A Comparative Evaluation of Finger and Pen Stroke Gestures

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ABSTRACT

This paper reports an empirical investigation in which participants produced a set of stroke gestures with varying degrees of complexity and in different target sizes using both the finger and the pen. The recorded gestures were then analyzed according to multiple measures characterizing many aspects of stroke gestures. Our findings were as follows: (1) Finger drawn gestures were quite different to pen drawn gestures in basic measures including size ratio and average speed. Finger drawn gestures tended to be larger and faster than pen drawn gestures. They also differed in shape geometry as measured by, for example, aperture of closed gestures, corner shape distance and intersecting points deviation; (2) Pen drawn gestures and finger drawn gestures were similar in several measures including articulation time, indicative angle difference, axial symmetry and proportional shape distance; (3) There were interaction effects between gesture implement (finger vs. pen) and target gesture size and gesture complexity. Our findings show that half of the features we tested were performed well enough by the finger. This finding suggests that "finger friendly" systems should exploit these features when designing finger interfaces and avoid using the other features in which the finger does not perform as well as the pen.

Author Keywords

Pen gestures; finger gestures; touch; gesture design; gesture recognition.

ACM Classification Keywords

H.5.2 [Information Interfaces and Presentation]: User Interfaces — *Interaction techniques.*

INTRODUCTION

Due to the rapid growth of touch screen devices, stroke gestures on touch screens are an increasingly important interaction modality. Until recently, the stylus (pen) has been the primary implement for drawing stroke gestures on touch screens. However, today's preferred implement for tapping and gesturing on touch screens is the finger or fingers.

CHI'12, May 5–10, 2012, Austin, Texas, USA.

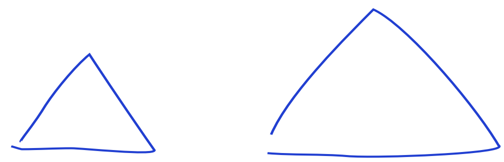


Figure 1. Two representative versions of a triangle gesture produced by the pen (left) and the finger (right).

Recent commercial product design has tended to avoid the use of the pen with a view to user convenience and simplicity. Such a contrast demands that we pay attention to how quantitatively similar or different finger drawn gestures are from pen drawn gestures, e.g., in precision, size, and other gesture characteristics (see Figure 1).

Past stroke gesture research has been focused on the digital pen as the drawing implement. Most stroke gesture HCI research work published to date, such as [2, 3, 11, 13, 15, 21] has been based on data collected from gestures produced with high quality inductive digital styli. It is questionable whether and how well these results apply to finger drawn gestures. Our investigations looked at the differences and similarities between finger and pen stroke gestures both of which have been neglected in the literature. There is a clear need to identify and characterize these differences where they are present. For example, if we know finger gestures are particularly poor at producing certain types of features, then future research and product design should exploit such knowledge and avoid relying on these features in their recognition algorithm and gesture set design. Understanding the quantitative difference between finger strokes and pen strokes can provide a foundation for differential designs of pen and finger interface or combinational designs of pen and finger input in the same interface [8].

To our knowledge little has been done in the HCI research community to address these pressing questions. We see gesture interfaces such as gesture keyboards but they were initially designed with the pen in mind [23] and have been increasingly transformed to finger use [24]. However, the costs and benefits of this unevaluated adaption switch are not known beyond anecdotal subjective impressions. A scientific approach, such as the one presented in our paper, has been pending for too long.

We set out to perform the first systematic comparative investigation between pen vs. finger gestures. We asked participants to draw a set of stroke gestures with a finger and a pen respectively as shown in Table 1. We then processed and analyzed the drawn gestures according to a set of measures and features that are either most basic (such as stroke articulation time) or that are likely to differentiate finger gestures from pen gestures (such as the precision of corner production). We then drew a set of conclusions that characterize the differences and similarities between finger vs. pen gestures.

RELATED WORK

There is a large body of HCI research on gesture interfaces, e.g. [5, 16, 20] for finger gesture and [2, 3, 11, 13, 15, 21] for pen gesture. It is unnecessary and beyond the scope of this paper to review that literature here. Instead, we only highlight a few lines of work that bear direct relevance to the questions we addressed and the methods we used in addressing them.

Human Motor Control Theory

Historically, the study on how humans control their motor behavior has centered on the debate between the centrists and the peripheralists among motor control theorists [19]. The centrists tended to view motor control behavior as an inside-out process, driven by “motor programs” from human internal representations. In contrast, peripheralists tended to emphasize motor control behavior as regulated by outside-in feedback from the environment. To our current questions regarding finger vs. pen gesture differences, a centralist would suggest that there is little difference between finger and pen gestures since their production are both driven from internal representations, as is indeed proposed in the effector independence theory [22] concerning writing. A peripheralist however would argue that the different feel and interaction with the touch screen surface afforded by the pen vs. the bare finger would impact how a gesture is produced.

Gesture Models

The complexity of a stroke gesture may have an impact on the difference between finger and pen gestures. Conceivably fingers are good (enough) at producing simple gestures. How to measure and characterize gesture complexity is a research topic. Simple measures such as the length or the number of line segments [10] in a stroke gesture may serve as complexity indicators. A more formal model, the CLC model [6] that computes a gesture’s production time based on sub models of curve, line, and corner production, is a more rigorous characterization of gesture complexity. We used the CLC model as a verification method in the design of our experiment.

