thumbs resulted in a more pronounced decrease in touch accuracy.

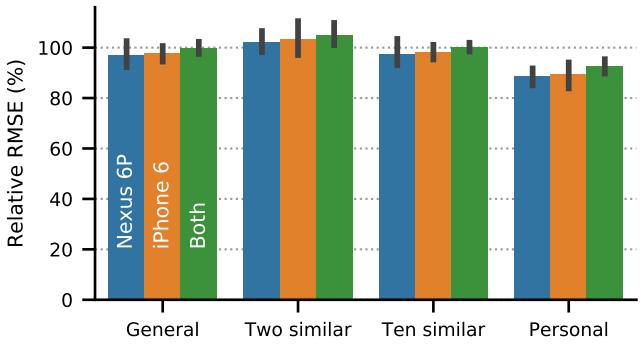

Figure 9: We trained offset models using Gaussian process regression to check how well errors due to differences in thumb length could be corrected. We found that training with data from similar users does not provide an improvement. Personal models significantly outperformed any models trained on other's data. This suggests that, while users with similar hands have similar overall error, their individual touch offsets do not share that similarity.

Thumb Length Guided Touch Offset Modeling

So far we have only described how error is related to hand features. However, ideally this information could be used to *decrease* that error. A user's actual touch locations would then be corrected, based on their hand size. Instead of training with personal data from each users, models based on hand size would ideally transfer between users. To investigate whether this is possible, we used an offset modelling approach, similar to work by Weir et al. [27]. As above, we focus on whether thumb length information is indeed helpful for correcting touch errors. We compared personal models with models trained on all other users' data and models trained on data from users with similar thumb lengths.

We used Gaussian process regression to build models of offsets required to correct for the touch error. In contrast to simpler linear models, this accounts for the complex change of touch error over the screen of a phone (as also seen earlier in Figure 6). Our offset models used either just an RBF kernel (personal models), or a combination of an RBF and a White kernel (all other models), and were implemented using GPy [10]. For models trained on data from more than one user, we used sparse Gaussian process regression.

We used the relative RMSE to evaluate correction performance. For each participant, we compared four different models: (1) models trained on their own data, (2) models trained on everybody else's data, (3) models trained using data from the two other participants with the most similar thumb length, and (4) models trained using data from the ten other participants with the most similar thumb length. For each of these models, we tested device-specific and device-independent variants.

Figure 9 shows how training a personal model yielded the largest improvement in touch error. We also found that there is no large difference between device-specific and device-independent models. Comparing the device-independent models with paired t-tests and after Holm-Bonferroni correction, we found significant differences between the personal model and the general model ($p < 0.01$). Personal models also significantly outperformed models trained on two other similar users ($p < 0.001$) and ten other similar users ($p < 0.01$).

These results show that offset correction is highly personal. Even when two users have similarly sized thumbs, that similarity does not extend to their overall touch behavior. Instead, performance of models trained on other users' data seem to mostly be influenced by the amount of training data. Training with data from only two users decreased performance over the general model. However, this difference was not significant; $p = 0.07$.

5 HOW THUMB LENGTH INFLUENCES HIGHER-LEVEL TOUCH INTERACTIONS

As we have seen, hand size has an influence on touch error. However, error is but one measure of touch interaction and hand size likely also has an influence on other aspects of touch input. For example, how users perform swipe gestures could, to some degree, depend on hand size as well. With the interaction data from the second phase of the data collection, we ran an exploratory analysis of how higher level interaction concepts are correlated with hand size. We focused on correlation with thumb length, because it emerged as the main factor in the preceding analysis.

Table 4: Correlation of thumb length with a selection of measures for each performed kind of interaction. As this is an exploratory analysis we only report correlations, but no p-values.

