Effect of Orientation on Unistroke Touch Gestures

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ABSTRACT

As touchscreens are the most successful input method of current mobile devices, touch gestures became a widely used input technique. While gestures provide users with advantages to express themselves, they also introduce challenges regarding accuracy and memorability. In this paper, we investigate the effect of a gesture's orientation on how well the gesture can be performed. We conducted a study in which participants performed systematically rotated unistroke gestures. For straight lines as well as for compound lines, we found that users tend to align gestures with the primary axes. We show that the error can be described by a Clausen function with $R^2 = .93$. Based on our findings, we suggest design implications and highlight the potential for recognizing flick gestures, visualizing gestures and improving recognition of compound gestures.

CCS CONCEPTS

• **Human-centered computing** → **Touch screens**; Empirical studies in HCI; • **Hardware** → *Touch screens.*

KEYWORDS

Touch unistroke gestures, touch input, orientation, gesture set, user study, design guidelines, mobile device.

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1 INTRODUCTION

Touchscreens are the dominant input technique for current mobile devices. By combining input and output in a single surface, user interfaces became more intuitive as users can directly touch desired objects on the touchscreen. With direct touch, many novel, and intuitive input methods emerged. Users can scroll by swiping with a finger over the screen, rotate by rotating two fingers and zoom by pinching/spreading two fingers. However, this combination also entails major disadvantages that are the focus of a wide range of previous work. Amongst others, input (e.g. an on-screen keyboard) and output (e.g., an image, or text document) have to share the same limited screen space.

Touch gestures are a widely used approach to overcome touchscreens' limitations. Gestures can be performed at any location on the touchscreen and do not require any dedicated space in comparison to on-screen keyboards or menus. Therefore, a large body of work proposed to use gestures for a wide range of functionalities, such as launching applications [21], managing the clipboard [11], hierarchic marking menus [16, 33], unlocking the smartphone [26, 29], improving text entry using gesture keyboards [15, 32], or overcoming the fat-finger problem on small devices [8]. Moreover, Appert and Zhai [1] showed that stroke-based gestures can be better learned and recalled in comparison to keyboard shortcuts with the same amount of practice. Users also interact with their smartphone in mobile situations, such as while walking and sharing their attention between the device and the environment. Bragdon et al. [4] showed that gestures offer significant performance advantages compared to soft buttons when the user is under environmental distractions.

A large body of work investigated how users perform gestures. Cao and Zhai [6], for example, presented a model to predict the production time of pen stroke gestures. The authors were mainly interested in production time but also showed that the orientation can have an effect on accuracy. In particular, they stated that horizontal and vertical movements tend to be more accurate. Following the work by Cao and Zhai [6], we assume that the accuracy of gestures performed with the finger is also affected by the orientation of the strokes. While it is likely that the accuracy is affected by orientation, it is unclear how the orientation affects the accuracy and how the accuracy can be predicted. Furthermore, meaningful gestures typically do not only consist of a straight stroke which makes it important to also analyze gestures consisting of multiple segments.

The main contribution of this paper is a deeper understanding of how gestures are performed by users. In a study, participants reproduced gestures consisting of one, two or three straight segments resulting 4,104 unique gestures. In total 40 participants performed 39,038 gestures. We show that the orientation of the gesture significantly affects users' accuracy and that a Clausen function can model the error with $R^2 = .93$. We provide design implications that can help to design rotation sensitive unistroke gesture sets. The contribution of this paper is three-fold: (1) an analysis of how humans reproduce presented gestures, (2) a model that describes the effect of orientation on rotation sensitive gestures and (3) design implications to improve rotation sensitive unistroke gesture sets.

2 RELATED WORK

Commercial devices already incorporate a wide range of touch gestures, such as swipe to unlock or letter-shaped gestures to launch pre-defined applications. Caramiaux et al. [7] investigated continuous gestures and not only used size and speed as input dimensions but also gestures' orientation. Poppinga et al. [21] further investigated these kinds of gestures in an in-the-wild study to derive a comprehensive gesture set for the frequently used actions. Previous work showed that gestures have a wide range of advantages, including eyes-free input [24], outperforming on-screen buttons while walking [4], and a better recall in comparison to keyboard shortcuts with the same amount of practice [1]. Previous work also developed a large number of approaches to recognize gestures, including GRANDMA [25], work that extended the considered features [18], learning-based approaches [12, 28], and even the use of kinematic theories for data augmentation [17].

