Experimental Analysis of Mode Switching Techniques in Touch-based User Interfaces

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ABSTRACT
This paper presents the results of a 36 participant empirical comparison of touch mode-switching. Six techniques are evaluated, spanning current and future techniques: long press, non-dominant hand, two-fingers, hard press, knuckle, and thumb-on-finger. Two poses are controlled for: seated with the tablet on a desk and standing with the tablet held on the forearm. Findings indicate pose has no effect on mode switching time and little effect on error rate; using two-fingers is fastest while long press is much slower; non-preferred hand and thumb-on-finger also rate highly in subjective scores. The experiment protocol is based on Li et al.'s pen mode-switching study, enabling a comparison of touch and pen mode switching. Among the common techniques, the non-dominant hand is faster than pressure with touch, whereas no significant difference had been found for pen. Our work addresses the lack of empirical evidence comparing touch mode-switching techniques and provides guidance to practitioners when choosing techniques and to researchers when designing new mode-switching methods.

ACM Classification Keywords
H.5.2. : User Interfaces- *Interaction Techniques*

Author Keywords
multi-touch; touch input; mode switching;

INTRODUCTION
Most interfaces have multiple modes in which input is mapped to different actions. In a touch interface, the current mode can change how a single touch is interpreted: for example, it could draw a line, pan the canvas, select a shape, or enter a command. Switching between modes can be frequent, so finding optimum *mode-switching* methods is important. There have been numerous experimental investigations comparing mode-switching techniques for pucks, mice, and pens [32, 13, 36, 54, 28], but there has been no comprehensive analysis of mode-switching techniques for touch input.

This is surprising considering that a number of touch mode-switching techniques have been developed. Some are unique to touch since they rely on features such as multiple contacts [10, 46], using knuckles or other parts of the hand [23, 39], or characteristics of finger contact [6, 47]. Some touch mode-switching techniques are similar to those evaluated with pens, such as using pressure [42, 25] or using the non-dominant hand [15, 57]. However, generalizing pen-based empirical results to touch is highly speculative, considering distinct touch characteristics like reduced precision from "fat fingers" [3, 14, 50] and greater friction [9]. This lack of formal comparisons of touch mode-switching techniques may be one reason why current mode-switching methods for touch seem limited compared to other input methods.

In this paper, we compare the performance of six mode-switching techniques for touch input on a tablet: the standard long press, pressing a button with the non-dominant hand, two-finger multi-touch, pressing hard, using the knuckle, and touching the thumb to the side of the finger. The investigated techniques include current methods, new methods recently made available in commercial devices, and techniques likely possible in the near future. Given the tablet mobility, we also control for two poses: seated with the tablet on a desk and standing while holding the tablet. Our evaluation protocol is based on Li et al.'s widely cited comparison of pen mode-switching [36]. This increases the replicability and validity of our work, and enables a discussion of touch versus pen mode-switching. Direct comparisons are possible for pressure, long press, and non-preferred hand, and to some extent thumb-on-finger and knuckle if considered analogues to Li et al.'s pen barrel button and eraser.

Our results contribute the following results and insights:

- Techniques ordered from fastest to slowest are: two-fingers, non-preferred hand button, finger-on-thumb, knuckle or hard press, and much slower long-press.
- A sitting or standing pose has no effect on speed and little or no effect on errors (only hard press and non-preferred hand error rates showed some interaction with pose).
- Pressing hard was perceived to be the least accurate, one of the most fatiguing, and hardest to learn technique.
- Compared to Li et al.'s results for pen, our touch mode-switching timings and error rates are higher (except for knuckle compared to eraser).
- Our results can inform design, returning to the opening example: one finger could draw, two fingers pan, thumb-on-finger to select, and knuckle for a command menu.

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BACKGROUND AND RELATED WORK

We build on, and extend research developing new mode-switching techniques and formal experiments to analyse them.

Mode Switching Techniques

Early mode-switching techniques focused on pucks, mice, and especially pens (styli). We provide a brief overview of pen techniques first since they have been arguably the most thoroughly studied and are the topic of Li et al.. We subsequently focus on multi-touch input, the most relevant to our work.

Pen Input

With pens, there is a common need to switch between an inking mode and a command input mode, but many techniques can be combined to support multiple modes. Perhaps the most straightforward method to switch the pen mode, other than the classic "long press" with the nib, is to press a button. This can be single-handed, using the barrel button on the pen [36], a touch sensor below the palm of the writing hand [51], or more commonly with the other (non-dominant) hand [40, 1, 33, 28]. Using two hands exploits the benefits of bimanual interaction [32, 27]. Li et al. [36] found a physical button activated by the non-dominant hand was both faster and more accurate. A later study by Tu et al. led to similar results [54].

Having a well-positioned button on a device is not always a practical solution and there is often a need to trigger multiple mode switches. Additional techniques have been proposed to overcome those limitations. On pen and touch tabletop systems, there is a large body of work examining different postures performed with the non-dominant hand on the surface to activate command modes for the pen held by the dominant hand [7, 31, 41]. Other techniques include short stroke gestures [26, 34, 20], pressing firmly or lightly [36, 54, 45], stylus rolling [5], contacting with different parts of a multi-faceted crayon [56], and pen-holding postures [52, 30].

Touch Input

Many mode-switching techniques designed for pens or other devices have been applied to direct touch input. For instance, typing capital letters by holding the shift key with the other hand is a simple form of non-preferred hand mode activation. Even the shape of the non-dominant hand [58, 61, 24] or the number of fingers used [60] can trigger a mode change. BiPad [57] and SPad [15] explore the possibility of using the hand holding a tablet to activate different modes by pressing soft buttons. Pressure [42, 25, 46] and grip-based [17] controls have also received much attention. Some of the latest mobile devices integrate pressure-based technology and functionality (3D Touch, Force Touch, Press Touch etc.) [53]. The number, shape and mobility of fingers afford further interaction possibilities. Multiple fingers performing similar path movement (two- three-finger swipes etc.) can be used to trigger different actions [35, 60] and if individual fingers can be identified, interactions can be made finger-specific [10]. Further properties of finger input such as contact size [6], slight rolling movements [47] and which part of a finger touches the display [23] can also be recognized to support mode-switching or general interactions.

Mode Switching Analysis

With many possible mode-switching techniques, it is no wonder researchers have attempted to develop models and evaluation protocols to rigorously assess their performance under different settings. Using the non-dominant hand for pen mode switching has been studied in detail by Ruiz et al. who developed a temporal model [48], Lank et al. [33] who show concurrent mode-switching is fastest, and Ruiz and Lank [49] who explore these aspects with multiple modes.

To compare performance of mode-switching techniques, a common methodology is Dillon et al's "subtraction technique" [11]. It determines the precise cost of mode-switching by subtracting the time to perform the same series of tasks using a single mode and when alternating between two modes. It is the approach for comparing pen mode switching techniques in Hinckley et al. [28], Song et al. [52], and Li et al.'s[36] highly cited comparison on which we model our work.