Gesture Measurements and Features

Blagojevic et al. [4] categorized a feature library of ink gestures and used this library with attribute selection algorithms to choose good features for gesture recognition. Their work revealed that feature selection can significantly improve recognition rates, which demonstrated the importance of selecting good features for gesture recognition. However, their study did not pay attention to either finger stroke gestures or

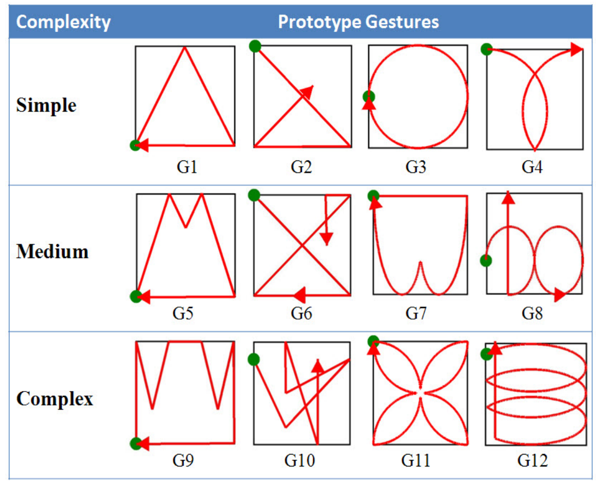


Table 1. Prototype gesture categories. The green dot signifies the starting point of a gesture, and the arrow denotes the end point and the direction of a gesture.

the difference and similarities between finger and pen gestures. Our study investigates the differences and similarities between finger and pen gestures, so as to find “finger friendly” features for finger gesture design and recognition.

Gesture recognition algorithms inevitably use a set of features to classify user input. These features can all be potentially used as measures of finger and pen gesture difference. For example, Andersen and Zhai [1] developed a set of measures to characterize gesture difference. SHARK^2 used proportional shape distance (PSD) as a key feature in classifying the user’s input on a gesture keyboard [11]. The PSD feature was more generally studied in Wobbrock et al. [21] showing that it produces comparable or stronger results than the well known Rubine recognizer [18] that combines a set of features through data training. Long et al. [15] used a set of features mostly taken from the Rubine recognizer.

Five features, namely proportional shape distance, indicative angle difference, time, speed, distance between the first and last points, from the above cited papers [1, 11, 15, 18, 21] appeared to be most relevant to the research questions we wanted to address in this paper.

GESTURES USED IN THE EXPERIMENT

In order to identify differences between finger and pen gestures, we designed and selected a set of gesture prototypes. Our goal was to have a small gesture set that covers a wide range of gestures across different categories.

Gesture Categories

Twelve gestures were used in our experiment. Their prototypes are shown in Table 1. Five of them were selected from previous studies (G1 [1], G2 [18], G3 [1], G4 [2, 3], G10 [23]). Four were designed based on previous studies (G5 [18], G6 [1, 2], G7 [1], G12 [15]). G8, G9 and G11 were newly designed for this study.

Based on visual appearance in terms of the number of corners, curves and line segments, the gestures were divided into three groups according to their levels of complexity, i.e., Simple, Medium and Complex as shown in Table 1. These classifications were also supported by simple complexity measures such as length and by their predicted production time[1].

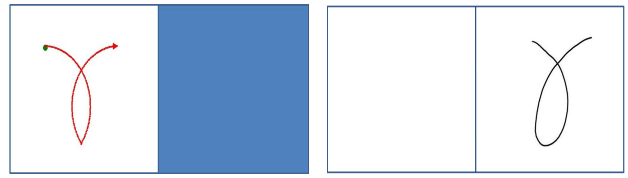
These gestures also vary in characteristics. Gestures G1, G2, G5, G6, G9 and G10 were composed of corners and straight lines, and Gestures G3, G4, G7, G8, G11 and G12 were mainly composed of corners and curves. Gestures G1, G3, G5, G7, G9 and G11 are closed gestures because their prototypes start and end in the same position. The rest of the gestures in the set are open gestures. Gestures G2, G4, G6, G8, G10 and G12 contain intersections, and the other gestures do not. The number of interaction points generally increases with gesture complexity. Gestures G2 and G4 have one interaction point each, G6 and G8 have two interaction points each, G10 has four, and G12 has seven interaction points. Gestures G1, G3, G4, G5, G7, G9 and G11 are symmetrical about the Y axis. The others are asymmetrical.

Target Gesture Size
Intuitively, stroke gestures can be more easily produced in smaller sizes with the pen than with the finger. This led us to repeat the same set of gestures in three different target sizes and ask the participants to reproduce them accordingly. The target gesture size of a prototype gesture was defined as the area in cm^2 of the target gesture's bounding box. From past research we know that pen gestures can be produced in rather small sizes. According to Ren and Zhou [17], the bounding box size 1.5×1.5 cm in length was set up as a baseline in our experiment, which should be rather comfortable for pen gesturing and we suspected that it would be more challenging for finger gesturing. To evaluate the gesture size factor, we also set up the medium (3.0×3.0 cm) and large target gesture sizes (4.5×4.5 cm) respectively. We expected these two sizes would be less challenging for finger gesturing.

EXPERIMENT

Participants
Fifteen volunteers, twelve males and three females, from 20 to 30 years of age, participated in the experiment. All participants were right-handed. Ten of them had prior experience using stylus, and also with finger operation. Three of them had prior experience with finger operation only on touch screen devices. The other two participants had no prior experience operating digital screens with either stylus or finger.

Apparatus
The study was conducted on a HP touchsmart tx2 tablet computer. The screen size was 12.1 inches and its resolution was 1280×800 pixels, which means the pixel pitch was 0.204 mm. The most important reason we chose this computer as the experimental apparatus was that it has two touch sensing mechanisms (one capacitive and the other inductive), hence supporting both pen and finger gestures [9]. This ensured that we measured finger and pen gestures under the same set of conditions and form factors. During the experiment the computer was folded in tablet mode and laid on the table with the screen facing upward.



(a) (b)

Figure 2. The display for gesture input.

Task and Procedure
The goal of the experimental task design was to simulate how people draw gestures from their memory instead of copying or tracing a template. Similar to the experimental design of [1], participants were asked to draw the gesture from memory as accurately as possible at a normal writing speed, using the pen and index finger of the dominant hand, after being shown the target gesture. As shown in Figure 2, the experiment window was divided into a display area and a gesture input area. In each test trial, a gesture prototype was displayed in the left window for 1.5 seconds, with a dot and an arrowhead indicating the starting point and ending point respectively; meanwhile the right window was hidden by blue color (see Figure 2a). After 1.5 seconds, the gesture prototype disappeared, along with the blue color in the gesturing area, prompting the participant to draw the same gesture in the right window (see Figure 2b) [2].

