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User Identification based on Touch Dynamics

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Abstract— Touch interaction has quickly become the de-facto means of interacting with handheld devices due to its perceived attractiveness and low hardware cost. This study proposes a strategy for identifying users based on touch dynamics. Users' touch behavior is monitored and several unique features are extracted including left versus right hand dominance, one-handed versus bimanual operation, stroke size, stroke timing, symmetry, stroke speed and timing regularity. An experiment involving 20 users reveals that the strategy is successful in identifying users and their traits according to the touch dynamics. The results can be used for automatic user interface customization. However, more research is needed before touch characteristics can be applied to increasing the security of handheld touch-based devices.

Keywords—component; user identification; biometrics; touch interaction; handheld device

I. INTRODUCTION

User interfaces and devices based on touch interaction have become commonplace in recent years due to technological breakthroughs. Users often perceive touch based interaction intuitive and easy. Touch technology is inexpensive and flexible. Touch based interfaces are currently found on most mobile phones, tablet computers and even some laptop computers. The research on touch interaction is still in its infancy and the literature on users and touch behavior is still limited. This study attempts to explore some of the information that can be gathered from the traces left behind by the users to learn about their unique traits. Such information has several useful applications. First, unique user characteristics can be used for various identification applications. Second, knowledge about an individual's particular style of interaction can help to dynamically customize an interface for enhanced performance and comfort.

Mobile devices are easily stolen or lost. Their material value is limited, but often such devices contain personal information and access to the owner's personal information and resources on the Internet such as e-mail, calendars, social networks, etc. Password protection is the primary means of securing the access to a device, but many users disable passwords on personal devices as these are often perceived as nuisances. Moreover, passwords do not help if a mobile device is snatched while it is being used by the owner. While using a mobile device a user may be less alert to their surroundings and vulnerable to mobile snatching. Therefore, identification based on users' behavior can be a means of protecting the content of the data. A device can be programmed to lock if the device suspects that the user is not

the authentic owner based on the thief's behavior. Consequently, one may prevent the thief from causing too much damage or extract sensitive information.

Learning about the user can help automatically customize the interface for a user. For instance, if the user is detected to be left-handed, or left hand dominant, the layout can be altered such that the buttons and links are repositioned to suit left hand use. If a user is detected to use both hands versus one hand, one can provide better support for this, for instance, virtual keyboards layouts specially tailored for one-handed use or bimanual use. Other customizations are also possible.

This study explores several measures for classifying users and extracting unique user characteristics such as left or right hand dominance, whether the user uses one or two hands, whether the user is novice, intermediate or experienced and the particular interaction style of the user. A user evaluation involving 20 individuals confirm the suitability of the measures.

II. RELATED WORK

There is a vast body of literature on biometric identification including fingerprint recognition [1], iris analysis [2], face recognition [3], handwriting recognition [4], keystroke dynamics [5] and gait recognition [6] and combinations of characteristics such as face and gait [7], to mention a few.

Most related to this study is the study of keystroke dynamics [5, 8]. One common approach is to measure the delay between successive key-down events. These studies have shown that users can be classified according to key-down to key-down times of various two-letter sequences known as digrams.

Several studies document mouse dynamics with biometric applications [9-12] and these have many similarities to touch dynamics. Features studied have included, mouse travel distance in pixels, travel time and direction [11]. One study on mouse dynamics concluded that users can be successfully identified, but recommend that identification is done in combination with other measures [12].

Although mouse dynamics have similarities to touch dynamics, there are also noteworthy differences. Mouse interaction is more indirect than touch. Touch involves obstructing the display with the hand which is not the case with a mouse. Dragging motions are detected through contact with touch, while with mouse dragging requires a button to be pressed while the mouse is moved. Touch does not have the notion of a right or middle mouse button in its

interaction vocabulary. Next, it is possible to measure the mouse motion paths between dragging motions as well as the paths of the dragging motions. With touch technology it is usually not possible to measure the path of the fingers between strokes. Consequently, the interaction style and interface functionality are different for mouse and touch.

The study of curves is also related to the identification of touch dynamics and several studies have explored the properties of curves [13]. One strategy is to explore curves invariant of size and rotation by the means of Fourier components [14]. This study does not focus on the shape properties as strokes are usually quite simple and unidirectional.

