Inferring Input Hand from Index Finger Interactions

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ABSTRACT

In this project a large amount of touch data was collected from 15 participants performing index finger touch interactions on a tablet device. By analysing this data I was able to find three touch parameters that differs, depending on whether the left or the right index finger is used for touch interactions. The most distinctive touch parameter is horizontal touch offsets, which takes place among all type of users (left/ right handed) and targets (occluded/non-occluded). Using a simple comparison of horizontal touch offsets mean values, I was able to classify for input hand with 93.33% accuracy on per session basis. The approach for inferring input hand proposed in this report can easily be implemented into a code of the existing touch applications.

Author Keywords

inferring input hand; index finger touch interactions; touch bias; finger slide; touch interaction time; input hand classification; handedness; touch interactions on a tablet device

INTRODUCTION

Nowadays capacitive touchscreens are the dominant input device for smartphone and tablet devices. While being quite precise and intuitive for direct user manipulation (e.g tap, drag, slide gestures), touch devices lack awareness about the context and settings they are being used within. One of these basic types of awareness that modern devices are still missing is the ability to know which hand is being used to interact with the device.

This missing knowledge can be beneficial in a number of situations. One of these is self-rehabilitation applications. Recent study performed by Knoche et al. [16] have achieved some promising results in the self-rehabilitation process of people with unilateral spatial neglect, which is a deficit in attending to a certain side of the visual field (caused by a stroke). One of the main requirements for this type of self-rehabilitation applications, is the ability of the system to control for the input hand, which is important if the missing brain functionality have to be restored. Having a system that can track for input hand dynamically and make participants aware if any mistakes occur, would make the self-rehabilitation process more effective for the patients and in the end also cheaper for the health care system.

Crowdsourcing is a field of study that can also benefit from knowing which hand is being used and in what context. Crowdsourced studies [12, 17] gathered large amounts of touch data from thousands of participants who downloaded the applications. However lack of knowledge about how these applications were used (e.g right/left hand, index/thumb interactions etc.), reduces the potential use of the data.

This project is seeking to fulfill missing knowledge about possible approaches for inferring input hand when using touch devices. As there are many different ways for interacting with smartphone and tablet devices (e.g thumb vs. index finger interactions), the scope of this project is limited to index finger interactions on tablet device, due to relevance for the industry and lack of scientific knowledge about finger data produced on this particular type of device.

RELATED WORK

In order to better understand the subject of hand classification when using touch devices, I introduce basic terminology used in this report to describe touch events and their properties. Afterwards, an overview of possible parameters produced by a finger touch is presented followed up by a short analysis of the previous studies that managed to infer input hand when using touch devices.

Understanding Touch

The following sections is going to introduce basic terminology used in this report to describe different properties and events related to touch.

Touch interactions are taking place on a two-dimensional plane surface (most often LCD screen). Therefore to describe the position of a touch, *X* and *Y* coordinates are being used (Figure 1).

Each touch event is taking place over a period of time and consists of several states. Wang et al.[24] have categorized a touch event into three states: *Land On*, *Stable* and *Lift Up*. *Land On* is taking place when a finger first touches the screen, and the system registers the initial coordinates of the touch. The deviation from these initial *Land On* coordinates to center of the target is referred as *Touch Bias* (or X_{bias} and Y_{bias}). I also use notion of *horizontal* and *vertical touch offsets* to

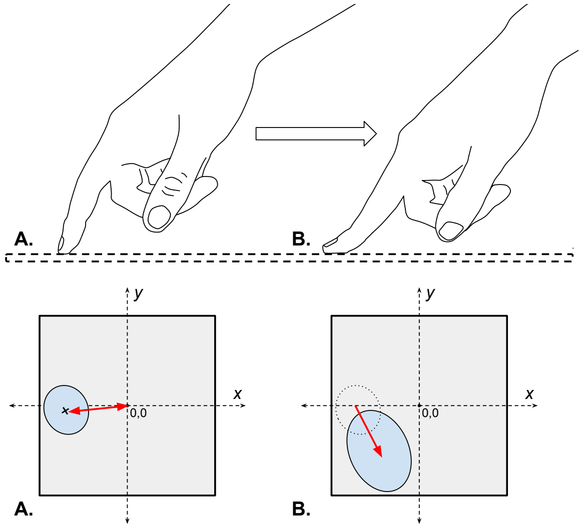

Figure 1: **A.** *Land-on* touch state, where touch bias (red arrow) appears **B.** *Slide Motion* caused by *Stable* touch state

describe a similar concept in the report (See Figure 1.A). *Stable* (Figure 1.B) refers to a state where the finger is stably in contact with the touch surface. This state can vary from a few milliseconds to a few seconds, depending on type of touch, target size, users' experience and other factors. *Lift Up* is the last state of touch, meaning the finger lifts up from the touch surface and the interaction process is interrupted.

The distance the finger travels from the initial land-on coordinates to the position where the finger is stabilized or/and lifted up is referred as *Finger Slide* or X_{Slide} and Y_{Slide}. Finger Slide can take place because a user is intentionally dragging his/her finger (e.g to perform a certain gesture), or because of the change in the finger posture (see Figure 1).

Previous studies [24, 25] distinguished between two specific types of touch, *vertical* and *oblique*. Vertical touch (Figure 3.A) is a 90°touch, meaning the input finger is perpendicular to the touch surface. Oblique touch (Figure 3.C) is approximately 15°, and requires full finger pad for the interaction. While vertical and oblique touches are distinctive from each other visually and in terms of data produced (see section *Contact Area and finger Posture*), these are not the most common type of touch for interaction with capacitive touch screen devices. Vertical touch is problematic for people with longer nails and can also be painful to perform over a long period of time. Oblique touch uses large finger area for the interaction, which makes it less accurate for target acquisition tasks (e.g typing on a virtual keyboard). Therefore to describe a touch "in-between" vertical and oblique I use notion of *45°* touch or *regular touch* (Figure 3.B). This type of touch refers to regular touch interactions on capacitive touch screens.

Finger Properties

Finger properties has been extensively studied on Vision-Based touch systems [24, 23, 25, 1]. Compared to capacitive touchscreens, vision-based systems (e.g FTIR [11]) are capa-

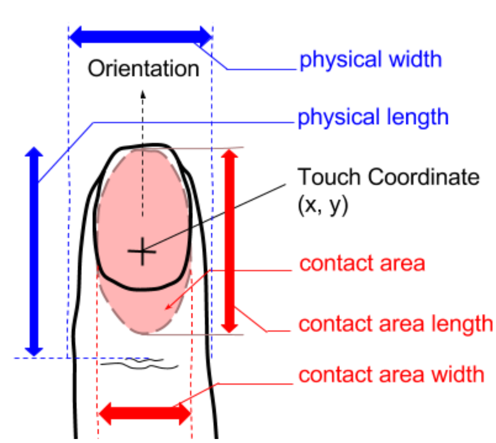

Figure 2: Available finger input properties. The image is re-drawn from the original report [24]

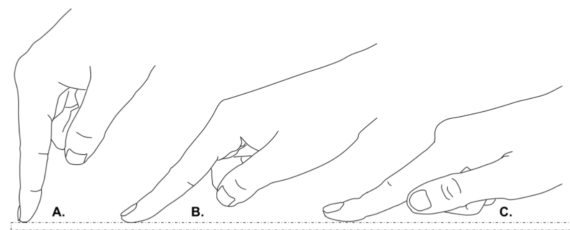

Figure 3: Three different variations of touch A) *vertical touch* B) *45°touch* or *regular touch* C) *oblique touch*

ble of providing much higher resolution of a fingertip due to a camera observing and registering all touch interactions below the touch surface. This approach makes it possible to obtain shape, size, orientation and intensities of a touch event. The findings has been used to improve multi-touch interactions [7], create new interaction techniques [23] and to understand touch behavior in general [24].

Studying finger properties on capacitive touchscreens has been done mostly in a context of input-improvement [12, 3] where systematic touch offsets has been discovered, though these offsets has only recently been linked to left or right hand use [16].

Contact Area and Finger Posture

Using FTIR system, Wang et al. [24] have identified several important properties of a finger touch such as *contact area, contact shape* and *contact orientation* (Figure 2).

Furthermore two different types of touch events were described- *oblique* and *vertical* touch (Figure 3). Besides having a quite distinctive finger postures while performing one of the two gestures, each of them have a different touch area.

The area of oblique touch is at least 5.5 times larger than the area of vertical touch. When a finger is in oblique touch state, the average width of the contact area is approximately

90% of the fingertip's physical size and the average length of the contact area is approximately 70-80% of the fingertip's physical size. In contrast to that the contact area of a vertical touch is approximately 30-40% of the fingertip's physical width and length.

On capacitive touch devices it is currently not possible to obtain precise touch area as it was done on visual-based touch systems. Android OS uses a function *getSize* to report approximation of the area of the screen being pressed. *"The actual value in pixels corresponding to the touch is normalized with the device specific range of values and scaled to a value between 0 and 1"* [9].

Finger Orientation

It has been argued [23][26] that Finger Orientation (FO) only can be obtained from an *oblique* touch, unless some extra hardware is being used to observe the input hand, e.g Zhang et al. [25] study. Wang et al. [23] considered the dynamics in the landing process of a finger to obtain Finger Orientation. They discovered geometrical patterns that appeared when the user's finger was landing on a touch surface (in order to initiate certain touch interaction). First the fingertip got in contact with the surface, as the fingertip move into *stable* state, the contact area increases hence the center of the contact region shifts inwards, towards the user's palm (similar concept can be seen on Figure 1). This geometrical pattern could only appear if an *oblique* touch was used for the interaction.