One focus of previous work was gaining a deeper understanding of the way users perform gestures on touchscreens. Cao and Zhai [6] investigated users' performance when performing pen stroke gestures and built a model that predicts the time to perform a gesture. In their model, they count straight lines, arcs, and corners to predict the execution time. Tu et al. [31] found that the number of included muscles and joints of the hand have an impact on accuracy. They compared stroke gestures using a pen, the index finger, and the thumb. While pen input performed best, index finger gestures performed better than thumb gestures. Finger gestures tended to be less accurate than pen gestures with regard to shape distance and shape errors. They found a significant bias in the gesture's orientation by about 3°.

Tu et al. [30] compared pen and touch gestures and found that while there are differences in size ratio and average speed, they were both similar in indicative angle difference, axial symmetry, and proportional shape distance. Similar results were presented by Arif and Sylla [2] who found that pen gestures were significantly faster and more accurate. Rekik et al. [23] report that pre-defined gestures produced with more fingers are larger in size and take more time to produce than single-touch gestures.

Previous work developed models to increase the accuracy of target selection tasks on touchscreens by compensating systematic errors [14]. Mayer et al. [19, 20] used a similar approach to improve the accuracy of mid-air gestures. However, these approaches relied on simple polynomials and it is unclear how to apply correction models to 2D gestures.

Overall, a significant body of research is devoted towards understanding how users perform gestures. In particular, Cao and Zhai [6] revealed a significant effect of orientation on straight lines. Further, they stated that horizontal and vertical movements tend to be more accurate. Later Burri et al. [5] also showed that the horizontal and vertical movements are significantly different from the diagonal unistroke gestures in both subjective performance and subjective physical demand. In this paper, we, therefore, aim to understand the effect of orientation on the accuracy of unistroke touch gestures and build a model with the potential to improve gestural interaction.

3 HYPOTHESES

Cao and Zhai [6] investigated how users perform pen stroke gestures. While they were mainly interested in production time, they also revealed a significant effect of orientation on accuracy for straight lines. Further, they stated that horizontal and vertical movements tend to be performed better both in orientation error but also in number of attempts. Moreover, Cao and Zhai [6] showed that gestures with *Corners* (*two-segment* gestures) the angle has a significant influence on orientation error and number of attempts. Here, they argue that the error is larger for around 67.5° than the extrema.

Finally, while Cao and Zhai [6] presented results on production time on polylines (*three- and more-segment*), they did not study orientation effects. We adopted the findings by Cao and Zhai [6] since Tu et al. [30, 31] stated that pen stroke gestures and index finger touch stroke gestures have similar orientation errors. Thus, our paper investigates the effect of orientation on connected straight lines and is guided using the index finger by the following four hypotheses:

Hypothesis 1 (**H1**): The orientation of a gesture systemically affects the error when performing the gesture.

Hypothesis 2 (**H2**): Adding straight segments to a gesture results in a larger variation to the orientation error.

Hypothesis 3a (**H3a**): Users skew the orientation of lines towards horizontal lines even if the visual representation is off by some degrees.

Hypothesis 3b (**H3b**): Users skew the orientation of lines towards vertical lines even if the visual representation is off by some degrees.

Hypothesis 4 (**H4**): Users perform straight diagonal gestures with a lower error than other straight gestures.

4 STUDY

We conducted a study to observe how users perceive and perform presented gestures. Therefore, we systematically manipulated the orientation of three types of gestures: *one-segment*, *two-segment* and *three-segment* gestures. Each segment is a single straight line (see Figure 1).

Design

For our study, we used a mixed-design to keep the time of the study reasonable for participants. As previously mentioned, participants performed three different types of gestures: *one-segment*, *two-segment*, and *three-segment* gestures. The three segment structure is inspired by Cao and Zhai [6] who used straight lines, corners, and polylines which respectively are represented by the three different segment gesture number. A selection of gestures is shown in Figure 2. For the *one-segment* gestures, we used one straight line which was systematically rotated by one degree, resulting in 360 gestures.

The *two-segment* gestures are built out of two consecutive segments with different orientations. The first segment is rotated around the full 360° circle in 15° steps, resulting in 24 different orientations. The second segment is rotated from −90° to 90° in 15° steps (skipping 0°), resulting in 12 different orientations.