Of the few studies related to touch it is argued that identification on tabletop surfaces is crucial to prevent shoulder surfing and promising results have been achieved using touch pressure as a parameter [15]. The value of pressure as a unique identification characteristic was also reported in an earlier study on mobile touch pads [16]. Another avenue of research investigates identification and touch in context of haptic multimodal user interfaces [17].

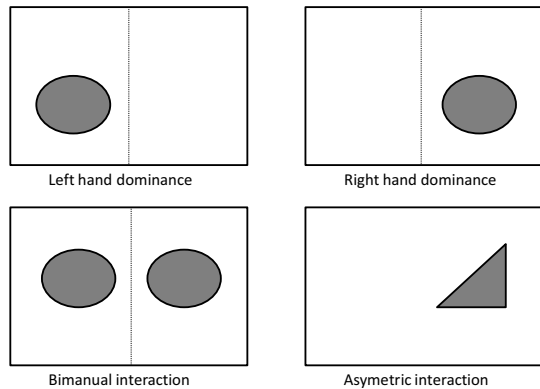


Figure 1. Impressionistic illustration of user traits during relative tasks, including left hand dominance, right hand dominance, bimanual interaction and asymmetric interaction. The four squares illustrate the display real estate and the grey shapes the accumulated user interaction area.

III. PROPOSED MODEL

Several features are proposed for capturing the unique characteristics of users' touch interaction. These characteristics include hand dominance, bimanual operation, size of motion, symmetry, timing, speed and regularity. These features are described in the following sections.

A. Hand and Dominance

Hand dominance is related to whether the user has a preference for using the right or the left hand. It is believed that approximately 70-90% of all people are right hand dominant [18], that is, they have a preference for using the right hand for fine motor tasks such as handwriting. The remaining 10-30% of the population are right hand dominant. The lack of accurate statistics is attributed to the fact that there is no agreed definition or measure of hand dominance. Hand dominance has also been found to affect how users make decisions in menu selections [19].

We propose that hand dominance reflects how a hand-held device is used for relative touch tasks, that is, tasks not relying on hitting absolute positioned targets. In particular, the hand dominance measure d defined as

$$d = \frac{\bar{x}}{X} - \frac{1}{2} \quad (1)$$

where \bar{x} is the mean x (horizontal) coordinate of the hand gesture touch points captured for the user and X the horizontal dimension of the screen. Both of these measures are in pixels. The user is right hand dominant if d is positive and the user is left hand dominant if d is negative. Right hand dominant users are more likely to use the right part of the display as this requires less energy ergonomically. For the same reasons, left hand dominant users use the left part of the display (see Figure 1).

B. Bimanual operation

Another important characteristic of touch interaction is that of one-handed versus bimanual, or two-handed, operation. Most daily activities in the physical world are carried out with both hands where fine motor tasks are performed with the dominant hand and positioning tasks are performed with the less dominant hand, also known as macro movements. Expert typists typically use two hands when they type on the keyboard, while mouse operation by itself is one-handed, unless it is simultaneously performed alongside another device. There are also other bimanual input strategies based on bimanual input devices such as double joysticks [20]. Touch devices are not limited to one hand and can be operated bimanually, especially by expert users. Bimanual operation means that operation is speeded up by overlapping interaction steps with both hands. As such, bimanual overlapping operation, such as typing, can thus be executed even with devices that do not support multi-touch.

A characteristic of one handed operation is that the interaction region, that is, the region of touch points is approximately the same size both horizontally and vertically, while with two hands, there are two such regions and the horizontal dimension will be about twice as large as the vertical dimension of the enclosing box. To quantify this relationship the bounding box ratio r is defined as

$$r = \frac{\sigma_x}{\sigma_y} \quad (2)$$

where σ_x and σ_y are the spread of the x and y touch coordinates for the user. The spread measure could be variance, standard deviation or inter quartile range. In this study standard deviation is used as the measure of spread.

With one handed operation the bounding box ratio r should be less than 2, while for bimanual operation the bounding box ratio r should be about 2 or more.

Another characteristic of bimanual operation is that the distribution of the x coordinates will be bimodal where the two modes signal the center of operation for the two hands.

On the other hand, the distribution of x coordinates for one-handed operation is unimodal. As a second measure of handedness a skew measure t based on the difference between the mode and the median is introduced

$$t = |\bar{x} - x_{\text{mode}}| \quad (3)$$

A large value signals bimodal use, while a smaller value signals one handed use. This measure is not normalized. One normalization alternative is to divide the measure by the spread.