Using this knowledge an algorithm was deployed, which first searches for *oblique* touches (using area measurements described earlier) and then it predicts FO according to the deformation process of the finger's center contact. The final study indicated reliable performance of the algorithm (FO recognition rate was 96.7%). Later Zhang et al. [25] have rejected the idea of finger landing pattern, as they found it unintuitive and unreliable without extensive user training. Roughly 20% of their trials resulted in inverted finger orientation, meaning the landing pattern was moving upwards instead of inwards towards the user's palm.

It is unknown whether there is landing patterns when users are interacting with touchscreen mobile devices. Furthermore there have been no studies found that managed to achieve FO on capacitive touch devices.

Touch Precision and Offsets

Due to a relatively small screen size, there has always been a great interest in enhancing touch precision of mobile devices. Multiple factors are affecting touch precision, like shape [5] and size of target [6], possible occludens of the target and odd shape of a finger (fat finger problem) [13], acquisition time to the target, target location in relation to screen borders [5, 20] and to other targets [15], finger posture [14], posture of the user (e.g sitting vs standing [10, 22]), tilt of the screen [5, 18], parallax [4] and ocular dominance, feedback from the target [5] (e.g whether the target is hit or not), fine motor skills of the user, possible vision impairments and other factors. Despite knowing a lot about finger touch, all the factors that contribute to touch accuracy are still not fully known.

Previous studies [5, 12, 3, 13, 16] have reported a systematic touch offsets in target acquisition tasks. The offsets are related to *Land On* event, meaning they appear when users' finger is landing on the screen. Azenkot et al. [3] found that user touches have a tendency to land below the key centers when they were typing on Android virtual keyboard. Furthermore they found that horizontal offsets were more pronounced than vertical. When the index finger was used for typing tasks, 19 out of 27 virtual keys (including space key) on a smartphone had touchpoint centers close to the right side of the key, indicating positive x-axis offset. For all three hand postures (single thumb typing, two thumbs typing and index finger typing) tested in the study, offsets were greater in magnitude on the left side of the keyboard than on the right. Additionally touch point spreads for keys were larger in the x-axis than in y, despite the fact that keys are much taller than they are wide. Azenkot et al. does not provide any explanation for this touch offset phenomena, however since right handed people were mostly represented in the study (31 out of 33 participants) and participants were only interacting using their right or both hands, it can be hypothesized that choice of input hand had an effect on touch offsets reported in the study.

Holz et al. [13] showed that both vertical and horizontal offsets are affected by *pitch* and *roll* of a finger. Pitch refers to the angle the finger is approaching the screen, e.g oblique and vertical touches mentioned earlier are just two variations of a pitch (15 and 90 degree). Roll refers to a part/side of the finger pad that is pressing the target (also measured in degrees). Despite showing the relationship between these two parameters and touch offsets (both in x and y axis), it is still unclear how much each of the parameters are contributing to touch offsets. The offsets vary among the participants which according to the authors was due to a individual mental model each person has about their own touch performance. This mental model is as unique to a person as their gait or handwriting and could potentially help identify a individual's touch performance from a number of different options.

Beringer et al. [5] described the effect of handedness on horizontal touch offsets. In their study right-hand dominant participants touched 3.175x3.175mm targets slightly to the right of the targets, whereas left-handed participants did the opposite. Beringer et al. addressed the problem to initial group differences (handedness) and not to feedback/training effects they were testing for in the study.

Knoche et al. [16] were the first who linked horizontal touch offsets directly to input hand. They made a tablet-based game Whack-a-mole (WAM) as an attempt to improve self-rehabilitation process among patients with unilateral spatial neglect (difficulty attending to one side of the visual field). To test the application they conducted a four week study where 43 patients were playing WAM on a daily basis. In order to spot input anomalies Knoche et al. were logging both horizontal and vertical touch offsets (X_{bias} and Y_{bias}). By analyzing these touch offsets, they were able to link rightward bias ($X_{bias}>0$) to right-hand touch interactions, and leftward touch bias ($X_{bias}<0$) to left hand touch interactions.

User Specific Behavior

Kolly et al. [17] showed that touch behaviour was user specific. They were inspired by Holz et al. [13] work who stated that *"the inaccuracy of touch is primarily the result of failure to distinguish between different users and finger postures, rather than the fat finger problem*". Using a crowdsourcing approach, the authors deployed a quiz-game on the Play Market in order to collect large amount of data for the analysis. More than 3 millions data samples were collected from more than 14.000 players around the world. To prove that touch data is user specific, a Bayes classifier was comparing one portion of data from a certain participant against multiple other options to find the similarity. The classifier was using mean and maximum pressure of touch events, point in time when a maximum pressure occurs, duration of touch events, mean *X/Y* positions and the variance of the touch event in *X* and *Y* direction. The classifier performed best when it had to find a correct person out of five different options (more than 80% predictions were made correctly). When the number of possible options/users was increased to ten, it affected predictions in a negative way (68% correct predictions).

Inferring Handedness on Touch Devices

Table 1 shows the previous studies that managed to infer input hand from touch interactions. Most of the studies [25, 2, 19, 26] were inferring input hand from a single touch interaction. This often comes at cost of not being able to control for input hand after it has been classified. Au et al. [2] required participants to use all five fingers on the tabletop in order to initiate hand classification process. The system was then measuring the distance and spanning angle between different touch points to classify for input hand. Löchtefeld et al. [19] were using screen unlocking procedure on Android smartphone to obtain input hand. When users were unlocking the device, they produced a distinctive sensory data for each hand (accelerometer measurements, device orientation, and touches). By using k-nearest classifier it was possible to classify for input hand by comparing new input data to previously recorded where input hand was known.

Studies [25, 26] have been able to obtain input hand and track it consistently. To do that they were using Finger Orientation, which is currently impossible to obtain on capacitive touch devices.

Another approach proposed by Goel et al. [8] requires the user to hold the device (a smartphone) in one hand and use the thumb of the same hand for touch interactions. This makes the approach impossible to implement on tablet devices.

The only known study that has managed to infer input hand when using a tablet device is the study performed by Knoche et al [16]. The authors used touch data collected from a four week study (see section *Touch Precision and Offsets*) to classify for input hand. This touch data was classified according to the mean values for horizontal touch offsets (X_{Bias}). If the offsets were positive ($X_{Bias}>0$), then right hand was used in the session (which lasted eight minutes), if the offsets were negative ($X_{Bias}<0$), then left hand was used in the session. The approach proposed by Knoche et al. has potential to be able to track for input hand in real time and perform new hand classification when the input hand has been changed (e.g due to fatigue). Despite promising results, it is unknown how many touches are required to perform classification. Furthermore the study required participants to perform touch interaction as fast as possible, which may had an effect on horizontal touch offsets. An additional study would be beneficial, in order to see how many interactions are required to perform a successful hand classification and if it is possible to achieve the same results when the interaction pace is decided by the participants.

THE EXPERIMENT

Purpose and Motivation

The main goal of the experiment is to collect as many different types of measurements, produced by the touch of a finger, as possible in order to see how these can be used for hand classification tasks. Most of the previous studies were only considering the *"Land On"* touch state, but there is more data being produced after a finger has landed on a touch surface. Potentially, this data can consist of some systematic offsets or vectors related to a certain input hand that has not been described before. Therefore in this experiment I am looking for finger parameters that are distinctive from hand to hand, from dominant to non-dominant hand or they could also be related to personal behavior, e.g mental model described by Holz et al. [13].

Another goal of the experiment is to verify previous findings regarding touch behavior in general. From the previous studies, we can expect that people will hit the targets slightly below midpoint. It is also expected that the participants' dominant hand would outperform the non-dominant hand in terms of accuracy, e.g right hand-dominant participants will have fewer target misses using right hand compared to left hand. I will also test two different type of touch events- an *oblique touch* and a *regular touch*, in order to see which type is better suited for hand classification task. And finally, I wish to verify systematic touch offsets related to left or right input hand reported by Knoche et al. [16] and how these differs between targets that are occluded (6x6mm) by the users finger when touching and non-occluded (20x20mm and 20x30mm) targets.

When all the parameters and data patterns has been described I will show their potential for hand classification using two different methods- Support Vector Machine classifier and comparison of touch bias mean values. Additionally, I will also identify one of the factors that affects the size of touch offsets, which is hand motion that takes place when input hand is moving from one target to another.

Experiment design

Three different test conditions were designed to acquire different type of touch data for the analysis. Each test condition have a number of buttons equally distributed across the screen. Arrangement of the buttons can be seen on Figure 4.