The experiment consisted of a training phase and an experimental phase. In the training phase, participants were first taught how to perform the experimental task. Then they were asked to draw the twelve gestures in three sizes using the pen and finger respectively as practice. In this training phase, the gesture prototype remained in the left window till the entire trial was completed. In the test phase of this within-subject experiment, each participant completed four blocks of all gestures in three sizes in two drawing implement conditions: pen vs. finger. Within each block, the order of the twelve gestures in three different sizes was randomized. In summary, the experiment data collection consisted of:

15 subjects ×
2 implements (pen, finger) ×
4 blocks ×
12 gestures ×
3 target gesture sizes
= 4320 drawing trials

[1]The length of a prototype gesture with the bounding box 3.0×3.0 cm was the sum of the distance between adjacent points in the prototype gesture's trajectory. The predicted production time for a prototype gesture with the bounding box 3.0×3.0 cm was calculated by the CLC model [6]. For example, the length and expected time for G1 are 9.7 cm and 1006 ms respectively, while for G12, the length and expected time are 22.67 cm and 2829 ms respectively.

[2]Pilot studies indicated that after a training period, this time period is long enough to allow participants to remember both the size and overall shape of the target gesture.

Feature Categories	Measures	Features
Algebraical Property Feature	Basic Measure	F1. Time Performance [18] F2. Average Speed [1, 18] F3. Size Ratio
Geometric Shape Feature	Local Shape Measure	F4. Aperture between the Start Point and the End Point of Closed Gestures [1, 18] F5. Indicative Angle Difference between Drawn Gesture and Target Gesture [21] F6. Corner Shape Distance
	Global Shape Measure	F7. Axial Symmetry F8. Proportional Shape Distance [1, 11, 21] F9. Intersecting Points Deviation

Table 2. Feature categories.

At the end of the experiment, a questionnaire was administrated to gather subjective opinions. Participants were asked to rate $pen\ input$ and $finger\ input$ on 7-point Likert Scales regarding $speed$, $accuracy$ and $hand\ fatigue$ (7 for highest preference, and 1 for lowest preference).

FEATURE SELECTION

As described in the section "Related Work", a lot of stroke features have been studied. For the purpose of our study, we chose five features from the literature and designed four new features (see Table 2). We suspected that all these features may reveal differences between finger and pen gestures. With features F1 and F2, the pen or the finger used as the drawing implement may lead to different performance due to either friction or dexterity differences. In addition, because the pen tip is sharper and allows more precision than the fingertip, the finger may result in different performance with respect to F3, F4, F5, F6, F7, F8 and F9.

Inspired by the feature classification method in [18], each feature was classified manually along two dimensions: algebraical property feature and geometric shape feature (see Table 2). As a basic measure, the algebraical property feature represents the basic features of a gesture, including stroke time, movement speed and size ratio. The geometric shape feature consists of the local shape feature and the global shape geometry feature. It focuses on what a gesture looks like.

We also conducted a pilot study to find differences between finger gestures and pen gestures by means of a set of commonly used gestures. We chose seven gestures from *Graffiti*, which is a single-stroke shorthand handwriting set widely employed in PDAs. The seven gestures denote the character "a", "b", "c", "e", "d", "j" and "%" respectively. In addition, we selected a square gesture and a five-pointed star gesture. Six participants took part in the pilot study. The experiment procedure was similar to that introduced in subsection "Task and Procedure". The experimental data were assessed in terms of the 63 features for single stroke gestures used in [4]. We found that the features with differences between finger and pen gestures mainly referred to movement speed, size and curvature, which had already been included in Table 2. Hence, it can be regarded that this feature set shown

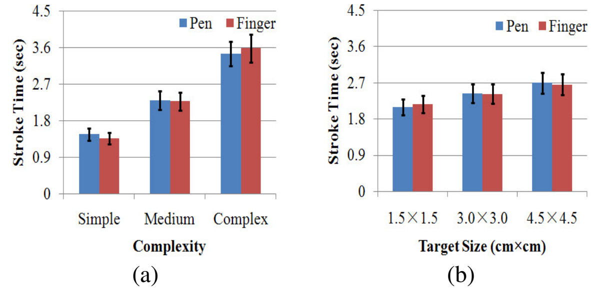


Figure 3. Stroke articulation time for each implement in different (a) complexities and (b) target gesture sizes. Error bars represent 0.95 confidence interval.

in Table 2 can demonstrate the main differences between finger gestures and pen gestures.

RESULTS AND ANALYSIS

In this section, we discuss the experimental results in terms of the gesture features listed in Table 2. Recall that each participant performed four blocks of trials in the experiment, we first checked the learning effect on stroke articulation time over the four blocks of trials to see if the data we collected had reached a level of stability. As to results, the participants' performance began to stabilize in the second block of trials for finger strokes and in the third block of trials for pen strokes. Therefore, data in the third and fourth blocks were applied to the rest of our analysis for pen strokes, and data in the second, third and fourth blocks were applied to the rest of our analysis for finger strokes.

Basic Measures

Time Performance

Stroke articulation time was defined as the duration from the moment the pen or finger touched the screen to the moment the pen or the finger was lifted from the screen. This is a basic measure of stroke performance. Conceivably, there could be a difference in this measure between the pen and the finger as the drawing implement due to either friction or dexterity differences. However, repeated measures ANOVA showed that the drawing implement (pen vs. finger) had no significant main effect on stroke articulation time. The mean stroke articulation time was 2408 ms in the pen condition and 2414 ms in the finger condition.