Interaction	Feature	Pearson r	Pearson r
Swiping left	Start X	0.82	0.25
Swiping left	Start Y	−0.18	−0.30
Swiping left	Radius	0.57	0.11
Swiping right	Start X	−0.80	−0.84
Swiping right	Start Y	0.24	0.08
Swiping right	Radius	0.08	0.40
Scrolling up	Start X	−0.35	−0.24
Scrolling up	Start Y	0.01	−0.07
Scrolling up	Length	−0.02	−0.05
Scrolling up	# of Swipes	−0.15	−0.23
Scrolling down	Start X	−0.38	−0.49
Scrolling down	Start Y	0.04	0.12
Scrolling down	Length	−0.32	−0.37
Scrolling down	# of Swipes	0.05	0.15
Panning	Mean X	−0.29	−0.33
Panning	Mean Y	−0.12	−0.12
Panning	Clutch X	−0.10	−0.23
Panning	Clutch Y	−0.35	−0.02
Typing	Mean IOI	0.09	0.22
Selecting	Selection Time	−0.04	−0.34
Selecting top row	Selection Time	0.12	−0.14
Selecting bottom row	Selection Time	0.06	−0.40

For each of the recorded interactions we collected all touch, action, and device motion data. While this would allow for an analysis of a large number of potential correlations, we restricted ourselves to those we deemed likely to be influenced by thumb length.

When **Swiping** left or right, users can perform that gesture anywhere on the screen. We expected users with longer thumbs to start further away from the grasp base. During a swipe gesture the thumb pivots at the base. A swipe from a longer thumb would thus form part of an arc with a larger radius than a swipe with a short thumb.

During the **Scrolling** task the start location can be freely chosen. When scrolling up, users likely start at the bottom of the screen and then drag upwards. Similarly, when scrolling down, users likely start high on the screen to have space for dragging downwards. Users with longer thumbs can reach further than users with shorter thumbs and thus likely start higher up when scrolling down. The overall length of a swipe might differ as well. At the same time, users with shorter thumbs might need a larger number of swipes to scroll the same amount.

In the **Panning** task users can use all of the screen for input. Users with longer thumbs might perform their panning gestures higher up or further away from the grip location. We hence analyzed the average location of all touches during panning. Similarly, where on the screen they perform clutching actions (i.e., ending one swipe before moving the thumb to the next start location) might differ by thumb length. For clutching, we only considered the final location of individual swipes.

During **Typing**, touch targets are close together in an area at the bottom of the screen. As we have seen earlier, longer thumbs are disadvantaged around this part of the screen. Hence, we expected that this would result in increased interonset intervals during typing.

As in typing, when **Selecting** the targets further away require more stretching from users with shorter thumbs. Similarly, targets in the bottom row could be harder to acquire with longer thumbs. These differences might show in selection times for those targets.

Table 4 shows the observed correlations between thumb length and the individual measures for each of the two phones. We considered interactions separately where appropriate (e.g., swiping left or right). The results show strong variation in correlations. For example, the highest observed correlation was between thumb length and the horizontal starting position while swiping right on the iPhone. Surprisingly, correlations often differ in magnitude (and sometimes even direction) between the two phones. Overall, this suggests that, while there is some connection of thumb length to measures of interaction, it is a complex one.

6 DISCUSSION

Our analysis has shown that hand size and thumb length in particular, has a measurable impact on touch input. Just the influence of thumb length can explain about 12 % of the variance of touch error. Touch error increases for users with longer thumbs, but not uniformly over the whole phone and differently for the two phones. This demonstrates that the relationship between hand size and touch performance is complex and other factors modulate its strength.

An example of this is the distribution of touch error over the screen (e.g., shown in Figure 5). We expected the error to be largest towards the top left, farthest away from where the phones were held. However, this is not the distribution we observed and instead the lower corners are where touch error was largest. These were also the locations where large thumbs were most disadvantaged. Initially, we assumed that long thumbs would make it *easier* to reach the top of the phone while not impacting acquisition of lower targets. However, that was not the case and thus some other factor likely influenced the touch behavior.