We are unaware of a comprehensive study systematically examining and comparing mode-changing techniques for direct touch input. The touch techniques explicitly or implicitly used to trigger mode changes that have been proposed have mostly been superficially or individually evaluated for non-frequent mode-switches. Therefore, it is not clear how well they fare compared to each other and in a context, where state changes are very frequent. Furthermore, the results for pen-based mode-switching may not transfer to touch input, not to mention that touch input enables other techniques such as multiple touches not applicable to pens.

MODE SWITCHING TECHNIQUES

We chose six mode switching techniques among those in current use, described in previous research, or soon plausible given emerging sensor capabilities. Some are analogous to the pen mode switching techniques tested by Li et al. [36]. All techniques were designed for a tablet when placed on a desk, or when supported with the non-dominant arm.

Long Press

Performing a long press (also called "press-and-hold" or "dwelling") is a common method to trigger command modes in current touch interfaces. For example, Android and IOS use a long press to organize app launch icons. We use a long press duration of 500ms , the default Android setting. Li et al. also included a pen long press, but used a 1000ms duration.

Long press detection begins after touch down with a "hold detection phase": as long as finger movement remains within a 3mm radius bounding circle centred on the initial touch point, the finger is considered held still. A circle 25mm in diameter is displayed around the touch point showing the progression towards the 500ms duration. If the finger remains in the box for 500ms, the mode is activated. If the finger exits the box before that time, the hold detection phase restarts with a new bounding circle centred on the new finger position. Our 3mm radius bound is twice that used by Li et al. to account for touch sensor noise. Once detected, the mode remains engaged until touch up regardless of subsequent finger movement. We did not implement a second "hold through" phase to cancel the mode switch like Li et al. because, to our knowledge, this is not used on touch input devices or needed for the experiment.

Two-Finger Multi-touch

One of the simplest distinctions for touch input is whether one or two fingers contact the display at the same time. This is common in Android and IOS, and researchers have used two fingers to activate marking menus [35] and distinguish between dragging and hovering in the DTMouse technique [12]. There is no equivalent technique with pen input.

A two-finger touch is detected when two correlated touches occur soon after initial touch down. For our experiment, two touches must be detected before crossing into the first rectangle (typically less than 80ms). To remain comparable with other single touch techniques, a single input position is defined using the midpoint between touch points. We selected the midpoint based on pilot tests examining the perceived input point for two touches. This positioning is also used for DTMouse in hover mode. Once detected, the mode remains engaged until touch up regardless of the number of touches.

Non-Preferred Hand

Touch interfaces can support using the non-preferred hand to activate a mode with soft buttons, a simple example is holding the SHIFT key while typing. Li et al. found that pressing a physical button was one of the fastest ways to activate a mode with pen input. Our equivalent technique uses a rendered touch button since it is more practical with current tablets.

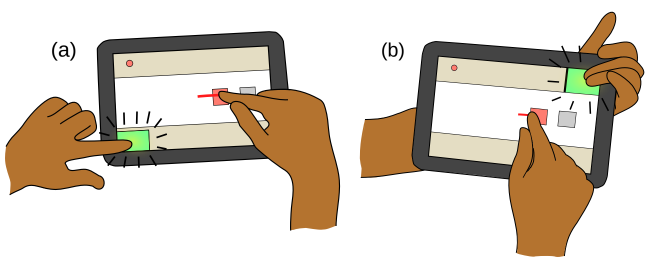

Figure 1: Position of the mode-switch button (in green) activated by the non-preferred hand when (a) sitting; and (b) standing.

To engage the mode, the non-dominant hand presses and holds a 45×25mm button before the dominant hand touches down. Once the touch down event occurs, the mode remains engaged until both the dominant-hand touch up event occurs *and* the mode switch button is released. We require the button to be pressed before the dominant hand touch down to be consistent with Li et al.. The mode button location is dependent on the participant's handedness and whether the tablet is supported by a surface (e.g. sitting at a desk) or supported by the non-dominant forearm (e.g. when standing). When supported by a surface, the button is displayed at the bottom-left (or bottom-right) corner (Fig. 1-left). When supported by the non-dominant arm, the button is displayed at the top-right (or top-left) corner (Fig. 1-right). This enables the user to reach and tap the mode switch button comfortably with the fingers of the hand holding the device, a common posture reported by Wagner et al. [57] We fixed button locations and sizes for our experiment, but techniques exist to automatically detect how a mobile device is held so such mode-switch button could be positioned accordingly [17].

Hard Press

Pressure-based touch interaction has been described in previous work [2, 4, 25, 46] and recent technology developments suggest pressure sensing will be supported on commercial touch devices in the near future [53]. Using pressure-based mode-selection for pens has been well studied (e.g. [45]) and it was a method evaluated in Li et al.'s experiments.

Most current touch devices report a simulated pressure reading based on the size of the touch contact. On vision-based tabletops the actual contact size is captured by a camera [4], but capacitive devices estimate it from the signal strength. We found simulated pressure with capacitive tablets is unreliable due to factors like skin moisture, relative humidity, and body hydration. To get a true measure of pressure, we initially experimented with placing multiple external force-sensitive resistors under the tablet and training a classifier to recognize touch events with normal and hard pressure. This worked reasonably well on a desk, but designing a housing for accurate sensing when standing proved difficult. Instead we detect hard presses indirectly, based on muscle tension sensed using a MYO electromyographic (EMG) armband. Benko et al. used the same technique with a similar EMG sensor [2]. Note that our objective is to simulate a future pressure sensing technique in our experiment; we are not proposing that people wear a MYO armband when using a tablet.

A simple threshold-based classifier is trained for each participant (Li et al. used a global threshold for pressure across all participants, but found it unreliable). To train, the participant crosses through five rectangles, alternating between a normal touch and a hard press touch according to rectangle colour. This is repeated 4 times. The data from the 8 armband EMG sensors are smoothed using the one-euro filter [8] and synchronized with the touch events and expected type of touch. The median and standard deviation of each sensor signal for normal touches and hard presses is calculated using events logged from touch down until the rectangle is entered. All sensors where the hard press median minus two standard deviations is greater than the normal touch median plus two standard deviations are considered *differentiating* sensors. If less than two differentiating sensors are found, the armband is adjusted and the training repeated. Otherwise, each sensor is assigned a threshold equal to the hard press median minus two standard deviations (EMG signals for hard press are always greater than normal press). Once trained, a touch is considered a hard press if two or more of the differentiating electrodes exceed the thresholds determined in training. A 5-person pilot found the method was almost 99% accurate.

To use hard press for mode-switching, sufficient pressure must be applied to the tablet screen to cross the threshold. During the experiment, a hard press must be identified before crossing into the rectangle. The mode is disengaged upon touch up.