Other independent variables influenced stroke articulation time. As expected, the level of gesture complexity had a significant main effect on mean stroke articulation time ($F_{2,28}$ = 127.88, $p < 0.001$). The target gesture size also had a significant main effect on mean stroke articulation time ($F_{2,28}$ = 67.14, $p < 0.001$). There was a strong interaction between implement and complexity ($F_{2,28}$ = 8.44, $p < 0.01$). As shown in Figure 3a, the mean stroke articulation time of the pen was longer than that of the finger in drawing simple gestures (1468 ms vs. 1370 ms), slightly longer in drawing gestures of medium level complexity (2306 ms vs. 2284 ms), but shorter in drawing complex gestures (3451 ms vs. 3587 ms). Also, there was a significant interaction between implement and target gesture size ($F_{2,28}$ = 12.08, $p < 0.001$). Figure 3b illustrates

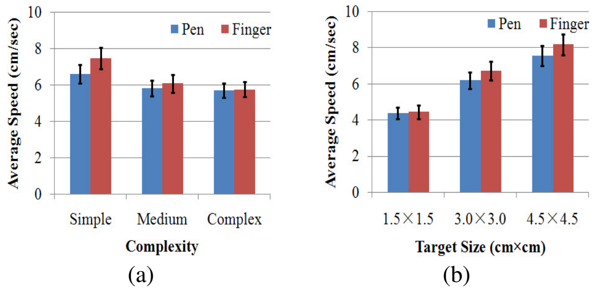


Figure 4. Average speed for each implement in different (a) complexities and (b) target gesture sizes.

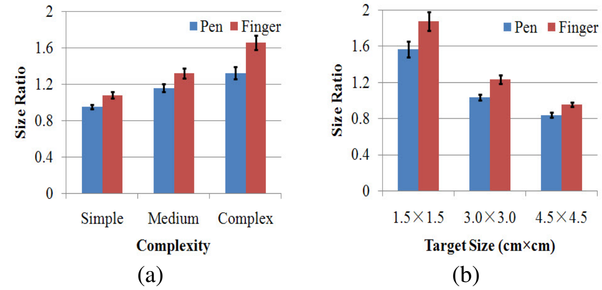


Figure 5. Size ratio for each implement in different (a) complexities and (b) target gesture sizes.

that for small target size, the mean stroke articulation time achieved with pen input (2092 ms) was shorter than that for finger input (2170 ms). However, for medium and large target sizes, pen input led to longer stroke articulation time than finger input (2435 ms vs. 2420 ms for medium size, and 2698 ms vs. 2650 ms for large size). The pen tended to be slightly slower in drawing simple gestures and large size gestures.

Average Speed

The average speed, calculated by the ratio of the gesture length and the stroke articulation time, was another basic measure of stroke gestures we used in this study.

Implement had a significant main effect on average speed ($F_{1,14}$ = 5.85, $p < 0.05$). The mean speed was 6.04 cm/s for pen gestures, 6.43 cm/s for finger gestures. Complexity and target gesture size had a significant main effect on average speed ($F_{2,28}$ = 59.72, $p < 0.001$ for complexity; $F_{2,28}$ = 144.78, $p < 0.001$ for size).

Implement significantly interacted with complexity ($F_{2,28}$ = 32.15, $p < 0.001$). As shown in Figure 4a, the average speed of pen drawn gestures (6.60 cm/s) was lower than the average speed of finger drawn gestures (7.46 cm/s) in simple gestures. In addition, in medium gestures, the average speed of the pen (5.84 cm/s) was lower than the average speed of the finger (6.08 cm/s), and the average speed of the pen (5.69 cm/s) was lower than the average speed of the finger (5.76 cm/s) in complex gestures. The results indicated that the pen performed slower than the finger in the simple, medium and complex gestures, but the difference decreased from simple to complex gestures.

There was a significant interaction effect between implement and target gesture size ($F_{2,28}$ = 24.85, $p < 0.001$)(see Figure 4b). The average speed of the pen was 4.37 cm/s, 6.20 cm/s, 7.56 cm/s for small, medium, and large target size gestures respectively while the average speed of the finger was 4.43 cm/s, 6.71 cm/s and 8.16 cm/s respectively. The finger performed faster than the pen in all three sizes, and the difference increased from small to large size.

Size Ratio

The participants may or may not draw the gesture exactly the same size as the target gesture displayed. There is a possibility that they would tend to draw the gesture in a larger size than the target gesture size, particularly when using the finger. The size ratio between the response gesture and the target gesture can therefore be an informative measure of the user's ability to gesture at a specified scale.

The target size (TS) of a prototype gesture has been defined in the subsection "Target Gesture Size," and the response size (RS) of a drawn gesture is defined as the area in cm^2 of the drawn gesture's bounding box. The response to target size ratio (SR) was measured by the ratio of the two ($SR = RS/TS$).

Implement was a significant main effect on size ratio ($F_{1,14}$ = 45.26, $p < 0.001$). On average both pen and finger drawn gestures tended to be larger, resulting in 1.15 and 1.36 size ratio values in pen and finger conditions respectively.

The complexity had a significant effect on size ratio ($F_{2,28}$ = 47.88, $p < 0.001$). Also, there was a significant interaction effect on size ratio for gesture complexity ($F_{2,28}$ = 38.64, $p < 0.001$). As shown in Figure 5a, when gesture complexity was simple, the size of drawn gestures was almost the same as the size of target gestures (mean size ratio was 0.95 for the pen, and 1.08 for the finger). Corresponding to the medium complex gestures, the mean size ratio increased to 1.16 (pen) and 1.32 (finger) respectively. For the most complex gesture, the mean size ratio increased to 1.32 (pen) and 1.66 (finger) respectively. Results showed that pen gesture led to smaller RS than finger gesture. In both pen and finger gestures, the size ratio increased as the gesture complexity increased.

The size ratio value strongly depended on the target gesture size ($F_{2,28}$ = 71.30, $p < 0.001$). Also, there was a significant interaction effect on size ratio for target size ($F_{2,28}$ = 11.67, $p < 0.001$). As illustrated in Figure 5b, when the target size was small, the response size of the drawn gestures was larger, resulting in mean size ratio values of 1.57 (pen) and 1.88 (finger) respectively. Corresponding to the medium size target, the mean response size of the drawn gestures was only slightly larger, resulting in mean size ratio values of 1.04 (pen) and 1.23 (finger) respectively. Corresponding to the large size target, the mean response size of the drawn gestures was in fact smaller than the size of the target, resulting in mean size ratio values of 0.84 (pen) and 0.96 (finger) respectively.