Condition 1 - Oblique Touch Condition- (OBLQ.T)

In this test condition a participant was required to activate all buttons using a flat fingerpad (see Figure 3). It is hypothesized that this type of touch will produce more *finger slide* compared to a regular touch, furthermore it is expected that this

Table 1: Literature table of the previous studies that has managed to infer input hand from touch interactions.

	body part(s)	device	acquired data	sensor(s)	constraint	acc.
Zhang [25]	index+hand	tabletop	touch + hand	camera	45°, oblique	90%
Au [2]	hand	tabletop	distance + angle	camera	5 finger touch points	97%
Löchtefeld [19]	thumb,index	phone	unlocking gesture	capacitive	one-handed	98%
Zhang [26]	finger(s)	tabletop	finger orientation	camera	oblique touch	91%
Goel [8]	thumb	phone	touch size, swipe shape, device y-axis motion	capacitive, gyro.	one-handed	84%
Knoche et al.	index	tablet	X_{bias}	capacitive	index finger interactions	95%

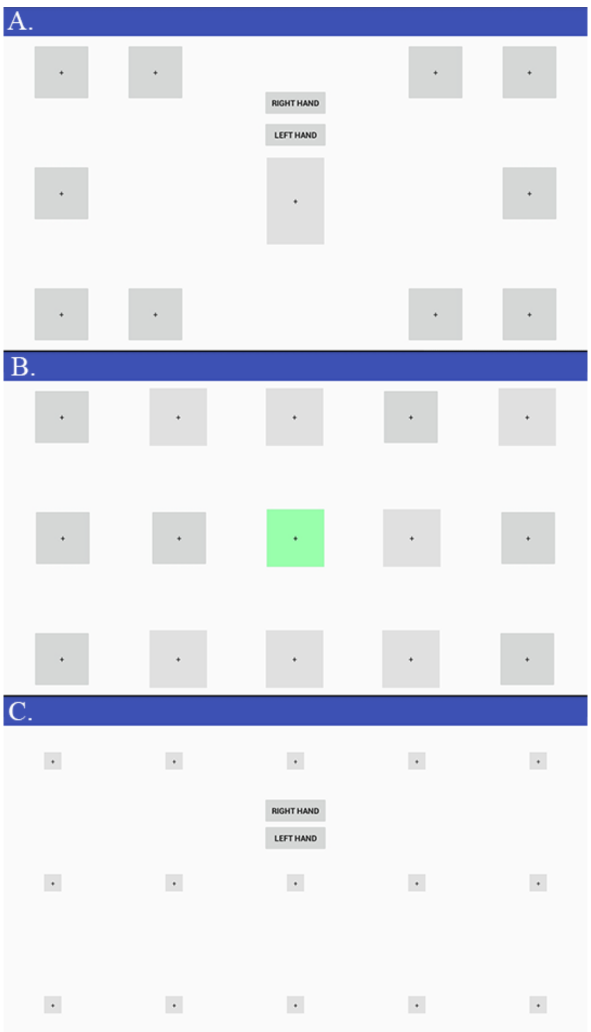

Figure 4: Three different application interfaces for the experiment A) *Oblique touch* condition B) (20mmx20mm) *Regular touch* condition C) (6mmx6mm) *Regular touch* condition.

type of touch will be less precise due to a larger finger area, which makes it harder to center a touch point accurately. A larger variation of data points (compared to other experiment conditions) could be a proof for this assumption.

Condition 2 - Regular Touch, 20x20mm targets- (20x20)R.T

In this test condition users are required to interact with the targets as they would normally do. Sixteen (20x20mm) targets were evenly distributed across the screen for that task. Target size is chosen because it is easy to interact with for most people, furthermore this target size is not occluded by the index finger during interaction process.

Condition 3 - Regular Touch, 6x6mm targets- (6x6)R.T

This test condition is similar to the previous one, except that the targets are now reduced to 6x6mm size. This makes interaction process more challenging in terms of precision as smaller target will get occluded by the fingertip, making it harder to predict the position of the target. In this situation, participants will likely rely on their individual mental model described by Holz et al. [13] For this condition it is expected that the occludens by the index fingers and smaller size of the targets will lead to a much higher number of errors/misses compared to other conditions in the experiment.

The three conditions for the experiment are designed to test both left and right hands. Every time a participant begins a new session (each condition consists of two sessions) in the experiment, they must chose input hand- otherwise the experiment will not start. When input hand has been chosen it will automatically initiate the selection process, meaning that a participant must click on series of targets in order to complete the session. The targets that require activation from the user are highlighted with green colour (See Figure 4, B), only one target at the time can be highlighted. After the required target has been selected it changes the colour back to default (grey colour), and provides auditory feedback (a short "click" sound) indicating a success selection. If the target is missed, there is another auditory feedback indicating an error and the target will continue to highlight until a success selection has taken place.

All 16 buttons in (20x20)R.T and (6x6)R.T conditions 'highlight' the same amount of times in each session (6 times per button). The order for choosing a new target that requires activation is completely randomized. In contrast to that the

OBLQ.T condition is semi-randomized, meaning the participants must activate the middle button first, and afterwards they must activate one of the side buttons (which are randomly chosen), this is followed up by activation of the middle button again and so on. This means that 50% of all registered touches in OBLQ.T condition are going to land on the middle button, while the remaining 50% are going to be equally distributed across the remaining buttons (still in a random sequence but equally distributed). OBLQ.T condition was originally designed to test for physical differences between left and right index fingers, however due to some technical problems in the experiment, the condition has been changed to test for oblique touches.

Software and Equipment

This project is using the Android platform for implementation and testing. For the testing device I chose to work with Asus Transformer Pad TF300T. The device has 10.1 inch 1280x800 IPS screen, screen density of 149 pixels per inch (ppi), 1GB RAM and 1.2 GHz NVIDIA Tegra 3 quad-core processor. The device is running on Android version 4.2.1 (API 17).

Logging Data

For each touch event that take place on the screen, the system is logging following parameters:

- *Touch ID*
- *X-Coordinate* of touch
- *Y-Coordinate* of touch
- *Interaction Time*
- *Touch Area*
- *Current/ Previous Target*
- *Hit/Miss* (if the target was hit or not)

Data from each condition and session is logged into a separate txt file.

Procedure

Before the experiment, each participant was asked about his/her preferred handedness in order to ensure a balanced number of participants represented in the study. The experiment took place in an isolated location where only one participant was present at the time, together with the test facilitator. Each participant was asked to fill out a short questionnaire investigating their gender, age, preferred handedness, education, experience with touch devices and currently owned touch devices. After completing the questionnaire, the person's index finger was photographed while lying on a piece of graph paper in order to measure the finger's length and width. The length was measured both for the pad and for the nail side (to see if the nail is extending beyond the finger).

Physical setup of the experiment can be seen at Figure 5. The height of each participant was measured from the floor and up to the eyes, an office chair was used to adjust for the correct height. The tablet device was "anchored" to the table using sticky tack in order to avoid any tilting or other unnecessary motion e.g if a participant was pressing too hard. For each new condition in the experiment, the screen of the tablet was cleaned- as finger marks can affect touch performance of the device. The order in which different conditions and hands appeared in the experiment was randomized to prevent any learning effects.

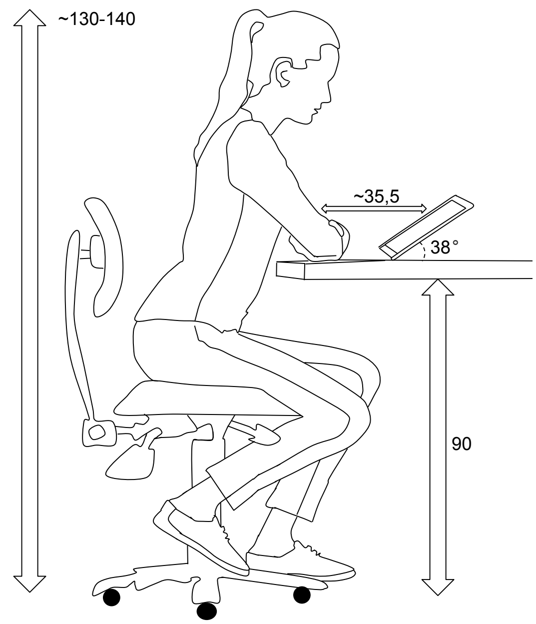

Figure 5: Setup of the experiment, all the measurements are provided in centimeters and degree.

In order to complete all three test conditions, each participant was required to perform a minimum of 480 correct button activations using left and right index fingers. As result, the final data table is expected to consists of at least 7200 touch events (15 participants x 480 touches). Each trial in the experiment took approximately 15 to 20 minutes to complete including the questionnaire, all the measurements and adjustments.

Participants

15 participants (12 males) in age 20 to 29 (mean 24.46) attended the experiment. The participants were recruited at the university, meaning all of them were students. The main inclusion criteria was diversity in handedness meaning that both left and right handed people are represented in the experiment. As result, the experiment consisted of ten right hand dominant, four left hand dominant and one ambidextrous person. Since left handed people only represent approximately ten percent of the world population [21] , four participants were found sufficient enough to represent this minority group of people. Other criteria for choosing the participants was familiarity with touch devices, since the data from the users is used to estimate the average touch produced by an index finger. All of the participants in the study was the owner of a smartphone device, meaning they were used to interact with a touchscreen on a daily basis. Additionally to that most of the participants

rated themselves as experienced touch technology users (mean 7.2 out of 10), only three users (two right and one left handed) felt less confident with touch technology (rated themselves as 6, 5 and 3). The physical size of the index finger was recorded for each participant in the experiment. Three different measurements are associated with the finger size- finger pad length, nail side length (e.g if a nail is extending beyond the finger) and finger width. The average finger pad length in the experiment was 27.16 mm and the average width of the finger was 18.83 mm. Six participants (one left hand-dominant and five right hand-dominant) had their nail slightly extending beyond their index finger (from 0.5 to 1.5 mm).

RESULTS

The following section is going to describe the experiment results. First a short overview of the data collected during the experiment is presented, followed up with logistic regression describing the parameters that are significantly different in relation to left/right index fingers. Afterwards these parameters will be tested for hand classification task, using support vector machine classifier (SVM) to see which condition and set of parameters are best suited for hand classification task on per touch basis. Finally, I will show how input hand can be inferred effectively using a small number of touch interactions and a method that does not require any machine learning, solely relying on mean values of horizontal touch offsets (X_{bias}).