Thumb-on-Finger

Pressing a "barrel button" is a classic way to change the mode using a pen, and this technique was included in Li et al's study.

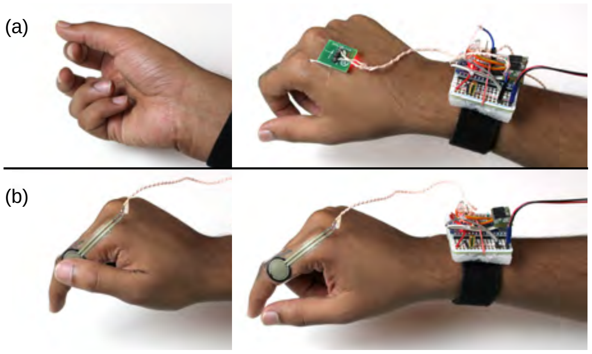

Figure 2: Hardware to robustly detect future input actions for the purpose of the experiment: (a) knuckle touches using accelerometer; and (b) thumb-on-finger using pressure sensor attached to index finger.

We approximate barrel button mode-engagement for touch input with a thumb press on the index finger, similar to techniques used for mid-air clicking [21, 55] and NanoStylus [62]. We anticipate that with technologies such as Project Soli [19], these types of gestures will be able to be sensed.

In our experiment, we use a wearable device with a force-sensitive resistor (FSR) taped to the proximal phalanges of the index finger (Fig. 2 b). We ensured this apparatus did not impede natural touch interaction with the tablet. The FSR is 12.7 mm in diameter and 0.47 mm thick. The sensing range is 0 to 175 psi and we used a global threshold of 51 psi to detect when the thumb lightly contacts the finger. The FSR is connected to an ATmega328 Arduino strapped to the wrist. The Arduino sends pressure readings to the tablet over Bluetooth. To reduce weight, an external battery is connected to the wearable device with a lightweight wire.

The mode is activated by pressing the thumb to the side of the index finger before touching down. Once the touch down event occurs, the mode remains active until both the touch up event occurs *and* the thumb is released from the finger.

Knuckle

Using the knuckle for touch input has been described in Marquardt et al. [39] and Tapsense [23]. Knuckle-sensing is already offered on some smartphones [16]. Turning the hand over to engage the knuckle also bears some similarity to using the eraser end of a pen, a mode-switching technique included in Li et al.'s study.

Our tablet does not sense knuckles natively, so we simulate a future knuckle sensor. An ADXL335 3-axis accelerometer mounted on the back of the hand with tape detects wrist rotation. Specifically, the mode is switched when the z axis of the accelerometer exceeds a 90 degree angle (it is 0 degree when the sensor is horizontal). This simple threshold is sufficient to differentiate between knuckle and normal finger pad touches. The accelerometer is connected to the same wrist-mounted apparatus used for thumb-on-finger sensing. In our experiment, all but one participant used their middle finger knuckle to perform this technique. Given the mechanics of the movement, the mode must be engaged before the first touch. The mode remains active until both the touch up event occurs *and* the wrist rotates back to the finger pad touch orientation.

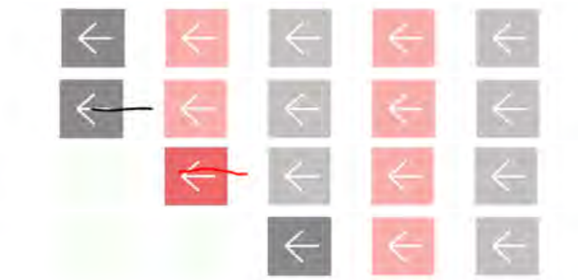

Figure 3: Compound task: five oriented rectangles (180° shown) are crossed while alternating between default and command modes. Each row above is a screen capture of the task (top to bottom): about to cross first baseline target; crossing first target; crossing second "moded" target; about to cross third baseline target. The baseline task looks identical except all rectangles are grey and only the default mode is used.

EXPERIMENT

The goal of this experiment is to compare mode-switching time, error rates, and subjective ratings for the six techniques described above. Given the mobile nature of tablets, both seated and standing poses are tested. The experiment task and design is a near-replication of Li et al.'s [36] pen mode-switching study.

Participants

We recruited 36 participants (mean age 24.1 SD = 2.4, 8 women, all right-handed). 24 participants had experience using multi-touch tablets. A $10 remuneration was provided.

Apparatus

The experiment was performed on a Google Nexus 10 tablet (1.7 GHz Cortex A15 CPU with 1 GB RAM) running Android OS 5.1.1. The tablet's 264 × 178 mm display has a resolution of 2560 × 1600 px, a density of 11.8 px/mm (300 PPI). The device weighs approximately 603 grams. The experiment task code was written in Processing using the Android export library. Using Ng. et al.'s method [44] and a 240 fps camera, end-to-end latency was 100 ms, comparable to current apps.

Tasks

Our experimental tasks are closely based on Li et al. [36]. Five 20 × 22 mm rectangles are crossed in succession where the 20 mm ends form two parallel crossing targets (Fig. 3). Note that 20 mm crossing targets are 63% larger than the minimum size recommend by Luo and Vogel to achieve a 4% error rate [37]. The rectangle is a simplification of the pie section used by Li et al.. All five rectangles are displayed in a horizontal row, all oriented in the same direction with the required crossing direction indicated by a white arrow.

There are two task variations. In the *baseline* task, five grey rectangles are shown and the participant crosses them using standard touch input. In the *compound* task, the five rectangles alternate between grey and red, with the first rectangle grey. The participant must cross each grey rectangle using standard touch input and each red rectangle using the specified mode-switching technique. All touches leave a trail for feedback, black for standard touches and red when the mode is engaged. Note that the red or black trails function only as an abstract representation of two different modes. A small circle in the top-left corner of the display also turns red when the mode is engaged. If there is any crossing or mode error, a beep sounds and the rectangle must be crossed again to continue. Error detection and classification are described below.

Design and Procedure

The experiment is a repeated measures mixed design. The participant POSE while using the tablet is a between-subjects factor (SIT or STAND). Half of the participants completed all tasks while seated with the tablet placed flat on a table and the other half completed all tasks while standing with the tablet held on their non-dominant forearm. The mode-switching TECHNIQUE is a within-subjects factor with levels corresponding to the six mode-switching techniques (LONGPRESS, TWOFINGER, NONPREF, HARDPRESS, THUMB, KNUCKLE).