The *three-segment* gestures are built out of three consecutive segments each with a different orientation. The first segment is rotated around the full 360° circle in 15° steps, resulting in 24 different orientations. The second and third segment is rotated from −90° to 90° in 15° steps (skipping 0°), resulting in 12 different orientations each.

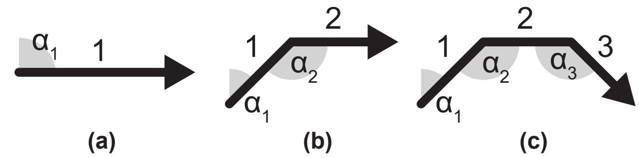


Figure 1: For *one-segment* gestures (a) we rotated α_1 around $360°$ in $1°$ steps. For *two-segment* gestures (b) we rotated α_1 around $360°$ and α_2 from $-90°$ to $90°$, both in $15°$ steps. We rotated *three-segment* gestures (c) around $360°$ at α_1 and from $-90°$ to $90°$ at α_2 as well as α_3, all three angles in $15°$ steps.

The combinations of segments result in 360 *one-segment* gestures, $24 \times 12 = 288$ unique *two-segment* gestures, and $24 \times 12 \times 12 = 3,456$ unique *three-segment* gestures, resulting in 4,104 unique gestures. As performing 4,104 gestures consecutively will cause fatigue effects, we decided to conduct an experiment with a mixed-design. Therefore, participants performed all 360 *one-segment* gestures. Additionally, they performed either all *two-segment* gestures or 25% of the *three-segment* gestures. Thus participants performed either 648 or 1,224 gestures. The order of the gestures within one segment type was randomized.

The real world size of the *two-segment* gestures was $3.0cm$, for the *two-segment* gestures the segments were $.85cm$ each, and for the *three-segment* gestures the size was $.85cm$ for the first and last segment, and $1.7cm$ for the middle segment.

Apparatus

We used an LG Nexus 5X (LG V10) smartphone with a 5.7″ screen ($2560 \times 1440px$) for the study. We developed an Android application to collect the gesture data. To avoid participants to trace the gesture on the screen to improve input accuracy, gestures were moving from the top to the bottom of the screen. Moreover, we limited input to the lower half of the screen as shown in Figure 3 while the gesture was only visible in the upper half. While participants reproduced the gesture, it stayed visible until it reached the bottom of the upper part, white part in Figure 3. This allowed participants to relate back to measure the actual input error and not possible memory error. In case a participant did not perform a shown gesture, it appeared again until it was performed.

Procedure

After the participants signed a consent form, we explained the procedure of the study and handed them the smartphone. Participants were seated during the study. As the first step, we asked them to fill out a demographics questionnaire on the smartphone.

The study started with a tutorial in which the participants were asked to perform 10 gestures randomly selected from

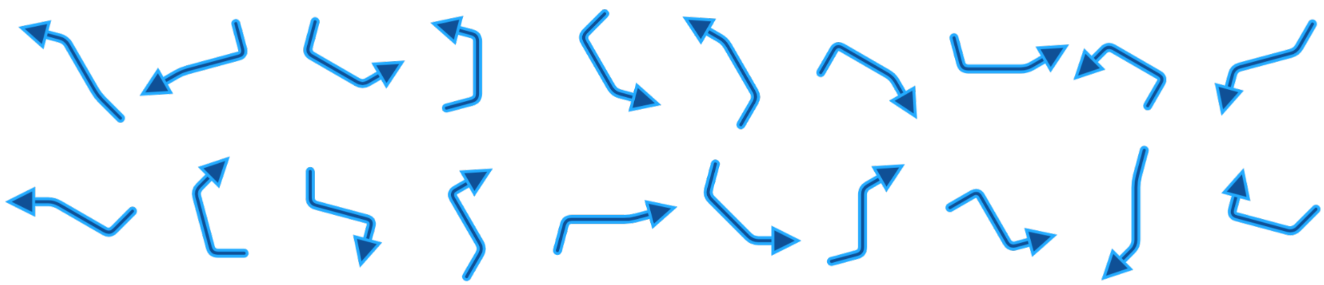


Figure 2: A selection of 18 *three-segmented* gestures used in the study.

the subset they had to perform. During the study participants hold the device in their non dominant hand, while performing the gestures with their dominant hand using their index finger. After each gesture, they got a score (0 = "worst", 10 = "best") for each input based on how well they reproduced the presented gesture. To increase participants' motivation, it was not possible to reach the highest score. We, therefore, present only scores between 3 and 7 which were randomly generated. The score was only shown in the tutorial phase of the study.