The Data

During the experiment 47576 data samples were collected for 6598 touch events (including misses and wrong selections), this corresponds to 7.2 data samples per touch event. All 15 participants involved in the study went through all three conditions in a randomized order. However due to some technical problems, the data for three left handed participants and one ambidextrous was excluded from OBLQ.T condition. As result, OBLQ.T condition contains data for only 11 participants (two left handed), which corresponds to 2654 touch events. Conditions (20x20)R.T and (6x6)R.T have all 15 participants included in the study, and contains 1801 and 1810 correct touch events, correspondingly (misses and wrong selections are excluded from all conditions).

Touch Precision and Errors

It was expected that the button size used in OBLQ.T and (20x20)R.T conditions would result in a much smaller number of misses because targets are not-occluded by the index finger interaction. This assumption turned out to be true as OBLQ.T condition has 0 % misses and (20x20)R.T condition has 0.49% misses while (6x6)R.T condition has 14.44% misses indicating some accuracy problems among most of the participants see Figure 6.

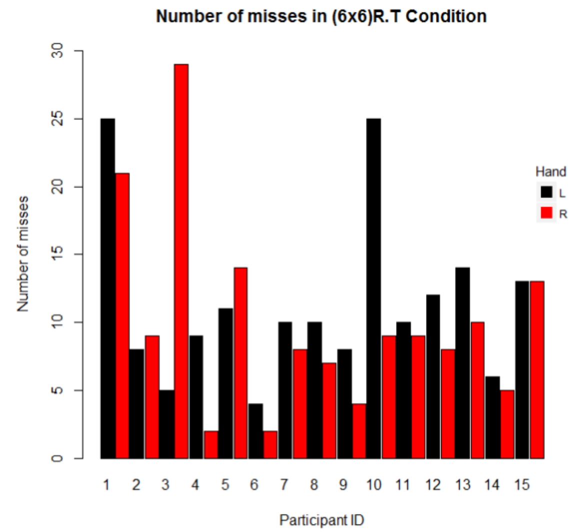

Figure 6: The number of errors is almost equally distributed across both hands- 47.05% of misses were produced by the right hand, remaining 52.95% were made by the left hand.

Besides looking for the imprecise touch events, I was also looking for the situations where participants have a clear representation of the required target, but instead chose some other target on the screen. I refer to these situations as *"wrong selection"*. While in (20x20)R.T and (6x6)R.T conditions the problem of wrong selections is not that significant (0.22% and 0.61% of all touches) in OBLQ.T condition 5.2% of all touches (corresponds to 146 touch events) were related to a wrong selection. This problem can be addressed to the design of the condition, which has a repeating pattern of the middle button activation followed by randomly assigned side button (see section *Experiment design*).

When looking at the distribution of the hands, the left hand produces 3.4 times more often a wrong selection compared to the right hand (L(113) - R(33)). The majority (72.6%) of all wrong buttons selections were related to the middle button activations.

Activation Time

As can be seen from Table 2, *MaxTime* is a significant parameter for all three conditions. The longest interaction time is taking place in OBLQ.T condition, due to a more complex touch gesture required from the participants to perform. Besides that the condition requires a higher number of touch interactions in order to complete the condition (240 vs. 120 touches in the two other conditions). A larger amount of touches could potentially have caused fatigue among some participants, which would then affect the interaction time of these participants.

Besides that I found an effect of target size on the duration of touch interactions. Occluded target in (6x6)R.T condition force participants to interact for a longer period of time, compared to non-occluded targets in (20x20)R.T condition. This is most likely due to lack of visual feedback from the occluded targets, meaning that participants must rely on the auditory feedback from the tablet. A smaller target size would also require a higher touch precision, which often takes longer time to perform.

Table 2: Logistic Regression show parameters that are significant in relation to input hand being used for the interaction (left or right). Results are based on 15 participants (10 right-handed, 4 left-handed and 1 ambidextrous).

Predictor(s)	Condition	z value	Pr (>|z|)	NonDominant.H (SD)	Dominant.H (SD)
X_{Bias}	OBLQ.T	9.87	<0.01	-0.09 mm (2.7)	0.42 mm (2.5)
$MaxTime$	OBLQ.T	-7.26	<0.01	179.9 ms (109.7)	146.7 ms (75.1)
$_{Max}X_{Slide}$	OBLQ.T	6.87	<0.01	-0.36 mm (3.1)	-0.18 mm (2.7)
X_{Bias}	(20x20)R.T	9.20	<0.01	-0.49 mm (2.7)	0.29 mm (2.5)
$MaxTime$	(20x20)R.T	-6.34	<0.01	122.4 ms (38.4)	104.3 ms (32.6)
X_{Bias}	(6x6)R.T	7.78	<0.01	-0.30 mm (1.38)	0.17 mm (1.23)
$MaxTime$	(6x6)R.T	-6.72	<0.01	168.3 ms (65.9)	132.9 ms (55.6)
$_{Max}X_{Slide}$	(6x6)R.T	-5.45	<0.01	-0.22 mm (0.64)	-0.33 mm (0.48)
$_{Max}Y_{Slide}$	(6x6)R.T	-2.91	<0.01	-0.42 mm (1.3)	-0.17 mm (0.47)

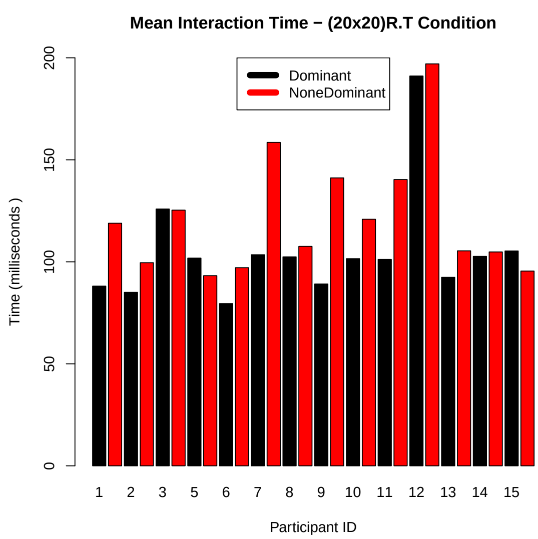

Figure 7: Interaction Time (*MaxTime*). Participants (1, 2, 3, 5) are left-handed, participant 4 is ambidextrous (not included), the remaining participants are right-handed.

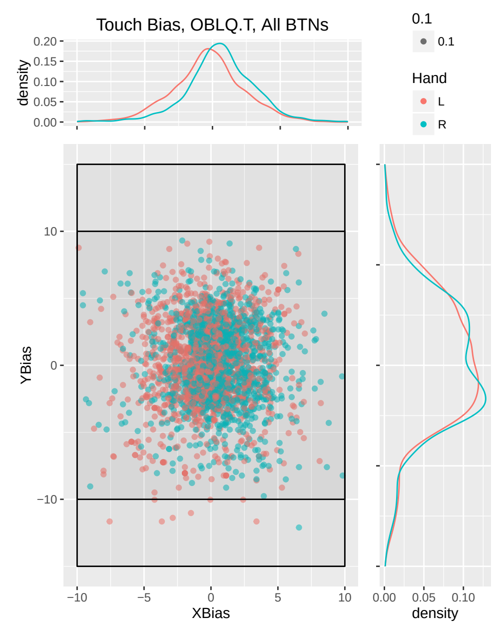

Figure 8: Finger landing pattern (*Land-on* touch state), OBLQ.T (All BTNs)

Table 7 shows that interaction time is more related to preferred handedness, rather than the use of left or right hand. In general, a dominant hand is interacting significantly faster than a non-dominant hand. E.g only three participants (p3, p5 and p15) have a higher interaction time with their dominant hand in (20x20)R.T condition (see Table 7). Furthermore (p5) stated before the experiment that he is a left handed person, but when it comes to use of electronic devices (phone, tablet etc.) he is normally using his right hand for the main interactions.

Touch Offsets

Figures 8, 9, and 10 show a distinguishable horizontal *Land On* pattern for both left and right index finger in all three experiment conditions. The most distinctive horizontal offsets are found in (20x20)R.T and (6x6)R.T conditions while the less distinctive are found in OBLQ.T condition (see Figure 8).

It is believed that finger posture and target size (which often forces people to change their finger posture) have an effect on touch offsets.

Looking at the Standard Deviation for horizontal offsets (Table 2), we can see that offsets vary more for a non-dominant hand meaning participants are more confident/skilled to use their dominant hand for touch interactions. This seems logical, as all participants in the experiment own touch devices and use them on a daily basis, meaning a dominant have a more 'established' approach on how to interact with a touch surface.

Using logistic regression analysis (Table 2) I found horizontal offsets to be the most distinctive parameters for hand classification task in all three conditions. And as regular touch conditions have the lowest variation of data and the most distinctive horizontal touch offsets, I expect regular touch conditions to outperform oblique touch condition in hand classification task (when horizontal touch offsets are solely used).

Vertical touch offsets are not related to input hand or handedness. However participants have a tendency to hit the targets slightly below the midpoint in the regular touch conditions. For the oblique touch condition, participants hit the targets almost perfectly in the middle.

Mean vertical touch bias (Y_{bias}) for each conditions is:

- 0.04mm, SD (3.24) - (OBLQ.T)
- -0.42mm, SD (2.77) - (20x20)R.T
- -0.34mm, SD (1.37) - (6x6)R.T

Effect of Hand Motion on Touch Bias

Hand motion in the experiment is represented in degrees (see Figure 14). I chose to split hand motion in nine different categories as some of the motion angles had a small number of data samples represented in the study due to a randomized order for choosing targets in each condition.