Participants were randomly assigned to a POSE condition and TECHNIQUE order was counter-balanced using a 6×6 Latin square. For each TECHNIQUE, there was a 1 to 3 min training period (after wearable hardware was attached and calibrated for HARDPRESS, THUMB, and KNUCKLE). Once training was over, the participant completed 9 BLOCKS of tasks. Odd numbered blocks were entirely baseline tasks and even numbered blocks entirely compound tasks. Before each block, the participant had to press a start button. Each block presented the task using 4 crossing directions (N, E, S, W) in random order. Note that Li et al.'s design had 8 directions, but they report no significant differences. Our four cardinal directions are representative of common actions like swiping, and a reduced number of directions enabled all six techniques to be tested in less than 1 hour with minimal fatigue. Participants were allowed to take breaks between blocks.

In sum there were: 6 TECHNIQUES $\times$ 9 BLOCKS (5 baseline, 4 compound) $\times$ 4 directions $\times$ 5 rectangle crossing = 1,080 rectangle crossings per participant.

Quantitative Measures

Three measures are calculated from experiment event logs.

Errors and Error Rates

Like Li et al., we identify three types of errors. A *crossing error* occurs if the touch stroke did not cross both ends of the rectangle in the correct order and direction. This captures errors related to crossing accuracy. An *out-of-target error* occurs if the touch stroke did not intersect with any part of the rectangle. This most often captures a case when the participant intentionally aborted a rectangle crossing. These errors are only possible on the current rectangle, strokes intersecting with other rectangles are ignored. A *mode error* occurs when the wrong mode is used to cross a rectangle. In other words, stroking a grey rectangle with red or vice versa. Mode errors are only possible in compound tasks.

We further distinguish between mode-in and mode-out errors. A *mode-in error* occurs when the participant fails to transition from standard touch input to the specified mode-switching technique. This is detected during the second or fourth rectangle crossing. A *mode-out error* is when the participant fails to transition from the specified mode-switching technique to standard touch input. This is detected during the third or fifth rectangle crossing. Finally, a *combined error* occurs if any of the errors above happen. Each of these error types are recorded as an indicator variable: 1 if the error occurred and 0 otherwise. The mean value of one type of indicator variable across trials produces the corresponding error rate.

Crossing Time

The crossing time is the duration between the touch up event after the previous rectangle was crossed until the touch up event after the current rectangle is crossed. There are four measurable rectangle crossings per task.

Mode-switching Time

Naively, one might directly compare crossing times in the baseline task with crossing times in the compound task (where a mode switch was required). However, both crossings share a common overhead of moving from the end of the previous rectangle to the start of the current rectangle. Therefore, we use the "subtraction method" used by Li et al. (adopted from Dillon et al. [11]) to isolate mode-switching time.

The method defines three cycles during a task. The first cycle is from the moment the start button is pressed until the touch up event after crossing the first rectangle. The second cycle begins immediately after, ending when all fingers are lifted after crossing the third rectangle. The third cycle begins immediately after, ending when all fingers are lifted after crossing the fifth rectangle. The second and third cycles are *full cycles*. During the compound task, each full cycle captures a complete mode-switch operation: the participant switches into a mode using the specified technique, crosses a rectangle, switches out of the mode, crosses another rectangle, and lifts their finger(s). The purpose of the first cycle is to ensure standard touch input is used before the second cycle. In each block, there are 8 full cycles (two cycles per direction). For each technique, each participant completes 32 full cycles with mode switching (in the 4 compound task blocks) and 40 full cycles with standard touch input only (in the 5 baseline task blocks).

The subtraction method isolates mode switching time using mean times from second and third cycles. For each block, the mean time for second and third cycle is calculated using error-free cycles (recall there are four task directions per block, so each full cycle is repeated four times). The mode-switch time is calculated by subtracting the mean full cycle time of two adjacent baseline blocks from the mean full cycle time from a compound block. In total, this provides 8 mode-switch time measurements per-participant, per-technique (2 per block).

RESULTS

All results, including subjective ratings, are continuous, so the same analysis procedure was used for all data. Specifically, we performed repeated measures ANOVA and pairwise t-tests with Bonferonni corrections when main or interaction effects were found. For interaction effects, we restricted pairwise tests to comparing means across factor dimensions independently. When the assumption of sphericity was violated, degrees of freedom were adjusted using Greenhouse-Geisser ($\epsilon < 0.75$) or Huynh-Feldt ($\epsilon \geq 0.75$). Non-normal skewed distributions, were corrected using a log transform or Aligned Rank Transform [59] depending on the severity and direction of skewness.

Data Pre-Processing

We examined error-free *crossing times* to identify outliers more than 3 standard deviations from the mean for each TASK divided by POSE. This removed 4.6% of the rectangle crossing trials (3.8% to 6.7% per technique), comparable to similar touch experiments [37].

Using the remaining error-free full cycles, we used the subtraction method described above to calculate *mode-switch times*. Visual inspection of the mode-switch times distribution suggested non-normality, confirmed by a Shapiro-Wilk and Anderson–Darling tests. To compensate, we log-transformed all data points for mode-switch time. There were 33 data points with slightly negative mode-switch times. This only appeared for TWOFINGER, the fastest technique. To compensate, we first added 306ms to all times to guarantee positive values required by the log function. Note that this log transformed data is used for statistical tests involving mode-switch time. All times presented in the paper are actual measured values. Error rate distributions did not suggest non-normality.

Learning Effects

To determine if performance changed during the four compound blocks, we tested for effects of POSE × TECHNIQUE × BLOCK on *mode-switch time* and *combined error rate*. We found no statistically significant interaction involving block indicating no learning effect across blocks. This matches the performance stability noted by Li et al. All blocks are used in subsequent analyses.

Mode-Switching Time

We expected POSE would alter how the techniques were performed, but there was no significant main effect of POSE, or POSE × TECHNIQUE interaction effect on MODE-SWITCH TIME. There was a significant main effect of TECHNIQUE ($F_{5,170} = 109.52$, $p < .0001$, $\eta_p^2 = .76$). Post hoc tests found all TECHNIQUES significantly different $p < .0001$, except HARD PRESS and KNUCKLE. Ranking TECHNIQUES from fastest to slowest mode-switch time: TWOFINGER (222ms); NONPREF (311ms); THUMB (408ms); KNUCKLE and HARDPRESS (500ms and 568ms respectively, not significantly different); and LONGPRESS (1244ms). LONGPRESS is more than twice as slow as the next fastest techniques and more than five times slower than the fastest technique.

Comparing the switching times of techniques used in Li et al., we notice that our values are systematically higher. For NONPREF and HARDPRESS, the authors report mean times of 139ms and 284ms respectively, which are roughly half of our values. Tu et al. [54] also evaluated those techniques and while the pressure-based technique is reportedly even faster (mean time 228ms), the timing for their version of NONPREF, 304ms, is very similar to ours.