The remainder of the study was divided into 6 phases separated by a short break in which an overview of their performance was shown. After performing a gesture participants were not allowed to correct their input. The *one-segment* gestures were performed in one phase while the *two-segment* or *three-segment* gestures were randomized over five phases. Participants had to perform a gesture while the gesture was visible on the screen. We allowed them to take a break at any point during the study as not performed gestures would appear again. We asked participants to fill out a raw NASA-Task Load Index (raw TLX) [13] after each phase to investigate the effect of potential fatigue effects. They were asked to use their non-dominant hand to hold the phone while performing the gestures with the index finger of the dominant hand. Overall, the study lasted about one hour per participant.

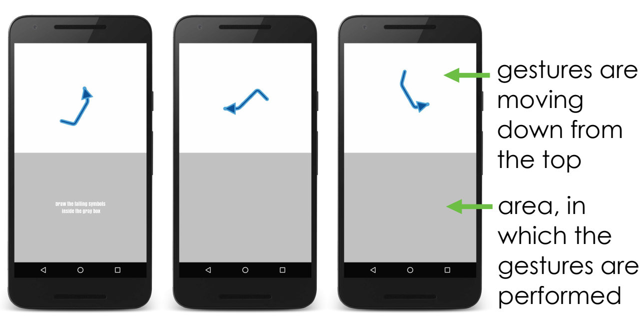


Figure 3: Three screenshots of the study apparatus. The screenshot on the left is showing the view in the tutorial. While the other two screenshots showing the state during the 6 phases.