The nine hand motion categories are:

1. Up (270°), down (90°), left (180°), right (360°) - these four basic types of motion are the most common motion types in all three conditions.
2. Up-Left-Diagonal, Up-Right-Diagonal, Down-Left-Diagonal, Down-Right-Diagonal - these four types are estimates of all the motion "in between" the four basic types mentioned previously. This means that the angles for (20x20)R.T and (6x6)R.T are slightly different due to a random appearance of the required targets in each of these conditions.
3. *0 Motion* or double tap- is a situation where participants are required to interact with the same target as they did previously.

Besides the approach angle, the knowledge of the input hand is also important and whether the input hand is moving away from the body (e.g right hand goes right/ left hand goes left) or whether the input hand is moving towards the body (e.g right hand goes left/ left hand goes right). I chose to classify these two concepts as motion into *ipsilateral* and *contralateral* direction. (see Figure 11).

Figures 13 and 12 show that both horizontal and vertical touch offsets changes according to the angle the input hand is approaching from. Furthermore the results for each condition are different. In (20x20)R.T condition the largest spread between left and right horizontal touch offsets is for *0 Motion* situations and for situations where the input hand is going *90°Down* or into *Ipsilateral* direction. The smallest horizontal spread is found for motion into *Contralateral* direction. For (6x6)R.T condition the results are the opposite. The smallest horizontal touch bias spread is found for the *0 Motion)/ double tap* situations, for the situations when participants are going *Upwards*, or into *Ipsilateral Direction*. The largest spread is found when motion into *Contralateral* direction is taking place.

A large spread between left and right horizontal touch offsets is important for the hand classification task. Therefore in order to obtain the most distinctive touch offsets for (20x20)R.T condition, it would be beneficial to include repetitive targets (*0 motion*) or to place the targets into *Ipsilateral* direction).

For (6x6)R.T condition, it would be beneficial to include hand motion into *Contralateral* direction in order to obtain the most distinctive horizontal touch offsets.

For both (20x20)R.T and (6x6)R.T conditions, vertical touch offsets are mostly affected when participants are either going 270°*Up* or 90°*Down*. When participants are going 270°*Up*, their touches will land below the target midpoint. While 90°*Down* hand motion make touches land more in the middle of the target.

Besides motion angles, I have also investigated whether the distance from one target to another had any effect on touch offsets, I was not able to find any evidence to confirm this theory.

Touch Slide

Touch slide motion occurred in all three experiment conditions. Table 4 show percentage of *Touch Slide X/Y* appearance for each condition in the experiment. The highest percentage of touch slides (per touch event) were found in OBLQ.T condition, where four out of five touch events contain slide motion. Furthermore Table 4 shows that oblique touch produces slide motion of more than double magnitude, compared to a regular touch.

The most common type of horizontal slide motion is *leftward* slide, more than half of touch events in all conditions are related to this type of finger slide. As can be seen from the Figures 16 and 17 *leftward* finger slide is more 'pronounced' when right hand is being used for the interaction. This is because the magnitude and appearance of the *leftward* finger slide are higher for the right hand in the regular touch conditions. The magnitude of *leftward* finger slide is on average 15% longer for the right hand in regular touch conditions and around 60% of all *leftward* finger slides are produced by the right hand interactions.

For the oblique touch condition the results are different, although *leftward* slide still is the most common horizontal slide, the magnitude of the slide is greater for the left hand (-2.24mm vs. -1.36mm) and appearance of this type of finger motion for both hands is almost equal (52% of *leftward* touch slides were made by right hand). I was not able to find the reason for why some of the finger motion went to the right and some to the left.

Looking at vertical axis of touch slides, (see Table 4) the participants had a tendency to go *downwards*, but *upward* finger slides also appeared in all three conditions. After analyzing how finger slide evolved over period of time (30 ms intervals and maximum duration of touch 300 ms) I was not able to find the reason for why some of the touch slides were going down and some were going up.

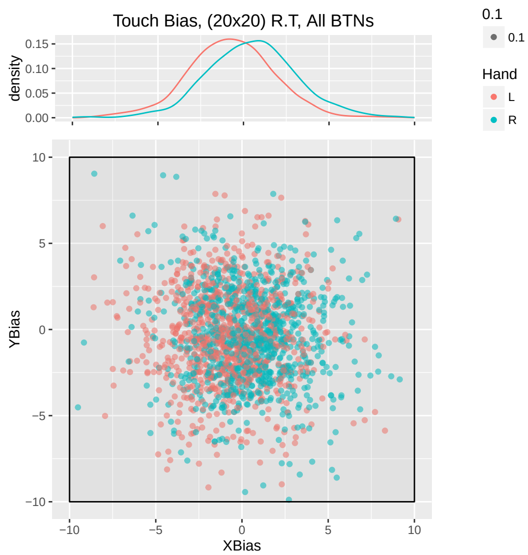

Figure 9: Finger landing pattern, (20x20)R.T (All BTNs)

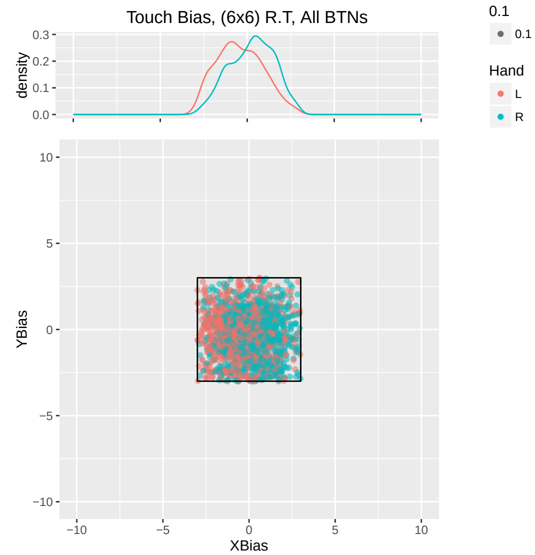

Figure 10: Finger landing pattern, (6x6)R.T (All BTNs)

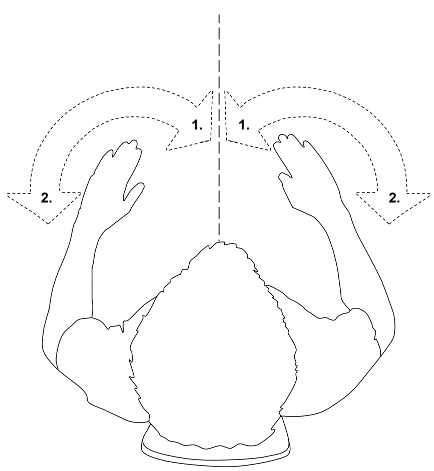

Figure 11: **1.** Hand motion into *contralateral* direction **2.** Hand motion into *ipsilateral* direction.

In each condition there is a large number of touch events (especially for the regular touch conditions) that contain zero vertical and horizontal touch slide (see Table 4). These touch events take on average much shorter time to perform. For OBLQ.T condition, zero-slide touch events take 41.57% less time to perform, compared to the mean time of the whole condition. For (20x20)R.T and (6x6)R.T conditions it takes 15.16% and 13.61% less time to perform a zero-slide-motion touch. The results show a correlation between interaction time (*MaxTime*) and finger slide motion parameters. Thus the longer time we interact with a target on a touch surface, the more slide motion we produce.

Finally, looking at Figure 15 we can see two distinctive diagonal slide patterns crossing each other. These diagonal touch patterns correspond to the overall finger orientations observed in OBLQ.T condition (see Figure 18). This means that theoretically it would be possible to extract FO from touch interaction on capacitive touch screen, although few oblique touches are required, as finger slide does not always appear for every touch event. Additional study is required to test for this hypothesis.

Effect of Hand Motion on Touch Slide

I have investigated the relationship between hand motion and touch slide. I was not able to find any proof that the size of touch slide is affected by the position on the tablet device where the interaction is taking place (e.g left/right side) or by the type of hand motion (*Ipsilateral/Contralateral*).

Hand Classification (Per Touch Basis)

I used Support Vector Machine (SVM) to classify for input hand on per touch basis. The classifier is designed for binary decision making tasks and is also used in the study [25] for

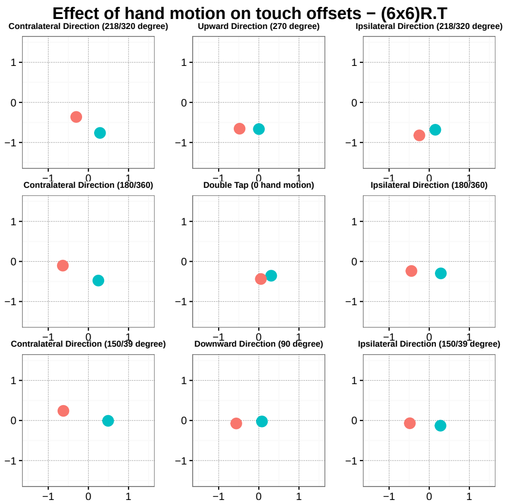

Figure 12: Effect of hand motion on touch offsets. Right Hand(Blue), Left Hand(Red).

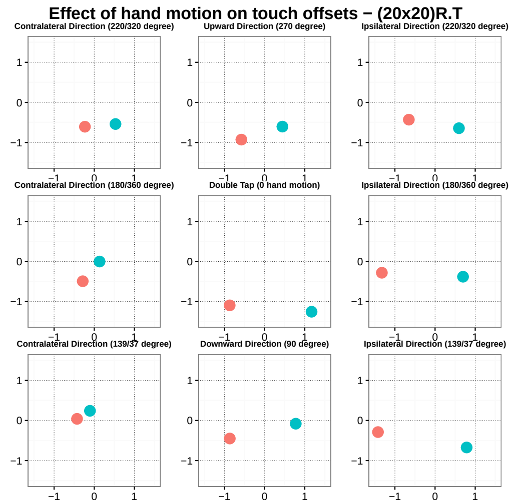

Figure 13: Effect of hand motion on touch offsets. Right Hand(Blue), Left Hand(Red).