Although there was no effect of POSE, we examine TECHNIQUE by POSE given our a priori control. For each POSE, we ran a one-way ANOVA for TECHNIQUE on *mode-switch time*. Main effects were found for SIT ($F_{5,85} = 69.60$, $p < .0001$, $\eta_p^2 = .80$) and STAND ($F_{5,85} = 44.42$, $p < .0001$, $\eta_p^2 = .72$). The pattern of post hoc differences was very similar to the TECHNIQUE main effect (all $p < .0001$). The only difference is for STAND: there was one other non-significant difference between THUMB and NONPREF. Without that one exception, the order of TECHNIQUES from fastest to slowest is consistent between POSES and with combined poses (see Fig. 4).

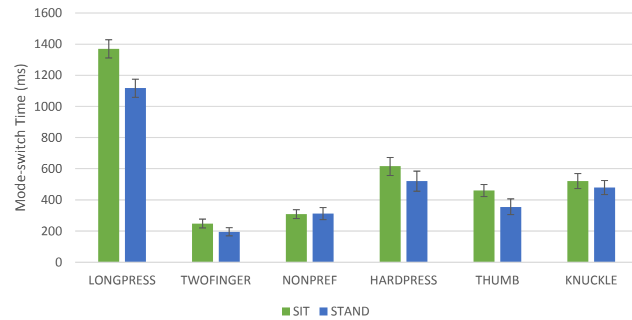

Figure 4: Mean mode-switch times by POSE and TECHNIQUE with 95% CI.

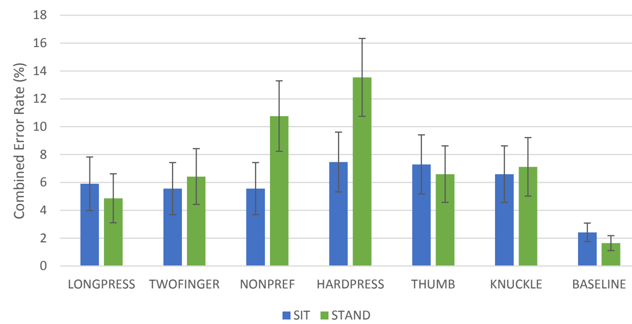

Figure 5: *Combined error rate* for TECHNIQUES by POSE

Error Analysis

Before examining specific error rates for techniques and poses, we note that the *overall error rate* for baseline crossing cycles is a 4.1% with no detectable differences between POSE. This rate suggests participants were balancing speed and accuracy [63] and is low enough to suggest using the subtraction method is valid. Li et al. do not report baseline rates.

Unlike mode-switch time, we did find a significant interaction for POSE × TECHNIQUE on *combined error rate* ($F_{3.40,115.66} = 3.02$, $p = .012$, $\eta_p^2 = .081$). There was a significant main effect for TECHNIQUE as well, but the interaction with pose is most relevant. To determine if the technique combined error rate was significantly different between poses, we performed six pairwise tests. With Bonferonni correction, only a borderline difference in HARDPRESS $p = .06$ exists. Like mode-switch time, it appears that POSE has little or no effect on overall error rate.

Continuing to explore the significant interaction, we examine if the technique *combined error rates* were significantly different using pairwise tests between techniques when considering SIT and STAND separately. For SIT, we found no significantly different techniques. The measured rates ranged between 4.8% and 7.5%. Again, we observe a contrast with Li et al.'s reported error rates, which are systematically lower. Their hold technique led to the most errors (due to a slippery screen) and NonPrefHand to the lowest rates. Tu et al. once more show different results (Holding being the least error-causing

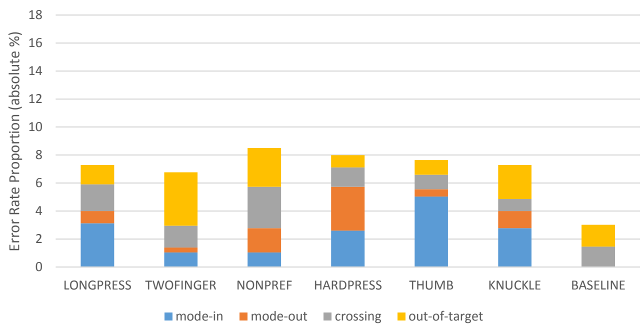

Figure 6: Proportion of specific error rates for TECHNIQUES for SIT. Note more than one type of specific error can occur during a cycle.

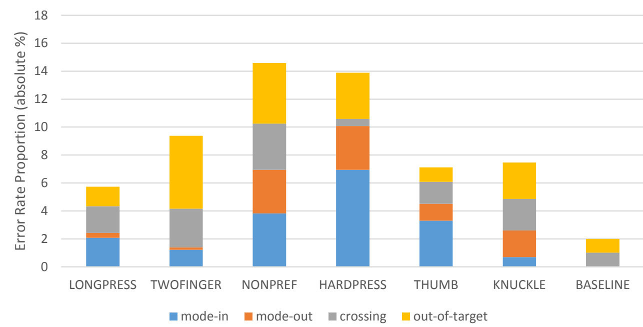

Figure 7: Proportion of specific error rates for TECHNIQUES for STAND. Note more than one type of specific error can occur during a cycle.

technique in their experiment) and error rate ranges that are partially closer to ours.

For STAND, we found significant differences between TWOFINGER and HARDPRESS, LONGPRESS and HARDPRESS (both $p < .05$), and a borderline difference between NONPREF and LONGPRESS ($p = .05$). The measured rate for HARDPRESS is 13.5% and NONPREF is 10.8%, with the remaining techniques ranging between 3.3% and 7.1%. This provides more evidence that, relative to the other techniques, HARDPRESS and NONPREF are harder to perform when standing.

We also investigate the effect of POSE and TECHNIQUE on specific types of errors (illustrated by POSE in Fig. 6 & 7).

For *crossing error rate*, we found a main effect for TECHNIQUE ($F_{5,170} = 3.97, p < .001, \eta_p^2 = .104$). Post hoc tests showed NONPREF had a higher rate (3.9%) than HARDPRESS (1.2%) and THUMB (1.5%). Measured rates were between 1.2% and 3.9%.

For *out-of-target error rate*, we also found a main effect for TECHNIQUE ($F_{5,170} = 5.41$, $p < .0001$, $\eta_p^2 = .14$). Post hoc tests showed the rate for THUMB (1.0%) was lower than KNUCKLE (2.6%), NONPREF (5.0%), and TWOFINGER (5.9%). Also HARDPRESS (2.5%) was lower than TWOFINGER. Measured rates were between 1.0% and 6.3%. Note that Li et al. had almost no out-of-target errors.

For *mode-in error rate*, TECHNIQUE had a main effect but we focus on the more relevant significant POSE × TECHNIQUE interaction ($F_{5,170} = 2.44$, $p = .036$, $\eta_p^2 = .066$). For SIT, post hoc tests showed TWOFINGER (1.0%) was lower than LONGPRESS (3.1%). For STAND, KNUCKLE (0.7%) was lower than HARDPRESS (6.9%) (all $p < .05$). Measured rates were between 1.0% and 5.0% for SIT and between .07% and 6.9% for STAND.