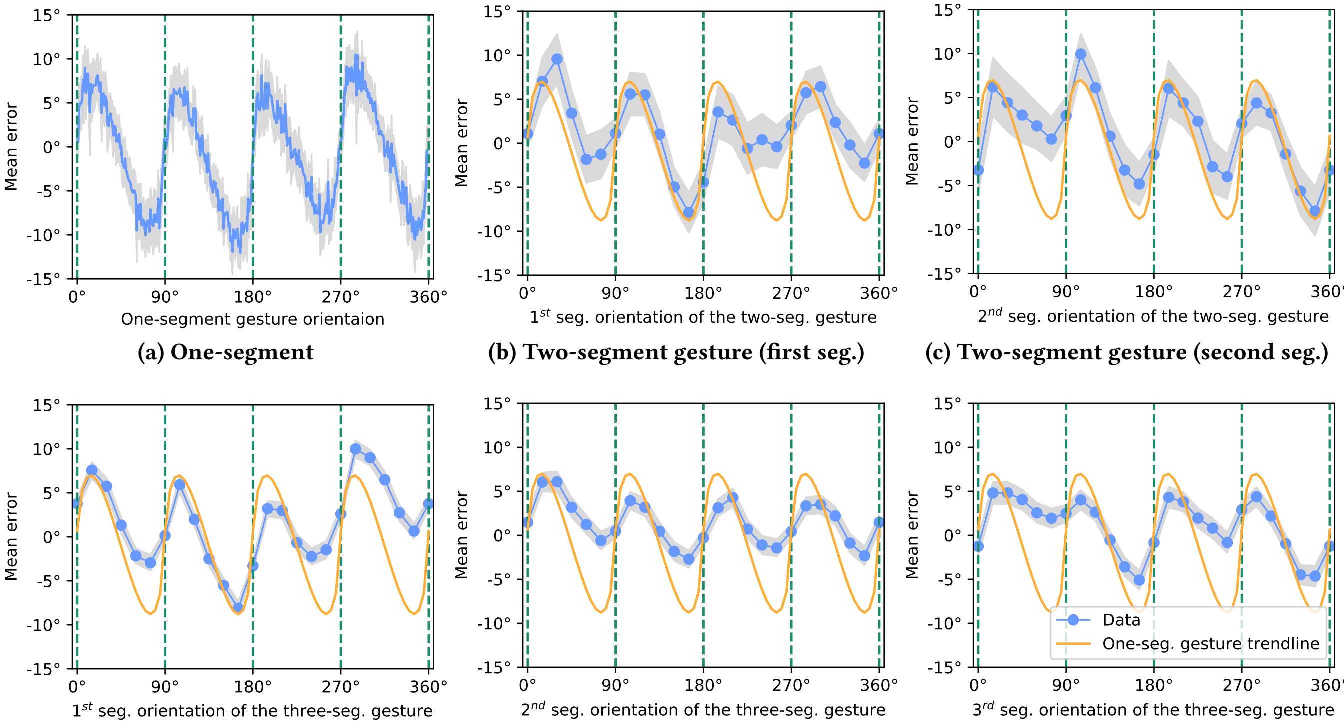
Participants

We recruited 40 participants (20 female) from the university campus via mailing lists. We rewarded them with € 5 for their participation. All participants described themselves as daily smartphone users. Participants were between 19 and 46 years old ($M = 24.2$, $SD = 5.4$). Two participants were left-handed. None had any mental or physical disabilities such as locomotor coordination problems.

5 RESULTS

While we conducted the study with 40 participants the analysis is based on 39 participants, as we excluded one participant due to server-client connection issues in the logging process. In contrast to Cao and Zhai [6] who adopted a normalized measurement from Kristensson and Zhai [15], we used the raw angular error as measurement for the orientation error. Our participants performed 43,128 gestures. We filtered the gestures for wrongly performed gestures using three times the standard deviation of the angular error per gesture type. Finally, we used the remaining 11,826 valid *one-segment* gestures, 2,287 valid *two-segment* gestures, and 22,151 valid *three-segmented* gestures for our analysis. We present the evaluation of the line orientations using angles based on the unit circle[1]. As left and right handed participants performed gestures with their dominant hand, we assume equal quality of the data and therefore applied no transformation to the left handed participants.

[1]In this paper, a line from the bottom to the top is defined to be as oriented with 0° and growing counterclockwise. Thus, a line from the right to the left is 90°, accordingly. The reported angles are in respect to the device screen orientation.



(a) One-segment **(b) Two-segment gesture (first seg.)** **(c) Two-segment gesture (second seg.)**

(d) Three-segment gesture (first seg.) **(e) Three-segment gesture (second seg.)** **(f) Three-segment gesture (third seg.)**

Figure 4: The average angle error for the three segments. The gray area shows the 95% CI. The yellow line represents the trend line for *one-segment* gestures as we showed that the trend line accounts for most of the variation and correlates with the variation in all other gestures.

Potential Fatigue Effect

First we analyzed the raw TLX to determine if we had to consider fatigue effects. After the first phase the mean raw TLX score was $M = 7.4$ ($SD = 3.1$), after the second $M = 6.9$ ($SD = 3.5$), after the third $M = 7.4$ ($SD = 3.5$), after the fourth $M = 7.4$ ($SD = 3.1$), after the fifth $M = 7.5$ ($SD = 3.2$), after the last phase $M = 7.5$ ($SD = 3.2$). A one-way repeated measures analysis of variance (RM-ANOVA) was conducted with trial number as factor. The analysis did not reveal a statistically significant effect, $F_{1,38} = .493, p = .487$. Thus, we assume that the effect of participants' fatigue was negligible.

Segmentation

We used recursive boundary splitting to segment the gestures as described by Sonka et al. [27]. First, the start and the end point of the gesture is used as x_1 and x_2. x_3 is the point with the largest distance to the line segment (x_1, x_2) and is used to split a gesture in two segments. These steps are applied recursively to the two resulting segments (x_1, x_3) and (x_3, x_2) [27].

After the segmentation, we approximated each segment using orthogonal distance regression (ODR) [3] to estimate the segment parameters. We took the orientation error as filter criteria. We filtered, as described above, all gestures where at least one segment exceed an error of $M \pm 3SD$.

One-Segment Gestures. The lines fitted to the *one-segment* gestures had an average R^2 of .95 (SD = .15). The average orientation error for the *one-segment* gestures is $M = -.9°$ ($SD = 9.$) while the root mean squared error (RMSE) is 9.1. The orientation errors are presented in Figure 4a.

Two-Segment Gestures. The lines fitted to the *two-segment* gestures had an average R^2 of .76 ($SD = 2.40$) for the first segment, $R^2 = .78$ ($SD = 1.90$) for the second segment. The average orientation error for the *two-segment* gestures is $M = 1.5°$ ($SD = 12.7$) with RMSE of 12.8 for the first segment, and $M = .9°$ ($SD = 13.5$) with RMSE of 13.5 for the second segment, see Figures 4b and 4c.