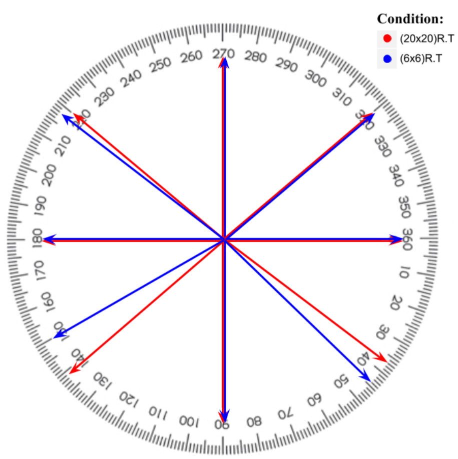

Figure 14: Hand motion angles in regular touch conditions used for the analysis. Angles are slightly different because of the randomized order for choosing targets in each condition. Blue arrow (6x6)R.T and Red arrow (20x20)R.T conidition.

inferring input hand. I have also tested *Naive Bayes* and *K-Nearest Neighbor* classifiers, but the best classification per touch basis was achieved using SVM classifier.

In order to train and test the classifier, the data set was split into a training set (70% of the data) and a testing set (30% of the data). For the prediction parameters I was using parameters that are found to be significantly different (for right and left hands) in the logistic regression analysis (see Table 2). Horizontal touch bias (X_{bias}) is tested solely for each condition as it is the most distinctive touch parameter found in this study.

In order to avoid imprecise estimations, I chose to run the classification process ten times, where I afterwards calculated the average results, which can be seen in table 3.

Regular touch conditions provide the best prediction results. It is believed that inaccuracy of oblique touch (caused by the larger finger area) is the main reason for why the predictions are worse for OBLQ.T condition.

In general, from the predictions results we can see that touch bias is the best parameter for predicting input hand in all three experiment conditions. Furthermore horizontal touch offsets provide flexibility, meaning they are effective to predict input hand with, in a variety of different situations and settings (e.g varying target sizes, gestures, users etc.). If we wish to enhance the prediction accuracy, interaction time (*MaxTime*) and Touch Slides are also good parameters to use. However there is a number of limitations for using interaction time as a parameter for predicting input hand. First we must know the interaction time for both hands of the same individual in order to predict handedness correctly. Second, we can only use interaction time for a small number of participants, ideally for a single person as the interaction pace differs from person to person, and is affected by a number of parameters (e.g preferred handedness, experience, task, etc.). And finally, *MaxTime* is not possible to use for predicting input hand if a

Table 3: SVM Predictions of input hand on a per touch basis

Condition:	**Prediction:**	$\mathbf{X_{bias}}$	***MaxTime***	$MaxX_{Slide}$	$MaxY_{Slide}$	***MaxArea***
OBLQ.T	61.31%	x	x	x		
OBLQ.T	60.29%	x	x	x		x
OBLQ.T	59.62%	x		x		
OBLQ.T	59.30%	x	x			
OBLQ.T	58.49%	x				
(20x20)R.T	61.15%	x	x			
(20x20)R.T	59.87%	x	x			x
(20x20)R.T	59.72%	x				
(6x6)R.T	62.52%	x	x	x	x	
(6x6)R.T	62.17%	x	x	x		
(6x6)R.T	61.53%	x	x			
(6x6)R.T	60.35%	x				

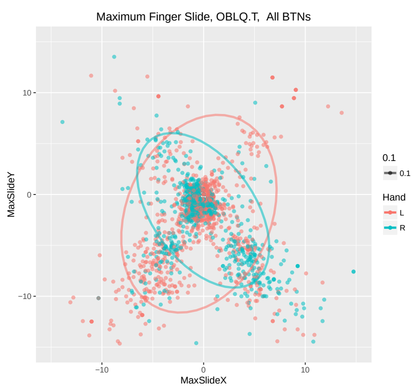

Figure 15: Max Finger Slide, OBLQ.T

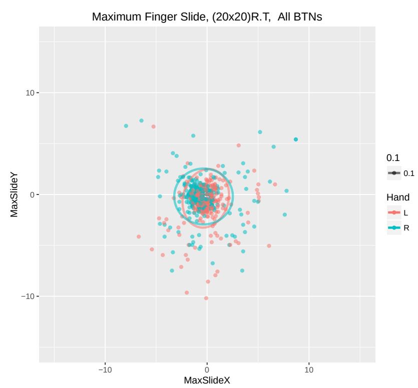

Figure 16: Max Finger Slide, (20x20)R.T

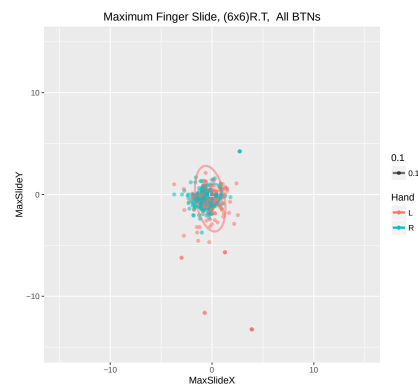

Figure 17: Max Finger Slide, (6x6)R.T

person is left hand-dominant or ambidextrous, since the results will be either "reversal" or close to be equal.

Hand Classification (Per Session Basis)

Besides performing classification on per touch basis, I have also performed classification on per session basis. I have compared two methods for classifying input hand.

First method uses SVM classifier and significant parameters found in the logistical regression analysis. Second method uses simple comparison of touch bias mean values from each session in order to establish input hand. If mean value is positive ($X_{bias}>0$) then input hand is being classified as right, if mean touch bias is negative ($X_{bias}<0$) then input hand is being classified as left. This method was used for input hand classification in Knoche et al. study [16]. SVM was classifying all touches in each session first, and then input hand was chosen according to which hand appeared most in the session. Positive/negative touch bias method was using all touches in the session to calculate for horizontal touch bias mean value and afterwards input hand was predicted according to whether the value was positive or negative.

The results from the classification can be seen in Table 5. Comparing performance of SVM classifier against negative/positive touch bias approach, I can conclude that negative/positive touch bias approach outperforms SVM classifier in two conditions, and only in one condition ((6x6)R.T) are the results similar.

The highest accuracy for predicting input hand is achieved in (20x20)R.T condition, where only two sessions out of 30 were misclassified as left hand input. In general, we can see that the more touches are used for the classification, the better the prediction results is.

Despite the fact that SVM classifier achieves the best prediction on per touch basis, it shows much worse prediction rate when each session needs to be classified. This happens due

Table 4: Touch Slide length and appearance in each experiment condition along with the percentages of all touches for which the conditions was satisfied (e.g. $X_{slide} < 0$)

Condition	**X_{slide}>0**	**X_{slide}<0**	**Y_{slide}>0**	**Y_{slide}<0**	**Slide X/Y(%)**
OBLQ.T	3.14 mm (24%)	-1.77 mm (57%)	2.43 mm (14%)	-3.05 mm (67%)	86 %
(20x20)R.T	1.37 mm (12%)	-0.76 mm (52%)	0.88 mm (15%)	-1.01 mm (43%)	69 %
(6x6)R.T	0.86 mm (6%)	-0.63 mm (52%)	0.63 mm (7%)	-0.77 mm (44%)	63 %

Condition	**Predictor(s)**	**Sessions**	**Touches**	**Classification**	**Acc.**
(20x20)R.T	X_{bias}	30	60	X_{bias}<>0	93.33%
OBLQ.T	X_{bias}	22	120	X_{bias}<>0	90.90%
(6x6)R.T	X_{bias}	30	60	X_{bias}<>0	86.66%
(20x20)R.T	X_{bias}	30	∼20	X_{bias}<>0	86.66%
(6x6)R.T	X_{bias}, *MaxTime*, MaxSlide X/Y	30	∼20	SVM	83.33%
(6x6)R.T	X_{bias}	30	∼20	X_{bias}<>0	83.33%
OBLQ.T	X_{bias}	22	∼40	X_{bias}<>0	81.81%
(20x20)R.T	X_{bias}, *MaxTime*	30	∼20	SVM	73.33%
OBLQ.T	X_{bias}, *MaxTime*, MaxSlide X/Y	22	∼40	SVM	72.72%

Table 5: Input hand classification on per session basis. Each condition contains two sessions- one session for the right hand and one for the left hand. Two methods are compared for the classification- Support Vector Machine classifier (SVM) and Comparison of Touch Bias mean values (X_{bias}<>0).