For *mode-out error rate*, TECHNIQUE had a main effect ($F_{3.56,121.07} = 6.28$, $p < .001$, $\eta_p^2 = .16$). Post hoc tests showed TWOFINGER (0.3%) was lower than NONPREF (2.4%) and HARDPRESS (3.1%) HARDPRESS was higher than THUMB (0.9%) and LONGPRESS (0.6%) (all $p < .05$). Measured rates were between 0.3% and 3.1%. There is some evidence that NONPREF and HARDPRESS both are more difficult to disengage.

Subjective Ratings

After completing trials for all techniques, participants provided subjective ratings of the techniques with respect to six aspects: ease-of-learning, ease-of-use, accuracy, speed, eye fatigue, and hand fatigue. All ratings were on a continuous numeric scale from 1 to 5, with 1 being the worst score (e.g. low accuracy, hard to learn, very fatiguing) and 5 the best (e.g. high accuracy, easy to learn, not fatiguing).

Table 1 summarizes subjective ratings by POSE. The distributions for ratings was non-normal due to high negative skewness, so the values were transformed using the Aligned Rank Transform method [59]. ANOVAs performed on this transformed data did not reveal any significant main effects or interactions involving POSE on any any of the ratings. However, there are significant main effects for TECHNIQUE regardless of POSE. We report the main results of pairwise comparisons between TECHNIQUE for each rating.

- For *hand fatigue* and *ease-of-use*, HARDPRESS and KNUCKLE were reported respectively more tiring and less easy to use compared to the other techniques (all $p < .032$). This is understandable, given the pressure and wrist efforts required. Participant feedback confirmed the difficulty and physical demand of HARDPRESS (seven people) with one participant commenting that it almost felt like breaking the tablet. As for KNUCKLE, two participants reported it was tiring and two pointed out that it resulted in increased occlusion; however, two people also said it was "fun". For NONPREF, four participants remarked that the technique required well-timed coordination and thus getting used to to be efficient. For the standing position, we also observed that participants with small hands (two in particular) sometimes had trouble reaching the button with the fingers of the non-preferred hand across the bezel of the tablet.
- In terms of *ease-of-learning*, HARDPRESS was rated significantly harder to master than LONGPRESS and TWOFINGER ($p = .0043$ and $p = .0102$ respectively). We believe this is because participants had to learn to adjust touch pressure levels to be able to activate the two different modes reliably as well as because of the extra training required for the EMG classifier.
- With respect to *accuracy*, HARDPRESS was consistently perceived as having the lowest precision ($p < .007$ compared to all other techniques). Note that HARDPRESS and NONPREF have the highest overall error rates, yet HARDPRESS was rated more accurate. Hence, there appears to be an increased perception of poor accuracy with HARDPRESS. For TWOFINGER, we observed that, during training, participants needed a

SIT	LONG PRESS	TWO FINGER	NON PREF	HARD PRESS	THUMB	KNUCKLE
Learning	$4.4_{\pm.21}$	$4.4_{\pm.20}$	$4.7_{\pm.13}$	$3.7_{\pm.32}$	$4.6_{\pm.14}$	$4.1_{\pm.23}$
Ease-of-Use	$3.9_{\pm.24}$	$4.2_{\pm.22}$	$4.0_{\pm.28}$	$3.0_{\pm.31}$	$4.3_{\pm.24}$	$2.7_{\pm.26}$
Accuracy	$4.3_{\pm.20}$	$4.1_{\pm.26}$	$4.5_{\pm.16}$	$3.2_{\pm.26}$	$4.3_{\pm.20}$	$4.2_{\pm.18}$
Speed	$2.6_{\pm.23}$	$4.3_{\pm.22}$	$4.2_{\pm.17}$	$3.4_{\pm.30}$	$4.2_{\pm.20}$	$3.4_{\pm.33}$
Eye Fatigue	$4.7_{\pm.15}$	$4.8_{\pm.10}$	$4.8_{\pm.12}$	$4.4_{\pm.25}$	$4.7_{\pm.17}$	$4.5_{\pm.21}$
Hand Fatigue	$3.7_{\pm.27}$	$4.1_{\pm.27}$	$4.4_{\pm.22}$	$3.0_{\pm.32}$	$4.0_{\pm.26}$	$3.0_{\pm.31}$
Combined	$3.9_{\pm.1}$	$4.3_{\pm.1}$	$4.4_{\pm.1}$	$3.5_{\pm.1}$	$4.4_{\pm.1}$	$3.6_{\pm.1}$
STAND	LONG PRESS	TWO FINGER	NON PREF	HARD PRESS	THUMB	KNUCKLE
Learning	$4.6_{\pm.22}$	$4.7_{\pm.16}$	$3.9_{\pm.32}$	$3.8_{\pm.26}$	$4.3_{\pm.24}$	$4.0_{\pm.27}$
Ease-of-Use	$3.9_{\pm.22}$	$4.2_{\pm.24}$	$3.2_{\pm.36}$	$3.0_{\pm.31}$	$3.9_{\pm.29}$	$3.2_{\pm.33}$
Accuracy	$4.5_{\pm.18}$	$4.2_{\pm.19}$	$3.9_{\pm.33}$	$3.1_{\pm.28}$	$4.1_{\pm.23}$	$3.8_{\pm.26}$
Speed	$2.8_{\pm.30}$	$4.6_{\pm.20}$	$3.4_{\pm.30}$	$3.3_{\pm.27}$	$4.1_{\pm.26}$	$3.4_{\pm.25}$
Eye Fatigue	$5.0_{\pm.0}$	$5.0_{\pm.0}$	$4.9_{\pm.05}$	$4.9_{\pm.05}$	$5.0_{\pm.0}$	$4.7_{\pm.17}$
Hand Fatigue	$4.3_{\pm.30}$	$4.5_{\pm.18}$	$3.6_{\pm.32}$	$2.9_{\pm.34}$	$4.3_{\pm.26}$	$3.6_{\pm.30}$
Combined	$4.2_{\pm.1}$	$4.5_{\pm.1}$	$3.8_{\pm.1}$	$3.5_{\pm.1}$	$4.3_{\pm.1}$	$3.8_{\pm.1}$

Table 1: Mean subjective ratings: SIT (top) and STAND (bottom).

short adaptation time to position their two fingers for the ink to appear at the desired spot.

- Finally, regarding *speed*, TWOFINGER was rated significantly faster than all other techniques except THUMB ($p < .01$), THUMB was judged faster than HARDPRESS, KNUCKLE and LONGPRESS ($p < .013$) and LONGPRESS considered significantly slower than all techniques except HARDPRESS ($p < .03$). All those results are consistent with the time measurements.