Three-Segment Gestures. The lines fitted to the *three-segment* gestures had an average R^2 of .57 ($SD = 10.01$) for the first segment, $R^2 = .65$ ($SD = 4.09$) for the second and $R^2 = .40$ ($SD = 10.37$) for the third segment. The average orientation error for the *three-segment* gestures is $M = -1.4$ ($SD = 13.4$)

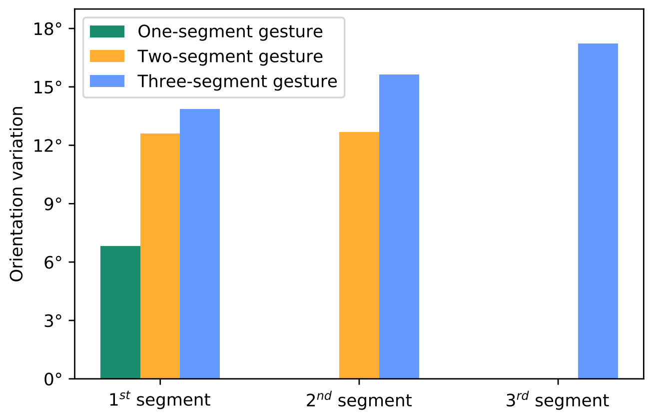


Figure 5: The orientation variation for the different SEGMENT × GESTURE.

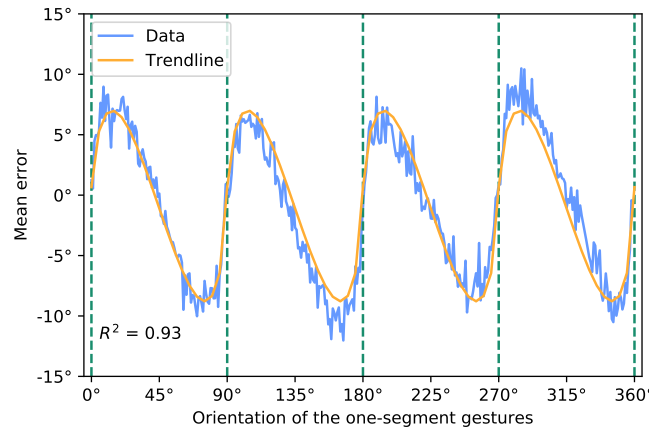


Figure 6: The average angle error for the *one-segment* gesture in respect to the performed gesture in blue. While the yellow line represents the trend line fit of the Clausen function, see Equation (3).

with RMSE of 13.5 for the first segment, $M = 1.1$ ($SD = 14.1$) with RMSE of 14.1 for the second segment, and $M = .89$ ($SD = 15.7$) with RMSE of 15.7 for the third segment. All errors for the three different segments are presented in Figures 4d to 4f.

Orientation Error

To understand how ORIENTATION, SEGMENT, and GESTURE affect the mean orientation error in degree, we conducted a three-way analysis of variance (ANOVA) on all samples. The orientation factor consisted of 24 orientation levels in 15-degree steps. Since the level of segments depends on the type of gesture (e.g., there is no 2^{nd} and 3^{rd} segment level in a one-segment gesture), the levels of factor SEGMENT (max 3 levels) are handled as nested factor of GESTURE. The analysis was conducted on subject level (averaged per participant) with subject as random factor.

We found a significant main effect for GESTURE ($F_{2,3359} = 227.630$, $p < .001$) but not for ORIENTATION ($F_{1,3359} = .897$, $p = .344$). There was a significant interaction effect for GESTURE × SEGMENT ($F_{3,3359} = 11.130$, $p < .001$) but not for GESTURE × ORIENTATION ($F_{2,3359} = .976$, $p = .377$). We also found a significant three-way interaction for GESTURE × ORIENTATION × SEGMENT ($F_{3,3359} = 19.891$, $p < .001$) which means that the combination of all three factors have a significant effect on the mean orientation error and have to be considered in the development of the model.

Orientation Variance Comparison

A two-way ANOVA was conducted to reveal the effects of GESTURE and SEGMENT on the variance measures (given as standard deviation of the orientation samples) between GESTURE and SEGMENT. We found a significant effect of GESTURE ($F_{2,474} = 1432.671$, $p < .001$), and SEGMENT ($F_{2,474} = 31.493$, $p < .001$) as well as a significant interaction effect of GESTURE × SEGMENT ($F_{1,2401} = 9.146$, $p = .003$) Bonferroni-corrected pairwise t-tests showed significant differences between all combinations ($p < .001$). All variance measures of the orientation are depicted in Figure 5.