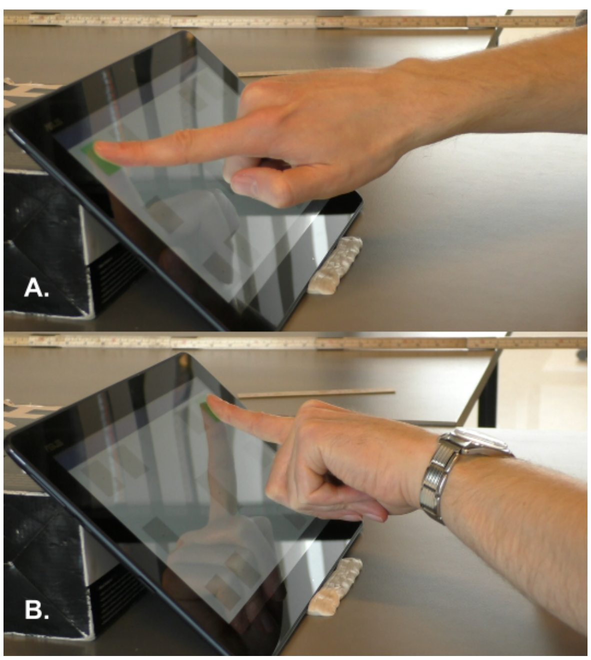

Figure 18: An example (P10) of a distinctive Finger Orientation when performing *oblique* touch. Visually FO on these two examples corresponds to the diagonal touch slides on Figure 15. A) Right Hand B) Left Hand

to a high diversity in SVM results, e.g (p9) had almost all touches classified correctly in regular touch conditions, while (p1) and (p2) had almost 2/3 of all touches misclassified in regular touch conditions (see Figures 20, 21). The diversity in the results comes from all the parameters that are included in SVM classifier, e.g *MaxTime* differs from person to person, and is therefore more useful for classifying a single person rather than a large group of people.

Discussion

I managed to achieve the main goal of the experiment- to collect a large number of touch data and show it's potential for hand classification task. I was able to identify three different touch parameters that are related to left/right hand touch interactions or handedness in general:

1. Horizontal touch offsets (X_{bias})
2. Interaction time (*MaxTime*)
3. Touch slides (X_{Slide} and Y_{Slide})

After performing logistical regression on touch data I was able to show that for all three conditions in the experiment, horizontal touch bias is the most significant parameter for predicting input hand. This means that people have a tendency to produce distinctive touch bias when targets are both *occluded* and *non-occluded*. The most distinctive touch offsets are produced in *regular touch* conditions, due to a smaller touch area when regular touch is taking place. Oblique touch condition (OBLQ.T) has also shown a reliable horizontal touch bias, except one single participant (p14) who had a "reversal" touch bias, meaning that left hand produced right sided touch bias and right hand produced left sided. The reason for why touch bias was "reversal" for this particular participant is unknown.

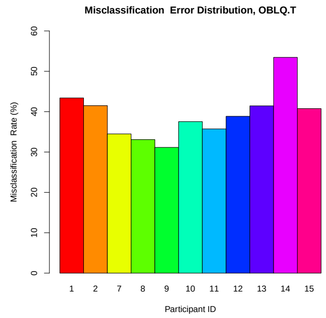

Figure 19: Classification Error on per touch basis (SVM), OBLQ.T

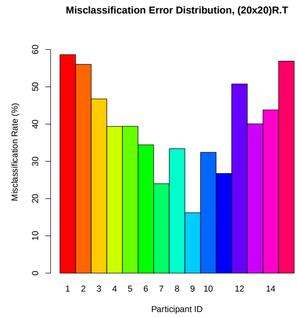

Figure 20: Classification Error on per touch basis (SVM), (20x20)R.T

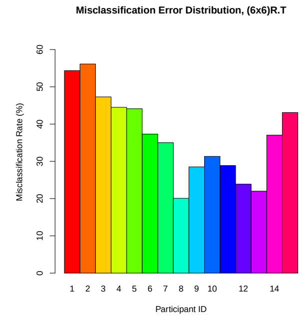

Figure 21: Classification Error on per touch basis (SVM), (6x6)R.T

Besides showing that touch bias is the most significant parameter produced by a finger touch I was also able to identify one of the factors that affects touch bias, which is *hand motion* that takes place when participants move their index finger from one target to another. The effect of hand motion is different depending on whether the targets are occluded or non-occluded. The most distinct (the highest spread) horizontal touch offsets are produced on non-occluded 20x20mm targets, when input hand is moving into *Ipsilateral* direction (see Figure 11) or when the input hand *double tap* on the target (see Figure 13). For the occluded 6x6mm targets *double tap* produces smallest horizontal touch offsets (see Figure 12) and *Contralateral* hand motion produces the largest spread between touch offsets.

Looking at other parameters that are significant in relation to the left/right index finger, *MaxTime* is a good parameter to identify preferred handedness of an individual. The hand that takes longest time to perform a touch interaction is a non-dominant. As 90% of world population are right hand-dominant, we can predict a correct input hand for this majority group of people. However there are some limitations for using interaction time as parameter for predicting input hand.

As interaction time differs from hand to hand, we cannot use a single measurement to obtain handedness of a specific person. Instead we must collect measurements both for left and right hand of the same person, in order to classify his/her handedness. Factors like touch type (regular/oblique) and target size (occluded/non-occluded) are also important as these affect the result. This restricts use of *MaxTime* as parameter for predicting input hand and preferred handedness in a wider context (e.g crowd source studies, where the context, person and settings are barely known).

Finally, I performed classification for input hand using touch bias and other parameters found using logistic regression. I used SVM classifier to do that, as it achieves the best prediction rate on per touch basis. The highest input hand prediction per touch (62.52%) was achieved in (6x6)R.T condition using X_{Bias}, *MaxTime*, and *X/Y Touch Slides*.

Besides performing classification on per touch basis, I have also classified for input hand on per session basis. I tested two approaches to see which provides the best results. First approach uses SVM classifier and significant parameters found

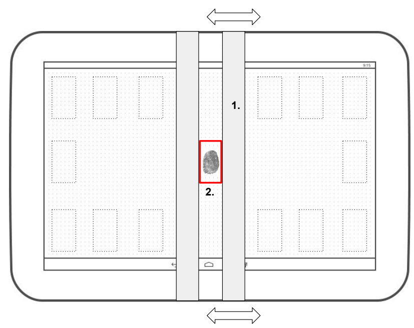

Figure 22: Finger borders- made of wooden chopsticks (6mm wide - 10mm high) and attached to the tablet device 2) Controlled finger area where touch data is collected.

using logistical regression. Second approach was inspired by Knoche et al. [16] study who performed input hand classification using positive/negative mean values of horizontal touch offsets. The results show that a simple comparison of X_{Bias} mean values outperforms SVM classification. The best condition for this type of classification is (20x20)R.T condition (see Table 5), where for 28 out of 30 (93.33%) sessions input hand has been correctly identified. Furthermore when taking 20 random touch events from each participant's session, it is still possible to identify input hand with 86.66% precision in (20x20)R.T condition.

Despite its complexity SVM was not able to perform a better classification on per session basis. This is because of the high diversity in the results where some of the participants have a very low misclassification rate while some of the participants have very high misclassification rate (see Figures 19, 20 and 21). This suggests that parameters like *MaxTime* and *X/Y Touch Slides* are more user specific, meaning they vary from person to person. It is hypothesized that for a more user-specific classification *MaxTime* and *Touch Slides* would be beneficial parameters, while for a more generalized approach these parameters 'confuses' the classifier, leading to a worse prediction rate.

Additionally, Support Vector Machine is very a 'heavy' classifier in terms of computation power required. This makes the classifier more problematic to implement on mobile devices, and also requires additional packages/libraries for the implementation. Opposite to that, a simple comparison of X_{Bias} mean values is possible to implement on most of the modern mobile devices. Furthermore this method does not require any additional packages/libraries and can easily be implemented into the code of the existing applications.

SECOND EXPERIMENT

Purpose and Motivation

The experiment is conducted in order to find additional explanations for the horizontal touch offsets related to use of left/right input hand observed in the first experiment. One of the possible explanations for the horizontal bias is the physical differences between left and right index fingers.

Besides physical differences, there could also be differences in the process of selecting the target that cause systematic touch offsets. This experiment aims to shed some additional light on touch bias phenomena that take place among all type of users (right/left hand dominant), touch types (oblique/regular) and targets (occluded/ non-occluded).

Experiment Description

To see if there is an actual difference between left and right index fingers a wooden "frame" is attached to the tablet device Figure 22.

The frame can be adjusted on the right side in order to match participants' finger width. The idea behind the frame is that it excludes all hand motion and provides equal touch area both for left and right index fingers. If any significant differences between left and right fingers occurs, then it could be possibly related to physical differences between left and right index fingers or/and a different approach for selecting a target with each hand, e.g different finger posture.

Software and Equipment

The software and interface (Figure 22) for the experiment was re-used from the first study. The equipment (tablet device, camera, table and chair) are also similar to the ones being used in the first experiment.

Participants

11 participants (one female) in age between 21 and 28 (mean 24.72) attended the study. As touch bias related to input hand appears both among right and left dominant hand users, there was no requirement for a specific handedness in the experiment. As results, all 11 participants recruited for the experiment were right hand dominant. All the participants were university students who are familiar with touch devices (experience with touch devices - 8.0 out of 10).

Procedure

Before the experiment each participant had the wooden borders on the tablet adjusted according to his/her finger width. The requirement was that the index finger is able to interact with the target without any additional friction from the borders. In order to ensure a higher precision and symmetry in the data, only the right wooden border was able to move in the adjustment process. Participants were asked to interact with the tablet as they would normally do and if no borders were presented. The average session including measurements and adjustments lasted between 5 and 10 minutes. Each participant was required to do 80 middle button activations and 10 activations for each side button (8 side buttons in total), meaning a minimum of 160 touch events are required to pass through the experiment. The number of touch events is equally distributed between right and left hands. At the end, each participant was required to place his/her left and right index fingers on the graph paper (one at the time) in order to take an image, which was used to compare for any potential differences e.g if one index finger has a much longer nail or the width of the fingers is not same.

Results

For the main analysis only the data related to the middle button activations is being used. This corresponds to 880 touch events or 3926 data samples (4.4 data sample per touch event) that were collected from 11 participants. A visual representation of *Land On* touch points for each hand related to middle button activations can be seen at Figure 23.