Overall, the results here show that it is difficult to draw small and complex gestures with either implement. The drawn gestures tended to be larger in these cases. These effects were slightly more pronounced with the finger than with the pen.

Local Shape Measures

Aperture between the Start Point and the End Point of Closed Gestures

To reflect the ability to draw a closed gesture, we measured the distance (aperture) between the start point and the end point. Conceivably the finger is at a greater disadvantage than the pen since the finger may more severely obscure the start point when getting close to it.

For drawn gestures corresponding to the prototype gestures G1, G3, G5, G7, G9 and G11 which start and end in the same position (see Table 1), we calculated the aperture between the start point and the end point. As we expected, there was a significant main effect for implement on the aperture of closed gestures ($F_{1,14}$ = 5.48, $p < 0.05$). The mean aperture was 0.20 cm with the pen and 0.24 cm with the finger respectively. Although no significant main effect was found on aperture for gesture complexity, target gesture size had a significant main effect on aperture ($F_{2,28}$ = 7.86, $p < 0.01$). The mean aperture was 0.18 cm for small size targets, 0.22 cm for medium size targets, and 0.26 cm for large size targets.

Indicative Angle Difference between Drawn Gesture and Target Gesture

The indicative angle was defined as the angle rotated from the horizontal vector whose starting point is the centroid of the gesture, to the vector formed by the centroid of the gesture and the gesture's first point. We calculated the indicative angle difference between the drawn gesture and the corresponding target gesture. It was found that no significant main effect for implement on indicative angle difference. The mean indicative angle difference was 0.32 degrees for the pen, and -0.13 degrees for the finger.

Corner Shape Distance (CSD)

The prototype gestures G1, G2, G5, G6, G9 and G10 (see Table 1) have sharp corners. How these corners change their shapes in the drawn gesture is yet another way to investigate local shape difference. We defined "Corner Shape Distance" (CSD) as mean distance between the corresponding corners in the drawn gesture and the target gesture.

To calculate CSD, as a first step we need to detect the vertex for each corner. We detected the vertexes of corners in the drawn gesture U based on the two-thirds power law in human motor control [14], which was also used for similar purposes in [1] to segment drawn gestures. We first calculated the speed for each point in drawn gesture U. Secondly, the points in U were sorted according to speed, and M (depending on the size and complexity of the corresponding target gesture) points with low speed were chosen. Third, K-means clustering was applied to partition the M points into K clusters ($K + 1$ was the number of corners in U. We did not consider the corner whose vertex is the start point, because in drawn gestures, the start point and the end point may not necessarily coincide to form a vertex.). Fourth, the point with the lowest speed in each cluster was chosen as the vertex of the corner as $VC_i, 1 \leqslant i \leqslant K$ (see Figure 6a).

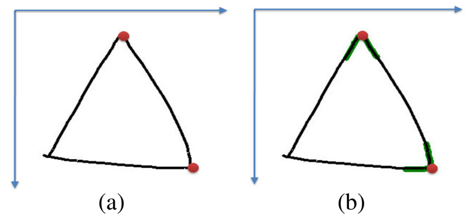


Figure 6. (a) Vertexes in a drawn gesture. The red dots denote the vertexes. (b) The point set for each vertex. The green dots denote the point sets detected by our algorithm.

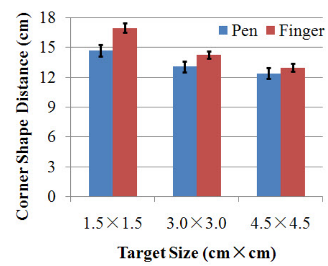


Figure 7. Corner shape distance for each implement in different target sizes.

For each corner, after detecting the vertex, we need to choose a set of points in two arms to represent the corner shape. The second step is to calculate a point set for each vertex (VC_i). For each corner in the drawn gesture U, we calculated the distance between the vertex VC_i and the points in its two arms, and chose the points whose distance was less than 0.8 cm. Then each vertex (VC_i) had a point set $PU_i, (1 \leqslant i \leqslant K)$. The points in PU_i were re-sampled into N ($N = 40$) points, which constituted a new point set $PD_{i,j}, (1 \leqslant i \leqslant K, 1 \leqslant j \leqslant N)$ (see Figure 6b). We also calculated the point set for each vertex in the target gesture V, as $PV_i, (1 \leqslant i \leqslant K)$, and the points in each PV_i were also resampled into N ($N = 40$) points, which also constituted a new point set $PT_{i,j}, (1 \leqslant i \leqslant K, 1 \leqslant j \leqslant N)$.

The third step was to calculate CSD_i $(1 \leqslant i \leqslant K)$. CSD_i was measured by calculating the distance between the point in PD_i and the corresponding point in PT_i, $(1 \leqslant i \leqslant K)$[3]. To calculate the CSD_i, we translated PD_i so its centroid coincided with the centroid of the corresponding point set PT_i. The CSD was calculated by the sum of all $CSD_i(1 \leqslant i \leqslant K)$.

$$CSD = \sum_{i=1}^{K} CSD_i = \sum_{i=1}^{K} \sum_{j=1}^{N} d(PD_{i,j}, PT_{i,j}) \qquad (1)$$

A significant main effect for implement was found on CSD ($F_{1,14}$ = 6.57, $p < 0.05$). The mean CSD of the pen was 13.38 cm, and the mean CSD of the finger was 14.73 cm. There is also a significant main effect on CSD for target gesture size ($F_{2,28}$ = 109.08, $p < 0.01$). Implement had a significant interaction effect with target gesture size ($F_{2,28}$ = 7.19, p

[3] In the following sections, $d(p, q)$ was used to denote the Euclidean distance between point p and point q.