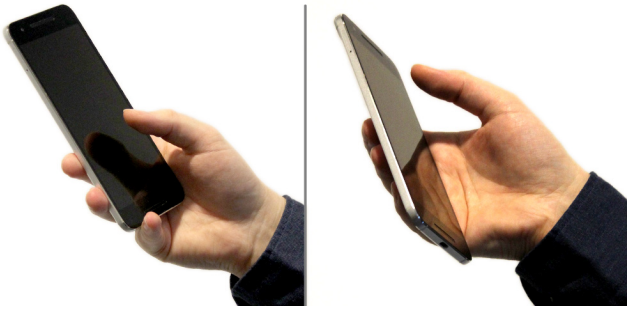

Figure 10: Two different kinds of phones grips: (1) holding the phone at the bottom, and (2) resting the middle of the phone on the fingers. While the former allows easier selection of lower targets, the latter allows easier selection of middle and upper targets.

One factor we observed during the data collection is participants' grip of the phone. Instead of holding the phones at the base, many participants switched to a grip where the middle of the phone rests on the fingers (see Figure 10). This allows for easier reach of the upper part of the phone, but at the same time makes lower targets harder to acquire. Due to the large size of current phones, this is likely a coping mechanism to avoid larger reaching motions. Yet, this necessitates a grip shift (e.g., by rotating the fingers slightly) to reach the lower targets. This grip behavior is a possible explanation for the observed error distribution.

The influence of a user's grip of a phone on touch performance is well known. Recent examples are work by Eardley et al. [6, 7] as well as by Lehmann and Kipp [18]. However, these papers only compared macro-changes in grip and not smaller grip adjustments such as the grips we observed. Our results suggest that small grip shifts might also have a noticeable influence, especially for larger phones and users with bigger hands. However, we did not control for grip and thus further studies are necessary to better quantify the interplay of grip and hand size on touch accuracy. Yet on the other hand, controlling for grip might prevent participants from using the phone in their preferred way, thus harming ecological validity.

As more information on the user is available, such as hand size or the current grip, touch input systems should ideally be able to correct for these factors. However, our results have shown that this is not trivial in the case of thumb length. Models trained on similar users yielded no improvement, while personal models were able to correct for some of the touch error. One potential explanation for this is that more data is needed. For example, for most thumb lengths we only had data from one participant. Furthermore, thumb length information might need to be augmented with additional data, such as the current grip or the phone's orientation, to have predictive power.

However, the larger issue with correcting for touch error is that information on the overall error is not sufficient. While we have shown that touch error increases with thumb length, the corresponding offset can be in any direction. There are overall trends (as shown in Figure 6), but individual differences seem to make applying one user's offsets to another infeasible. Yet, this does not mean that knowing about a user's hand size is of no benefit to an application. For example, buttons could be uniformly scaled to be bigger for people with larger hands or fit more buttons for people with smaller hands. The *direction* of the offset in that case would not matter.

Finally, while our results show correlations of hand size with touch error, they do not necessarily imply a causal relationship between the two. Unfortunately, the nature of this kind of investigation makes it impossible to only vary one factor. For example, as hand measures strongly correlate, participants with longer thumbs will also have larger hands in general. As more work on touch input occurs we can better understand how individual factors influence each other and the resulting touch accuracy. With this work, we contribute additional data on hand size influences, yet cannot claim overall causal relationships just based on that.

7 CONCLUSION

We have investigated the influence of hand size on touch input. Thumb length in particular impacted touch accuracy, explaining about 12 % of the variance. Furthermore, we have shown how measures of higher level touch interactions, such as swipes, also correlate with thumb length.

The detected influence of thumb length varies by user, complicating correction for the touch error. However, our investigation further adds to the understanding of touch and what aspects of the technology and the user impact touch input. While correction for touch errors is currently mostly done with black box machine learning models, we hope that in the future a better understanding of *why* these errors occur will allow for adaption of touch interfaces on a more fundamental level. This paper contributes to this understanding.

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