C. Size of Motion

Touch interaction comprises sequences of strokes. A noticeable characteristic of touch interaction is the size of such strokes. Some users tend to produce small strokes and others larger strokes. A simple measure of stroke is spread, in particular the spread along the vertical axis as the horizontal spread is different from one handed and bimanual operation. This study explores the use of two spread measures, namely standard deviation and inter quartile range (IQR).

The spread of all measurements is an overall description of motion size. Size can also be quantified at stroke level. One simple measure is the Euclidean distance between the start point and the end point of a gesture i , namely the gesture length gl given by

$$gl(i) = \sqrt{(x_{\text{end}}(i) - x_{\text{start}}(i))^2 + (y_{\text{end}}(i) - y_{\text{start}}(i))^2} \quad (4)$$

Similarly, the Euclidean distance between the end point of the previous gesture and the start point of the current gesture gives the distance between the previous and current gesture, namely inter gesture length, given by

$$igl(i) = \sqrt{(x_{\text{end}}(i-1) - x_{\text{start}}(i))^2 + (y_{\text{end}}(i-1) - y_{\text{start}}(i))^2} \quad (5)$$

The median of the gesture length and inter gesture length are used as measures as these are robust to outliers.

D. Symmetry

A visual inspection of the touch trace plots produced by the participants in this study revealed that some users exhibit more symmetric and regular patterns compared to other users whose pattern were more asymmetric and triangle-like. Therefore, a symmetry measures s based on the absolute skew of the distribution of x and y coordinates are proposed:

$$s = \sqrt{x_{\text{skew}}^2 + y_{\text{skew}}^2} \quad (6)$$

where the skew of a distribution is given by

$$skew = \frac{\frac{1}{2} \sum_{i=1}^N (x_i - \bar{x})^3}{\left(\frac{1}{2} \sum_{i=1}^N (x_i - \bar{x})^2\right)^{\frac{3}{2}}} \quad (7)$$

for N samples. Low values of s signal symmetry, while large values signal asymmetry.

E. Timing

Temporal attributes have often been found to reveal recognizable traits of users [8]. In keystroke biometric research the time between consecutive key-down events are often used. This is logical as the goal of text entry is high speed, and typing can be a closed loop activity whereby the user does not consider feedback from the system. This measure is not applicable to touch interaction as it is an open loop activity dependent on the feedback cycle, that is, repeated cycles of observing the contents of the display, setting goals and executing action through touch as is described by Norman's action cycle [21]. Text entry involves key-down durations, but no particular importance is connected to this measure. However, touch strokes are more involved tasks and it is hypothesized that stroke time significant can contribute to understanding the user. Given a stroke start-time and end-time, the duration is simply

$$t_{\text{duration}}(i) = t_{\text{end}}(i) - t_{\text{start}}(i) \quad (8)$$

Similarly, the time between consecutive strokes is defined as

$$t_{\text{pause}}(i) = t_{\text{start}}(i) - t_{\text{end}}(i-1) \quad (9)$$

It is hypothesized that users broadly can be divided into four categories according to stroke-time and inter-stroke time, namely a) fast-fast, b) fast-slow, c) slow-fast and d) slow-slow. These categories can be interpreted as follows: Fast-fast users are experienced and have short interaction-reading cycles, while fast-slow users are experienced and have longer interaction-reading cycles with more time spent on reading. Slow-fast readers can also be experienced, but may signal individuals that read while dragging the content. We hypothesize that there are fewer individuals in this group as reading while dragging as this requires complex eye-hand coordination in relation to eye-fixations and the reading of moving text. Moreover, while panning the hand is partially obstructing the display. The last category, slow-slow signals an inexperienced user, or a user engaged in two or more simultaneous tasks as it signals slow movements, and long pauses between each movement. This could be the pattern of a user browsing some material slowly, and then paying attention to another task before returning to the particular application.