6 MODEL TO IMPROVE UNISTROKE GESTURE INPUT

As we noticed a cyclic behavior of the orientation error for the *one-segment* gestures, we first used a Sinus function to model the orientation error:

$$fit_{sin}(x) = a * sin(c(x - d)) + e \quad (1)$$

Using ordinary least squares regression, we fitted parameters to the function $fit_{sin}(x)$. With our first attempt, we achieved a R^2 of .85. We then modeled our error with a skewed Sinus function, a Clausen function [9]:

$$S_n(x) = \sum_{k=0}^{\infty} \frac{sin(kx)}{k^n} \quad (2)$$

To fit the skewed Sinus function to the data, we added fitting parameters to stretch or compress the function if needed. We again used ordinary least squares to estimate the fitting parameters a to e for our fitting function:

$$fit(x) = aS_b(c(x - d)) + e \quad (3)$$

Using the skewed Sinus function we achieved a fit of $R^2 = .93$. The coefficients to model the orientation error are $[7.7218, 0.0698, -0.5702, -0.8924, 1.8915]$, respectively from a to e. The fitted function is shown in Figure 6. The local maxima are located at $[14.84°, 104.84°, 194.84°, 284.84°]$ and local minima are located at $[76.3°, 166.3°, 256.3°, 346.3°]$. While the zero of the function is at $[14.84° + i * 90.°, 76.3° + i * 90.°]$ *with* $i \in \mathbb{Z}$, see Figure 6.

7 EVALUATION

We used leave-one-participant-out cross-validation. We fitted one model for each training set and tested with the remaining participant. The average remaining orientation error is $M = .023°$ ($SD = 6.7°$) while the RMSE is 6.9°. This is a reduction in mean orientation error of 97.41 %, 25.24 % in *SD*, and 23.77 % in RMSE for the *one-segment* gestures.

Next, we show how well the correction model for the *one-segment* gestures will represent the error of the *two-segment* gestures and the *three-segment* gestures. Therefore, we used a method proposed by Fisher and Lee [10] to study the cyclic effect of angular data. Their method calculates the correlation ϱ between two directional variables. The significance of this correlation can be assessed by the p-value.

For the *two-segment* gestures, the correlation of the first segment is $p < .001$ and $\varrho = 0.7808$. The correlation of the second segment is $p < .001$ and $\varrho = 0.8361$. Therefore, on average the function describes 80.84% of the variance of the *two-segment* gestures, see Figures 4b and 4c.

For the *three-segment* gestures, the correlation of the first segment is $p = .002$ and $\varrho = .7405$. The correlation of the second segment is $p < .001$ and $\varrho = .8748$. The correlation of the third segment is $p < .003$ and $\varrho = .7485$. Therefore, on average the function describes 78.79 % of the variance of the *three-segment* gestures, see Figures 4d to 4f.

8 DISCUSSION

We found no significant effect on the raw TLX over time. Further, participants stated that they were motivated to reach higher points for the gesture performance in the next phase after a completed phase. Thus, we assume that performing gestures for one hour did not influence the gesture quality. Moreover, we note that from our observation, participants were motivated to perform the gestures well due to the motivation of the tutorial were we presented them scores.

Second, our analysis focused on the five hypotheses on which we based our study. We show that the error can be modeled by a skewed Sinus function for the *one-segment* gestures. We further show that the model can describe the error of the *two-segment* gestures and the *three-segment* gestures. The model accounts for more than 78% of the variation for both multi-segment gestures. Thus, the model confirms **H1**.

Third, our analysis of the *two-* and *three-segment* gestures revealed that the variance of the segments significantly differs. Further, post-hoc tests of the variance showed that the variance in orientation error is significantly higher in the subsequent segment when performing consecutive straight line segments. We, therefore, confirm **H2**.

Our results show that the average error is almost 0° for horizontal and vertical lines. We further show that the orientation error increases around straight horizontal and vertical gestures, see green dotted lines in Figure 4. We assume this is due to a shift of the gesture towards a perfectly horizontal or vertical gesture. This can be further supported by the extremum being shifted towards the primary axes (horizontal and vertical lines). Between the extrema to both sides of the primary axes ($-14.8°$ to $13.7°$), humans tend to ignore variation in orientation and perform a horizontal and vertical line. Thus, we confirm **H3a** and **H3b** .