< 0.01) (see Figure 7). For small target size, the mean CSD of the pen was 14.67 cm whereas the mean CSD of the finger was 16.95 cm. For medium target size, the mean CSD of the pen was 13.07 cm whereas the mean CSD of the finger was 14.25 cm. For large target size, the mean CSD of the pen was 12.39 cm whereas the mean CSD of the finger was 12.98 cm. The results showed that the pen performed better than the finger in all three target sizes.

Global Shape Measures

To investigate purely global shape aspects of a drawn gesture, we disregarded the drawn gesture size by normalizing ($scaling$) the drawn gesture's size to the largest target gesture size (4.5 × 4.5 cm), and also by scaling the corresponding target gesture's size to 4.5 × 4.5 cm. In other words, if the drawn gesture maintains the exact relative dimensions as the target gesture except that it is drawn in larger or smaller scale, the normalized shape measures would still give perfect scores (zero distance). We therefore report the three shape geometry measures with $scaling$ (i.e. normalization). To calculate each measure, the drawn gesture was translated so its centroid coincides with the centroid of the target gesture ($translation$).

Axial Symmetry (AS)

The prototype gestures G1, G3, G4, G5, G7, G9 and G11 (see Table 1) have axial symmetry. For simplicity, we explained the algorithm of AS calculation by taking G4 as an example. In order to measure the drawn gesture's axial symmetry, we firstly scaled the drawn gesture to 4.5 × 4.5 cm size and then re-sampled it to N ($N = 500$) equidistant points. $X = X_a$ is the axis which crosses the centroid of the drawn gesture and is perpendicular to the X axis (see Figure 8). For straight lines $Y = Y_i$ ($Y_{min} \leq Y_i \leq Y_{max}$, Y_{min} and Y_{max} are the minimum y value and the maximum y value of the drawn gesture respectively, Y_i increases 1 pixel each time), there are two intersecting points between the drawn gesture and $Y = Y_i$: $(X_a - XL, Y_i)$ in the left of $X = X_a$ and $(X_a + XR, Y_i)$ in the right of $X = X_a$, in which XL is the distance between $X = X_a$ and $(X_a - XL, Y_i)$, XR is the distance between $X = X_a$ and $(X_a + XR, Y_i)$. The mean distance difference can be calculated as

$$AS = \frac{1}{Y_{max} - Y_{min}} \sum_{i=Y_{\min}}^{Y_{\max}} DA_i \qquad (2)$$

Where DA_i is the absolute value of $(XR - XL)$. The greater the AS is, the less symmetrical the drawn gesture is. For G5, G7, G9 and G11, the algorithm gets more complex, but the basic idea is the same.

No significant main effect was found for implement on AS. The mean AS was 0.44 cm for the pen, and 0.43 cm for the finger. In other words, the finger gestures and the pen gestures did not significantly differ in symmetry. However, a significant main effect was found on AS for gesture complexity ($F_{2,28}$ = 202.87, $p < 0.001$) and target gesture size ($F_{2,28}$ = 252.89, $p < 0.001$). In addition, there was a significant interaction effect on AS for gesture complexity ($F_{2,28}$ = 8.26, $p < 0.01$). The mean AS of pen drawn gestures (0.27 cm) was larger than that of finger drawn gestures (0.21 cm) for simple gestures, and for medium gestures, the mean AS of the pen (0.42 cm) was larger than that of the finger (0.39 cm), but the mean AS of the pen (0.62 cm) was smaller than that of the finger (0.68 cm) in complex gestures. Results showed that the finger resulted in smaller AS than the pen for simple and medium gestures, indicating that the finger performed better than the pen for these gestures.

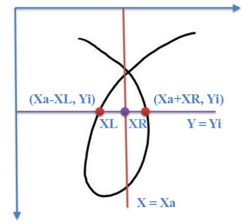


Figure 8. The illustration of axial symmetry in a drawn gesture corresponding to G4.

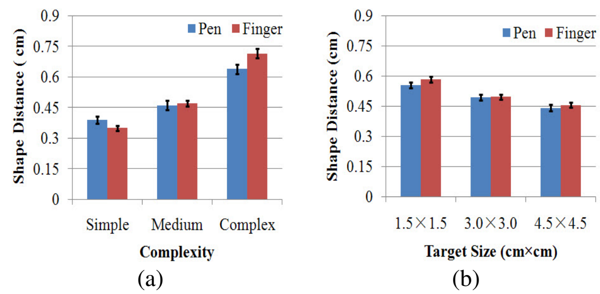


Figure 9. Proportional shape distance in normalized scale for each implement in different (a) complexities and (b) target gesture sizes.

Proportional Shape Distance (PSD)

After $scaling$ and $translation$, the drawn gesture U and the target gesture V were re-sampled into N ($N = 100$) evenly spaced points. We denote these transformed points by $U(i)$ and $V(i)$ ($1 \leq i \leq N$) for U and V respectively.

The proportional shape distance (PSD) is defined as

$$PSD = \frac{1}{N} \sum_{i=1}^{N} d(U(i), V(i)) \qquad (3)$$

Interestingly, there was no significant main effect for implement on PSD. The mean PSD was 0.50 cm for the pen, and 0.51 cm for the finger. The PSD measure was sensitive to both gesture complexity ($F_{2,28}$ = 128.72, $p < 0.001$) and target gesture size ($F_{2,28}$ = 150.79, $p < 0.001$). As one would expect, the PSD measure increased with gesture complexity (see Figure 9a) since the accuracy to replicate more complex gestures should decrease. Furthermore, PSD decreased as target gesture size increased (see Figure 9b). Although target gesture size had no significant interaction with implement, there was a significant interaction effect on PSD for gesture complexity ($F_{2,28}$ = 7.91, $p < 0.01$). For simple gestures, the mean PSD produced by the pen (0.39 cm) was larger than that for the finger (0.35 cm). Nevertheless, for more complex gestures, the mean PSD achieved with the pen was smaller (0.46 cm and 0.64 cm for medium and complex gestures

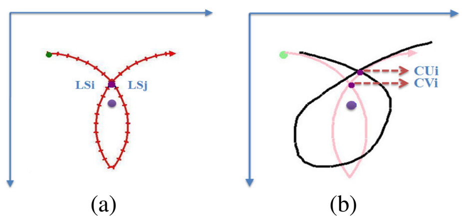


Figure 10. (a) Detecting intersecting points in the target gesture G4. LSi and LSj are two line segments. (b) The intersecting points in G4 (CV_i) and in the drawn gesture corresponding to G4 (CU_i).

respectively) than that for the finger (0.47 cm and 0.72 cm for medium and complex gestures respectively). The results showed that the pen resulted in more accurate performance than the finger for complex gestures, but the finger achieved more accurate performance than the pen for simple gestures.