From the remaining buttons (side buttons) there was collected a similar number of touch events and 3915 data samples. A visual representation of touch landing points for the side buttons can be seen at Figure 24

Data Verification

Before analyzing the data I went through all the finger images of the participants and was not able to find any visual differences that would affect touch performance. All participants in the experiment had 'normal' index fingers- meaning no anomalies that can potentially affect the results, were detected.

Logistic Regression

Table 6 show logistical regression results and parameters that are significantly different depending on which hand is being used for the interaction. Comparing the results to the initial study, *MaxTime* is no longer a significant parameter although there is still a small difference between dominant (right hand) and non-dominant hand in terms of activation time. Same as previously, a non-dominant hand takes longer time to interact with the button (mean 116.1 vs. 114.9 milliseconds).

The reason for *MaxTime* is no longer a significant parameter is most likely due to the presence of the finger borders that has an effect on the participants touch performance. When looking at the logistical regression analysis for the remaining/side buttons (Table 7), *MaxTime* again becomes a significant parameter, similarly to what it has done in all three conditions in the initial study.

Horizontal Touch Offsets

As can be seen from the logistic regression results, touch events are significantly different in terms of horizontal touch bias. Similarly to the initial study, touch events related to the right hand interaction tend to land more on the right side of the button, while touch events related to the left hand interactions, tend to land more on the left side of the button (see Figure 22).

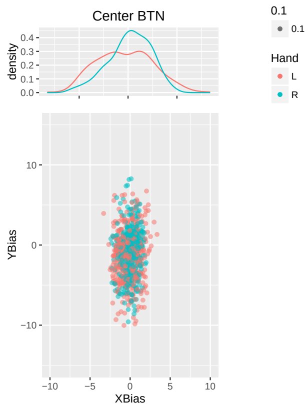

Figure 23: Touch bias on 20×30mm target with finger constrained by the borders attached to the tablet.

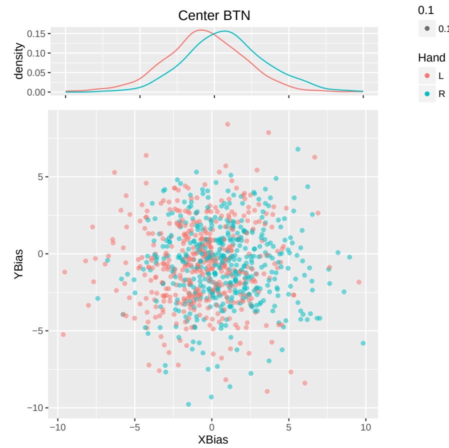

Figure 24: Touch bias for 20mm×20mm non-center targets (no finger borders/ regular touch)).

Table 6: Overview of significant predictors of input hand. Data is from 11 right-handed participants and analyzed using logistic regression. The data is collected from Center Button interactions.

Predictor(s)	**z value**	**Pr (>|z|)**	**Left.H (SD)**	**Right.H (SD)**
X_{bias}	2.495	0.0126	-0.13mm (1.14)	0.08mm (0.87)
Y_{bias}	2.158	0.0310	-1.41mm (3.16)	-0.94mm (2.86)
MaxArea	-1.969	0.0489	0.269 (0.034)	0.255 (0.029)

Looking at the upper density plot in Figure 22 we can see that the right hand has a much smaller variation of data compared to the left hand. This means that the participants have a more established/controlled way to interact with their dominant hand which is characterized by a distinctive "peak" of data in the density plot for the horizontal touch interactions. On the same plot, the left hand does not produce any distinctive "peak" and has a more "smooth" and "wider" shape, meaning that the data has a larger spread for the left/ non-dominant hand. This larger spread of data can be explained by the larger finger area produced when using a non-dominant hand in the interaction process.

Vertical Touch Offsets

In the first experiment Y_{Bias} was not a significant parameter in any condition. It is fully unknown why Y_{Bias} is a significant parameter in the second experiment, but I hypothesize that the wooden frame attached to the tablet had an effect on vertical offsets as this is the main difference between two experiments. Furthermore the side buttons in this experiment did not produce any significantly different vertical bias when left or right index fingers was used for the interaction. Possibly, a combination of the borders and index finger above them occludes the target making it harder to predict actual position of the target. This "occlusion" is more different than "occlusion" in the (6x6)R.T condition, as the target is occluded not only from the top (by the fingertip) but also from the sides by the finger borders, making it harder to predict the target position precisely.

Another possible/additional explanation for the different vertical offsets is again the significant differences in Finger Area. As Finger Area increases in a touch event, the center of a touch shifts both horizontally and vertically. A similar process can be seen at Figure 1.

Hand Classification (Per Session Basis), Side Buttons

I performed an additional hand classification on the side buttons using negative/positive touch bias comparison described earlier in the report. For the testing data I was using side buttons from the study, as these were not influenced by any borders and allowed for regular touch interactions. A total of 22 sessions with 40 touch events in each session was classified. Only a single session out of 22 was misclassified as right hand input (p11, *Left Hand* X_{Bias} = 0.38mm), this means that 95.45% of sessions were correctly classified. The result indicates a reliable performance of the hand classification based only on mean values of the horizontal touch offsets.

Discussion

Although the experiment has shown that even in a controlled condition we can expect horizontal touch offsets, these offsets are not related to physical differences between left and right index fingers. Instead, the data from the experiment suggests that the offsets is a result of a various finger postures that take

Table 7: Overview of significant predictors of input hand (logistic regression). The data is collected from Side Buttons interactions.

Predictor(s)	z value	Pr (>|z|)	Left.H(mean)	Right.H(mean)
X_{Bias}	7.449	<0.001	-0.677 mm	0.830 mm
MaxTime	-3.042	0.002	100.54 ms	94.63 ms

Table 8: Horizontal touch bias for different experiments and conditions

Condition	Left Hand	Right Hand	Difference
OBLQ.T	-0.30 mm	0.63 mm	0.93 mm
(20x20)R.T	-0.73 mm	0.51 mm	1.24 mm
(6x6)R.T	-0.41 mm	0.27 mm	0.68 mm
Exp2 (MidBTN)	**-0.13 mm**	**0.08 mm**	**0.21 mm**
Exp2 (SideBTNs)	-0.677 mm	0.83 mm	1.507 mm

place when a person is using his/her non-dominant hand to interact with the tablet device.

Looking at the size of horizontal offsets (Table 8) we can see that the spread between left and right hand touch bias points in a controlled setting is more than seven times smaller than the spread for the side buttons in the same condition and almost six times smaller compared to (20x20)R.T condition. This suggests that finger posture is partly responsible for the horizontal offsets, however it is not playing the major role in causing horizontal touch offsets, which has been observed among all type of targets (occluded/non-occluded) and touch (oblique/regular).

Besides checking for differences between left and right index in a control setting, I have also classified the remaining touches from the side buttons. Only a single session out of 22 was misclassified as right hand input. The result indicates a reliable performance of the classification approach solely based on the comparison of horizontal touch bias mean values.

Finally, it is important to note that the finger borders attached to the tablet device had an effect on participants' touch performance, e.g activation time (*MaxTime*) was no longer a significant parameter and for the first time vertical touch offsets (Y_{Bias}) became a significant parameter. It would be beneficial to re-do the experiment using FTIR/DI or some other vision based system, in order to get a higher resolution of a finger touch. A different setup could potentially exclude the need for the finger borders which I strongly believe restricts the performance of a truly authentic and natural finger touch.

LIMITATIONS

The approach for inferring input hand presented in this study is limited to the use of buttons and index finger interactions in order to obtain horizontal touch offsets. Additionally the data is collected from interactions on a tablet device and it is therefore unknown whether the horizontal touch offsets will take place when a smartphone device is being used for the interaction. Furthermore it is unknown whether thumb interactions are also causing any systematic touch offsets that can be used for hand classification task.

FUTURE WORK

Despite good results in classifying input hand per session basis it is believed that these results can be further enhanced by using a certain arrangement of the targets on the screen, e.g if we include more motion into *ipsilateral* direction when interacting with non-occluded targets, we would expect to get a more distinctive horizontal touch offsets.

It would also be interesting to test whether the horizontal touch offsets are taking place when a smartphone is being used for the interaction, ideally we can combine findings from this study with the findings from Goel et al. study [8]. In theory, we will obtain a smartphone device which is able to distinguish between one/two handed usage, thumb interaction vs. index finger interactions, right and left hand distinction both when using index fingers and thumbs for the interaction.

Finally an additional study to find the nature of finger slides would be beneficial. Currently it is fully unknown why slide motion is taking place and why it is going in one direction or another. Additionally, we can try to obtain Finger Orientation using finger slide motion from *oblique* touch interactions. If we obtain FO we can use simple approach for inferring input hand presented by Zhang et al. [25] (if $FO<90°$, then right hand is being used, otherwise left hand is being used).

CONCLUSION

In this project I managed to collect a large amount of touch data from various types of users. Analyzing this data I was able to identify three touch parameters that are distinctive between left and right index finger touch interactions. These touch parameters are interaction time with a button (*MaxTime*), touch slides (X_{Slide}/ Y_{Slide}) and horizontal touch offsets (X_{Bias}). The best parameter for predicting input hand is horizontal touch offsets, where a simple comparison of mean values is able to provide reliable hand classification results. The best hand classification results are obtained when a regular touch is taking place, and the targets are non-occluded by the input finger. This resulted in 93.33% correct input hand predictions (per session basis) in the first experiment and 95.45% correct input hand predictions (per session basis) in the second experiment. The results show that it is possible to obtain input hand from index finger touch interactions, and approach presented in this study is possible to implement in the code of the existing applications.

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