DISCUSSION

Our results provide evidence that regardless of whether a tablet is used flat on a desk, or held by the non-dominant arm while standing, the performance characteristics and subjective impressions of these techniques are comparable. This may bolster the validity of other non-mode-switching touch input studies evaluated only when a tablet is laid flat on a desk (e.g. [38, 18, 43]). However, more styles of touch input need to be tested in sitting and standing poses to verify any general claims.

Regarding mode-switching techniques, our results show long press is the worst and two-finger multi-touch the best, unless target accuracy is critical. When accuracy is needed, thumb-on-finger is the best option with lower out-of-target errors than two-finger (and others) and lower crossing errors than non-preferred hand. Subjective ratings for thumb-on-finger do not indicate a pattern of any strong preference or dislike. One caveat is that, although there were no significant differences for thumb-on-finger in mode-in errors, the measured values are high (Figs. 6 and 7). Given the high variance preventing statistical difference, individual mastery of thumb-on-finger mode-switching varies.

When considering mode-switching time only, non-preferred hand, knuckle, and hard press are all within 100ms from the mean time for thumb-on-finger. At first this may suggest they are all comparable, but high rates of mode-switching errors and a pattern of lower subjective ratings cast doubt on using pressure for touch mode-switching. Although there is subjective support for the non-preferred hand, it has a higher mode-out error rate than other techniques and a surprising pattern of frequent crossing and out-of-target errors.

Given the novelty of using a knuckle for touch input, we were surprised to see it perform as well as it did. It has an overall error rate comparable to the best techniques with one of the lowest mode-in error rates. Although out-of-target errors are higher than some, there is no statistical evidence of a higher crossing error rate. This is encouraging considering we expected the increased occlusion to make knuckle crossing wildly inaccurate. However, subjective ratings and comments show a pattern of mild dislike due to higher fatigue and perceived slower speed. Note that only two-finger and knuckle *instantly* combine the mode-switch with the initial touch position. This "merging of command selection and direct manipulation" has been shown to be beneficial [22].

Subtraction Method Validity

Like Li et al., we confirm that we can apply the subtraction method in our experimental protocol since drawing and positioning movements are not strictly fixed as in Dillon et al.'s point-connecting task [11]. We accomplish this by comparing the *total movement distance* in a full cycle between baseline and compound tasks. A sufficiently small difference indicates that movements required for the two types of tasks were similar. Due to how we logged multiple simultaneous touches, automatic calculation of movement time for non-preferred hand and multi-touch proved error-prone. We chose to not include them in this analysis. Among techniques, non-preferred hand and multi-touch are arguably the most similar to non-mode touching crossing movements.

For the remaining four techniques, we found a mean movement distance for a full cycle to be 55.2mm (690px). This is 1.4mm greater than the baseline condition, in which mean movement distance was 53.8mm (672px). This difference of only 2.7%, compares favourably with Li et al.'s difference of 4.7mm (20px)[1], or 3.4%. Li et al. also report a similar single full cycle mean movement distance of 66 mm (290px). This demonstrates using the subtraction method was valid.

Temporal Pattern Analysis

We analyse the temporal submovements pattern to understand different techniques, and use this to classify them into different temporal models. This is directly based on the "keystroke level analysis" performed by Li et al.. We use the same models and compare our results with their findings.

A full cycle can be decomposed into four submovements with corresponding times:

$$T_{cycle} = T_{P1} + T_{C1} + T_{P2} + T_{C2}$$

where T_{Pi} is the time taken to position the finger in the air before crossing the i^{th} rectangle and T_{Ci} is the time taken to drag the finger on the display and cross the i^{th} rectangle. T_{Pi} begins on touch up of the previous rectangle and ends on touch down of the i^{th} rectangle. T_{Ci} begins on touch down and ends on touch up after crossing through the i^{th} rectangle.

Each two-rectangle full cycle during a compound task requires crossing rectangle 1 (the 'red' one) with the mode engaged and crossing rectangle 2 (the 'grey' one) with the mode disengaged.

[1] Li et al. used a 12.1" diagonal, 1024 × 768px TabletPC.

	BASELINE	LONG PRESS	TWO FINGER	NON PREF	HARD PRESS	THUMB	KNUCKLE
T_{P1}	323	392	375	486	415	502	546
T_{C1}	196	1239	210	189	420	276	267
T_{P2}	317	415	435	419	514	433	510
T_{C2}	195	220	200	208	234	218	218
T_{ENG}	N/A	1130	401	318	459	536	544
T_{DIS}	N/A	51	100	421	91	61	531
T_{GES}	N/A	552	284	779	466	303	799

Table 2: Cycle decomposition times (ms).

Therefore, the mode is engaged either during T_{P1}, or near the beginning of T_{C1}. The time to engage a mode T_{ENG} is the duration from the start of a cycle until the mode is engaged. Note that T_{ENG} equals T_{P1} if the mode is engaged precisely at touch down (e.g. knuckle); T_{ENG} may be less than T_{P1} if the mode can be engaged before touch down (e.g. non-preferred hand); and T_{ENG} may be greater than T_{P1} if the mode is engaged after touch down (e.g. hard press). T_{GES} is the time spent gesturing, defined from the later of mode engagement and touch down until touch up. Beyond these durations defined by Li et al., we define a mode disengage time T_{DIS} as the duration from disengagement until touch up.

Table 2 provides mean times for these submovements for all techniques. A further verification that the task and subtraction method worked as it should is that the T_{C2} times are the same for the baseline task and all techniques. As in Li et al., our absolute timings for T_{C2} all appear close to the baseline. To verify this, we conducted a one-way ANOVA for the effect of technique (including baseline) on T_{C2}. There was a main effect ($F_{4.07,138.27} = 9.5754$, $p < .001$) and post hoc tests reveal that all but two-finger multi-touch are significantly different. However, the differences between all techniques and the baseline is less than 40 ms.

Temporal models

All techniques follow the temporal models described in Li et al.'s keystroke level analysis. Although the authors did not perform statistical tests on timing decompositions, we provide this extra level of validation when applicable.

Using Non-Preferred Hand and Thumb-on-Finger

The two techniques obey the same temporal model, as they require the mode to be engaged before touch down, with release possible during, or after completion of the gesture. As in Li et al., we calculate an estimate of the gesture engagement time by subtracting T_{P1} of the baseline task from T_{P1} of the compound task. We obtain 164ms for NONPREF and 179ms for THUMB, with no significant difference between them. This contrasts with Li et al., where the mode engagement time for NonPrefHand and BarrelButton were 65ms and 144ms respectively, a greater difference.

Disregarding the absolute timings which are systematically lower for Li et al., we believe there may be two reasons for this greater difference. First, it may be easier and faster to hit the index finger with one's thumb than to reach and press a barrel button on a stylus. Second, although our participants held their finger poised above the touchscreen button before each non-dominant hand trial, Li et al.'s NonPrefHand participants could exploit the physical button by resting their finger on it to minimize activation and eliminate targeting. The physical button may have been the primary reason for the very strong performance of NonPrefHand in Li et al.. Perhaps the full potential of non-preferred hand mode-switching cannot be realized on a touchscreen.