Intersecting Points Deviation (IPD)

Gestures G2, G4, G6, G8, G10 and G12 (see Table 1) had one or more self crossing intersecting points. How much these intersecting points change in the drawn gesture from the corresponding intersecting points in the target gesture is another indication of the shape difference between the two. We define the "Intersecting Points Deviation" (IPD) as the mean distance between the intersecting points in the drawn gesture U and the target gesture V (see Figure 10b).

In order to detect the intersecting points in the drawn gesture, the first step for U was $scaling$ and $translation$, which was introduced at the start of this subsection. U was divided into $N-1$ ($N = 40$) line segments (LSi, $1 \leq$ i $\leq (N-1)$) by resampling into N equidistant points (see Figure 10a). Then, the LSi ($1 \leq i \leq (N-1)$) was compared with other line segments LSj ($1 \leq j \leq (N-1)$, $j \neq i$) to check whether or not there were any intersecting points. If an intersecting point was detected, it would be recorded in a point set CU. We can also detect the intersecting points in the corresponding target gesture V as a point set CV.

If the count of intersecting points in $CU(N_{CU})$ was equal to the count in $CV(N_{CV})$, the IPD between U and V was calculated as

$$IPD = \frac{1}{N_{CU}} \sum_{i=1}^{N_{CU}} d(CU(i), CV(i)) \qquad (4)$$

Else, IPD was calculated as 0 ($Intersection\ Miss$).

$Intersection\ Miss$ rate, defined as the ratio of $Intersection\ Miss$ count and total trial count for IPD analysis, was firstly calculated. We found that the $Intersection\ Miss$ rate for pen input and finger input was low (3.15% and 2.09% respectively), so we continued the analysis of IPD using repeated measures ANOVA.

A significant main effect was found for implement on IPD ($F_{1,14}$ = 11.74, $p < 0.01$). Pen input resulted in IPD with 0.40 cm and finger input produced IPD with 0.44 cm. Target gesture size had significant main effects on IPD ($F_{2,28}$ = 20.86, $p < 0.001$). There was a significant interaction between implement and target gesture size ($F_{2,28}$ = 11.34, $p < 0.01$). As illustrated in Figure 11, the mean IPD was 0.42 cm for the pen and 0.50 cm for the finger in small target size. The mean IPD was 0.40 cm for the pen and 0.42 cm for the finger in medium target size, and the mean IPD was 0.38 cm for the pen and 0.39 cm for the finger in large target size. Therefore, the pen performed better than the finger in all three target sizes.

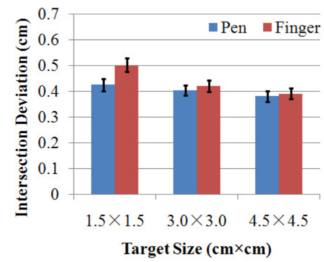


Figure 11. Intersecting points deviation in normalized scale for each implement in different target gesture sizes.

Subjective Evaluation

A significant main effect was found on $speed$ ($F_{1,14}$ = 7.15, $p < 0.05$). The mean preferences of the pen and the finger were 5.53 and 4.13 respectively. A significant main effect was also found for $accuracy$ ($F_{1,14}$ = 5.59, $p < 0.05$). The mean preferences for the pen and the finger were 5.27 and 3.87 respectively. However, there was no significant main effect on $hand\ fatigue$, suggesting that pen gestures and finger gestures are similar in difficulty for users. Overall, users generally felt that the pen can achieve greater accuracy and faster speed than the finger for gesture input.

DISCUSSION

Implications for Finger Gesture Design

Past stroke gesture research has been primarily based on the digital pen as a drawing implement. However, recent commercial product design has tended toward finger input and tends to avoid the use of the pen. Such shifts raise the question of how quantitatively different or similar finger stroke gestures are from pen stroke gestures. Therefore, we conducted a first study to quantify the differences and similarities between finger and pen gestures. Our work has provided a methodology to investigate and quantify the performance of finger and pen gestures, in which finger and pen gestures were analyzed according to multiple features that characterize stroke gestures. Some features revealed similarities between finger and pen drawn gestures, but some features were less accurate with the finger. Based on the evaluation in terms of these features, the implications for finger gesture design were presented as follows.

First, four of the nine features studied revealed similarities between finger and pen drawn gestures, including stroke articulation time (F1), indicative angle difference (F5), axial symmetry (AS) (F7) and proportional shape distance (PSD) (F8). This means that if the gesture recognition algorithm relies on features based on these measures, we should not expect finger gestures to be less effective than pen gestures. Given that proportional shape distance (PSD) based recognition is already used in both research and practical large-scale gesture systems (specifically the ShapeWriter gesture keyboard, although in more complex ways than in this paper), it is reasonable to expect that "finger friendly" recognition algorithm can be designed within the feature space outlined by findings reported above.

Second, five of the nine features studied revealed significant differences between finger and pen drawn gestures, including the average speed (F2), size ratio (F3), aperture between start point and end point (F4), corner shape distance (CSD) (F6) and intersecting points deviation (IPD) (F9). Finger drawn gestures tended to be larger than pen drawn gestures, indicating a somewhat obvious drawback of finger operation - which requires a larger touch screen surface than pen operation. Average speed analysis revealed that the finger performed faster than the pen for gesture input, particularly for simple gestures. While the overall proportional shape distance (PSD) of finger gestures is no worse than pen gestures, some aspects of shape, such as intersecting points deviation (IPD) and corner shape distance (CSD) tend to be larger in finger gestures than in pen gestures. These features tend to be less accurate with the finger and thus should be avoided in "finger friendly" recognition algorithm design.