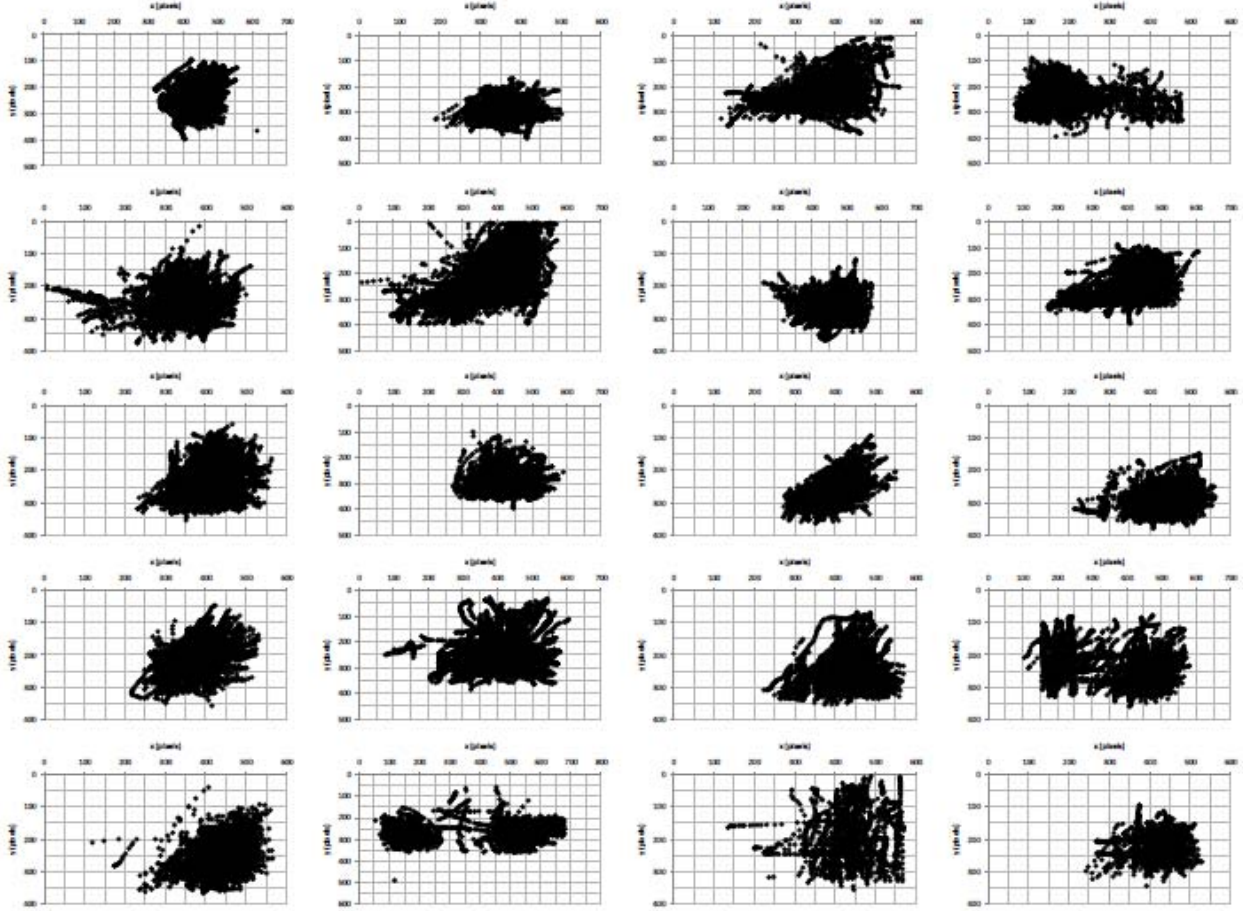


Figure 2. Impressionistic Touch trace signatures for the 20 participants.

F. Speed

Stroke speed is hypothesized to be a trait specific to individual users. Speed is defined as distance in pixels travelled per time unit, here given in seconds, or more precisely

$$v = \frac{l}{d} \quad (10)$$

Speed can possibly signal characteristics of the user. An experienced user is likely to execute faster strokes than slow strokes. Moreover, familiar situations are more likely to provoke fast strokes than unfamiliar situations where users are exploring the situation. The median stroke speed is used to characterize the speed of a user.

G. Regularity

Rhythm is an important temporal property of human behavior and has been found to be distinct in several areas of research. In this study the notion of the pair wise variability index is proposed for quantifying the stroke rhythm of the user. The pair wise variability index was first used in human

computer interaction in the field of text input [22], and is defined as follows.

$$pvi(i) = \frac{|d(i) - d(i-1)|}{d(i) + d(i+1)} \quad (11)$$

Where $d(i)$ is the duration of stroke i . The pair wise variability index is a measure of timing regularity. In this study the median pair wise variability index is computed for the sequence of stroke durations. It was hypothesized that a small pvi reflects an experienced user with a regular interaction pattern, while a large pvi signals less experienced users with irregular interaction patterns.