Using Long Press (Hold)

Li et al. note that there is a difference between the T_{P1} timings of Hold and the baseline even though gesture mode engagement is started upon touch down and thus, at first glance, the two T_{P1} should be close. They attribute this difference to an additional preparation time needed when slowing down the pen movement to hold it in a steady position. We also observe this phenomenon with a statistically significant difference of 69.5ms between the T_{P1} timings ($p < .0001$), albeit a much lower one.

Li et al. also calculate the time participants took to respond to the feedback showing that the mode had been engaged (a full circle) using the formula:

$$T_{response} = T_{ENG} + T_{P1} - Holdtime$$

Their response time is 137ms. Ours is: $1130 - 392 - 500 =$ 238ms.

Using Hard Press (Pressure) and Two-Finger Multi-touch

In Li et al., Pressure is the technique with the lowest T_{P1}, but again, without statistical analyses we do not know if timings are significantly different from other techniques. Even though HARDPRESS appears to be third best only from the mean values, ANOVAs and post hoc tests do not reveal any significant differences between the T_{P1} values for HARDPRESS, TWOFINGER and LONGPRESS and hence we are not able to conclude which of the three techniques has the shortest positioning time.

Similar to Li et et al., we calculate the time to increase touch pressure to the required level in order to activate the gesture mode: $T_{ENG} - T_{P1} = 45$ms. This value is much lower than their 176ms. We attribute that to the possibility that it might be easier to sense and apply the required pressure level using direct input than with an instrument such as a stylus. The fact that we used an EMG armband with a high data rate and adapted pressure thresholds for each participant might also have been factors.

Like Li et al, we observe that drawing with HARDPRESS takes more time than without (the difference between the two T_{C1} values is 223ms, which is significant). The difference is likely even more pronounced with a finger than with a stylus due to the increased friction of dragging (Li et al. report a drawing time of 176ms, but, once more, we cannot determine if the differences are significant).

The model for TWOFINGER is similar, as the mode is engaged after touch down and has to be maintained throughout the moded action. However, we expect the time to engage the mode after touch down to be very short, as the two fingers are usually put down almost simultaneously. Similar to hard press, we calculate the engagement time after touch down, which is $T_{ENG} - T_{P1} = 26$ms. A t-test confirms that the difference with HARDPRESS is significant ($p < .0001$).

Using Knuckle

Our knuckle technique follows the temporal model of the Eraser in Li et al.. The authors notice very similar T_{C1} timings for the Eraser and the baseline task, meaning that drawing with the eraser end of the stylus requires no extra effort. This was not the case with KNUCKLE. Drawing with the knuckle took an extra 71ms, statistically significant compared to the baseline ($p < .0001$). Li et al. further calculate times to turn and revert the pen in order to use the eraser by subtracting the T_{P1} and T_{P2} timings. They report values of 661ms and 555ms. A stylus being typically longer and the rotation required to use its eraser larger, our wrist-rotation times for KNUCKLE are predictably lower: 223ms and 193ms respectively.

Improvements to Mode-Switching Techniques

None of the techniques we tested were perfect in all aspects. Even two-finger multi-touch suffers from accuracy problems when the demands for targeting and tracing precision are high. To improve that, a cursor could appear between fingers when approaching the screen (assuming pre-touch sensing is available [29]). For hard press, it would be interesting to see if a device with built-in touch pressure sensors and a smart adaptive thresholding algorithm could improve the measured and perceived accuracy as well as reduce fatigue.

For KNUCKLE, our realisation of the technique is based on the rotation of the wrist, which causes both strain and occlusion problems. Those issues might be alleviated if knuckle interaction could be performed without turning the hand (i.e. by bending the finger and using the distal interphalangeal joint).

Regarding techniques which require the mode switch to be engaged before touch down, mode-in errors would presumably be reduced if that condition is relaxed so the mode change could occur after touching the device. This has been shown in pen mode-switching for direct manipulation contexts that permit late mode activation [33, 48]. The extended period allowed for the switch could be chosen depending on the application context and which functions the moded and non-moded actions are mapped to: a long period if late mode engagement has minimal disturbance (e.g. changing stroke style) and a short period when late mode engagement would be disruptive (e.g. switching between panning and inking).

Hybrid techniques are an interesting avenue for exploration. For example, pressure-based activation could be combined with non-preferred-hand to simulate behaviour of a physical button: the fingers of the non-preferred hand could rest on the screen to minimize activation time and eliminate targeting. This might be especially helpful when supporting the tablet with that non-preferred hand, as the holding posture is maintained at all times and therefore stability is likely increased. It would be particularly interesting to see how techniques can be combined to support several mode changes, such as combining two-finger or knuckle with non-preferred hand.

LIMITATIONS

While our experiments provide insightful results, we acknowledge their scope of validity and the limitations within which they can be interpreted. First, since our study design followed Li et al., we operate with the same constraints regarding a single mode switch applied with a relatively high and regular frequency in a synthetic linear task. This design allowed us to perform fine-grained analyses, but further studies could validate our results in more realistic and less controlled tasks. Furthermore, applications often include more than two modes, so techniques could also be evaluated with multiple modes to assess scalability.

Although we strived to design optimized and representative techniques, there are possible limitations in the way they were implemented. Knuckle, hard press, and pressure required participants to wear extra sensors. Although none reported any particular impediment or discomfort, results for those techniques might change if alternate sensing was used. For non-preferred hand, the size and position of the trigger button was fixed for all participants. Prior work and several pilot tests informed our final design, but size and position could be personalized to individual people, especially when used in a standing position. Finally, the dwell time used to activate a long-press naturally influences the performance and accuracy of the switch. Our choice of 500ms is used in popular operating systems, but this could be further optimized.

CONCLUSION

We presented a detailed analysis of touch input mode-switching techniques. Our results can be used as guidelines for selecting mode-switching techniques. When restricted to current device capabilities, two-finger multi-touch should be selected if accuracy is not critical and a non-preferred hand button otherwise. As more advanced sensors are available, touching the thumb to the side of the finger will also be a good choice. Using the knuckle works surprisingly well, though many people perceive it as being inaccurate and uncomfortable. In most cases, long press should be avoided. In contrast to reasonable performance for pen pressure mode-switching reported by Li et al. [36], using pressure for touch mode-switching appears problematic. It is possible that hard press performance and perceived inaccuracy may improve on a device with built-in pressure sensors, but we suspect this has more to do with touch friction and fatigue.

Though numerous experimental investigations have compared mode-switching techniques for pucks, mice, and pens, we believe we are the first to do so for touch input. This work fills an important knowledge gap, especially when considering how fundamental mode-switching is to touch interaction.

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