Finally, as part of our study, we also investigated diagonal lines (45°, 135°, 255°, and 315°) which where suggested by Cao and Zhai [6] for fast but not precise input to be more error-prone but faster than the primary axes lines. Our results show low orientation errors for the four diagonal lines as the zero of the fit was found to be at 42°. Therefore, we also confirm **H4**.

Limitations

Cao and Zhai [6] described a phenomenon which they called "*corner-cutting behavior*" in which humans tend to perform an arc instead of straight lines when they change direction. Quinn and Zhai [22] further present an in-depth analysis of potential reasons. This might influence the results for the *two-* and *three-segment* gestures. However, when segmenting gestures, we considered how many corners a gesture had. Furthermore, the use of orthogonal distance regression minimizes the effect of corner-cutting on the line orientation. While corner cutting might still cause noise in the data, to address the orientation error we needed to fit straight lines.

One limitation of our study is that we cannot distinguish whether wrong perception or locomotor inaccuracy of the participants caused the error as our model only accommodates the motor control aspect of unistroke gestures. This could be examined by varying the visual feedback, which should be investigated by further research. While this work focused on analyzing the accuracy of performed unistroke gestures consisting of straight lines, there is a need for analyzing the effect of orientation for other kinds of gestures. This includes gestures consisting of arcs, corners, and the combination of arcs, corners, and straight lines. Analyzing these gestures aims to identify how additional gesture features, like the bending factor of the composition of different segment types, affect the users' accuracy.

Implications

The findings have a number of potential implications for the design of new gesture or gestures sets. Furthermore, the results can also be used to improve the recognition of simple flick gestures' orientation, the visualization of gestures as well as the accuracy when recognizing compound gestures.

Design Implications. Based on the five confirmed hypotheses, we derived five general design implications which can be used by developers when creating gestures consisting of straight-lines.

(1) for a new gestures set start with the two horizontal and vertical gestures in each direction
(2) for large gesture sets, combine horizontal and vertical lines to complex gestures
(3) keep in mind that the variance is increasing with an increasing number of segments
(4) for even large gesture sets, use 45° diagonal segments to reduce variance
(5) cover the full 360° input space to maximize the distance in orientation between two gestures

Flick Gestures. Flick gestures can be used to quickly move 2D planes such as maps or move through 3D spaces as in games. Using our correction model for one-segment gestures the directional error while flicking can be corrected. Thus, the accuracy of the movement direction, particularly while moving over large distances can be increased.

Gesture Visualization. A number of fast-paced mobile games visualize the users' gestures through animated trajectories (e.g., in *Fruit Ninja* to cut the fruit). To optimize the visualization in such games, our correction model can be used to optimize the visualization or physical simulation caused by the input gesture.

Improving Gesture Recognition. The accuracy of template matching-based gesture recognizers, such as the $P-familiy, can be improved by applying the correction model before feeding a gesture into the recognizer. Even learning-based gesture recognizers can benefit from the correction model if gestures should be rotation invariant. For rotation invariant gestures, the orientation errors for individual segments changes when users rotate a gesture. Thus, reducing the orientation error can reduce the variance during training and inference.

9 CONCLUSION

In this paper, we systemically investigated the effect of orientation on straight-line unistroke gestures. We conducted a study with 40 participants which performed gestures with their index finger constructed out of one, two, or three line segments. We analyzed how the variation of the orientation and the angles within the gestures affected users' accuracy. Our analysis revealed that users tend to approximate segments to the closest horizontal or vertical segment. We further show that each consecutive segment adds significantly more variation. Hence, our key finding suggests avoiding the use of orientations close to horizontal or vertical segments. The results of this work can be used to predict users' accuracy for gesture sets. We hope that the presented considerations can help designers to develop better gesture sets and developers to build better gesture recognizers. Finally, the presented work is a first step in modeling and understanding how unistrok gestures are affected by orientation error.

While the aim of this paper was purely to understand the effect of orientation on unistroke gestures performed by the index finger, the orientation could also have an effect on production time. Cao and Zhai [6] excluded the orientation in their formula for production time as they hypothesized a small effect. However, based on our findings we conclude that future work should investigate the production time for different gesture orientations. Moreover, as Tu et al. [31] showed a difference in orientation error between thumb and index finger input, future work should systemically investigate the orientation error of the thumb.

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