Finally, there were also a few interaction effects that may have design implications. According to time performance (F1) analysis, pen gestures led to shorter time in drawing more complex gestures. This was also reflected in movement speed (F2). The finger tended to be much faster than the pen in drawing simple gestures, but achieved similar speed in drawing complex gestures. For shape features, pen input led to more accurate axial symmetry (AS) (F7) than finger input for complex gestures. Furthermore, pen input is more exact than finger input for drawing complex gestures according to proportional shape distance (PSD) (F8), but for simple gestures, finger gestures are more accurate than pen gestures. Overall these interaction effects suggest that finger friendly gesture set design should not contain gestures which are overly complex.

All of the foregoing analysis could also be interpreted as in favor of the pen since at least in some measures it is more accurate than the finger. From daily experience in, for example hand writing and signing signatures, we can all appreciate that the dexterity of the pen is unmatchable by the finger. Note that these examples differ from the gestures tested in this experiment in at least two aspects: they tend to be more complex and they are well-learned and memorized patterns. In light of the centralist vs. peripheralist views discussed earlier in this paper, one could argue that these well learned gesture patterns may include pen operation as part of one's "motor programs".

Some interesting results were found in the subjective evaluation. In respect to speed evaluation, over half of the participants felt that pen input was faster than finger input. They stated: "The pen tip is more smooth than the finger pad". However, from average speed analysis, the finger led to higher speed than the pen for drawing gestures. Some participants reported that the finger was easier to control than the pen when drawing gestures, so they thought the finger produced higher speed than the pen. From this, we suspect that the greater degrees of freedom afforded by pen input may lead to lower drawing speed. With regard to accuracy evaluation, participants believed pen gesture input was more accurate than finger gesture input. This is consistent with the results in the analysis of corner shape distance (CSD) and intersecting points deviation (IPD), but contrary to proportional shape distance (PSD) analysis. Some participants reported: "It is difficult to draw intersections or sharp corners with the finger". When drawing gestures, participants may have felt more control of some features such as corner shape distance (CSD) although no difference was made to other features such as proportional shape distance (PSD).

Prototype Gestures and Feature Selection

Admittedly gesture selection is a tricky balance of many considerations. We needed to cover common gestures in current usage, but we also needed to see how different types of gestures interact with various levels of complexity (simple, medium and complex) so the choices were not so many in each combination. Thus, we conducted the pilot study with a set of commonly used gestures (Graffiti gestures). Results showed pen and finger gestures differed in some features, which helped us to select features for the formal experiment. However, we did not use these Graffiti gestures in the formal experiment for two reasons. First, it is difficult to classify these gestures into simple, medium and complex levels because they are overall quite simple, i.e., these gestures can not meet the requirement of our study. Second, some features in which pen and finger gestures may differ, such as the aperture, can not be tested using these gestures because they are not closed gestures. Instead, we selected and designed twelve gestures which are suited to the purpose of this study. Results showed that these gestures in each of simple, medium and complex gestures levels differed in terms of time performance, average speed and proportional shape distance (PSD), suggesting these gestures were selected properly. Furthermore, the gestures chosen for this study proved effective for our examination of the differences between finger and pen input gestures; they enabled us to reveal many plausible findings. This means that these prototype gestures may be useful also for future research when designing pen and finger gestures.

Regarding the selection of features for gesture performance measurement, although a large number of features have been proposed and used in previous studies [1, 4, 15, 18], study on all stroke gesture features is beyond the scope of our study. We only focused on some features which may reveal differences between pen and finger stroke gestures with reference to the structures and characteristics of strokes as well as the gesture input performance due to the different characteristics of pen and finger input. By means of the nine features selected or designed by us, a number of differences and similarities were found between finger and pen gestures, for example speed, size and accuracy. Furthermore, using the methodology of our study, other features can be examined for gesture design.

Sensing Mechanisms of the Experimental Device

The study presented here revealed that pen gesture and finger gesture differ in several features. Though we believe that the differences are caused by the intrinsic properties of the pen and the finger respectively, one may well ask whether or not the sensing qualities of different sensing mechanisms used in this study had an effect on the experimental results.

The experimental device, HP Touchsmart tx2, has two different touch sensing mechanisms, i.e., capacitive for finger input and inductive for pen input. The position accuracy and sampling rate may differ between the two sensors [7]. Regarding position accuracy, the pen tip is sharper than the finger tip, which is an inherent difference between the pen and the finger. The sampling rates in these sensors may vary depending on the number of fingers used [7]. We therefore conducted a test to measure the sampling rates of these sensors in a condition similar to our experiments. We asked all the participants to draw freely on the screen with the finger or pen. The program recorded the number of sampling points within one second. The sampling rates were 141 Hz (SD = 1.89) for pen input and 107 Hz (SD = 0.65) for finger input; both are sufficiently high for our purpose and should not affect the gesture quality measures used.

CONCLUSION

The rapid ongoing development of touch screen devices requires the HCI field to understand the impact of finger vs. pen as gesture implements on these devices. We conducted a first study of the differences and similarities between finger drawn and pen drawn gestures. We selected a set of gestures of varied complexity and characteristics and presented in three target sizes to a group of participants who reproduced them with both the finger and the pen. The drawn gestures were then analyzed with a broad set of measures, five selected from the literature and another four designed specifically for this study.

Our findings have demonstrated the importance of our study: when applying principles, methods and findings from pen-based gesture systems to finger-based gesture design, it is vital to consider the differences and similarities. As finger gesture interaction is gaining popularity in application design, it is important to design stroke gestures that avoid features in which the finger does not perform as well as the pen, as shown in our study. Our work is one step in this exploration.

ACKNOWLEDGMENTS

This study has been partially supported by Grant-in-Aid for Scientific Research (No. 23300048) in Japan. We wish to thank the members of Ren Lab in Kochi University of Technology for their assistance.

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