IV. METHOD

A. Participants

To evaluate the suitability of the measures proposed herein 20 participants were recruited, of these 10 male and 10 female. The students were recruited from the international student population of Oslo and Akershus University College of Science and Technology. The students are thus from various parts of the world and all in their 20s. Most of the

users considered themselves computer literate, but not all owned touch devices.

B. Materials

A comic book reading task was designed based on a 26-page pdf-file of a Simpsons comic. The comic is not reading intensive, it is fun and entertaining and thereby contributing to the naturalness of the task. Moreover, the zoom level was fixed and the participants had to pan with their fingers on the touch display to move across the page, and between pages.

An open source Android pdf-reader was modified and finger event logging functionality was inserted into the application. The experiments were conducted using a 7" Samsung Galaxy Tab tablet computer running the Android operating system. User interactions were logged to the internal device storage media.

C. Procedure

The participants were given instructions on the task and explained the operation of the device. The participants read the comic under the supervision of the second author. Most participants completed the task in about 10-15 minutes and no participants took more than 20 minutes to complete the task.

D. Manual classification

As a basis for performing the analysis in this study the data acquired was plotted as two dimensional traces for each of the users. Each plot was manually inspected and classified. One user (user4) was as identified as a left hand user due to the preference for the left side of the display. Three of the users (user4, user16 and user18) were identified as performing bimanual operation due to two visible interaction clusters on the interaction plots. Next, each plot was impressionistically classified as large or small depending on the size of the cluster. Half of the plots were classified as small and the other half as large. Finally, the plots impressionistically were classified as circular or triangular according to the shape of the touch cluster. A total of 8 plots were classified as circular and the other 12 as triangular. The plots used for the manual classification are shown in Fig 2.

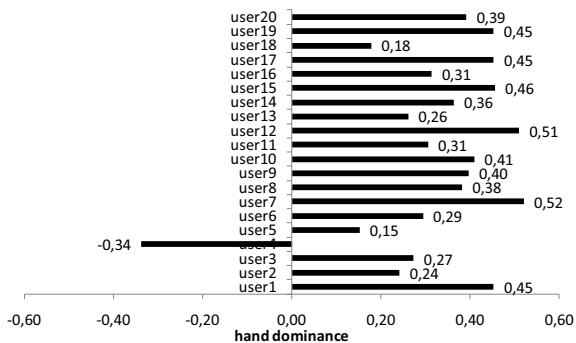


Figure 3. Hand dominance.

V. RESULTS AND DISCUSSION

A. Hand Dominance

Figure 3 illustrates the results obtained applying the hand dominance measure to the data collected. The plot clearly shows that a majority of the participants are right hand dominant as their hand dominance factors are all positive and in the range 0.15 to 0.52, while participant 4 is left hand dominant with a negative hand dominance factor of -0.34. This result is consistent with the manual observations of the subjects. The hand dominance factor thus appears to be successful in classifying users into left and right hand dominance.

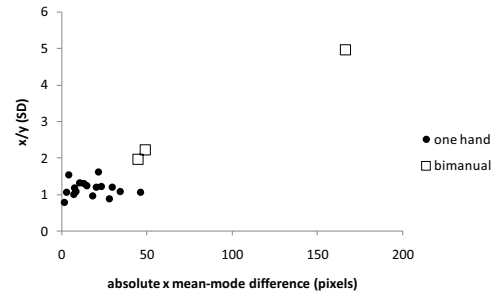


Figure 4. One-handed versus bimanual operation.

B. Bimanual Operation

Figure 4 illustrates the two measures proposed for detecting bimodal operation, namely the absolute mean-mode difference of the x coordinates and the ratio of the standard deviation of the x and y coordinates. The results show that the standard deviation ratio successfully divides the one handed and bimanual users into two groups, while for the mean-mode difference there is a one-handed user who is overlapping with the bimanual users. By combining these two measures bimanual and one handed use was successfully classified.

C. Gesture Size

Figure 5 summarizes the results of the size measures. Figure 5a shows that the standard deviation of the y coordinates partially separates the users with small and large motions into two classes, while the inter quartile range measure is unsuccessful in separating users.

Figure 5b shows the stroke length plotted against the distance between the end point of a stroke and the start point of the successive stroke. The plot shows that there is a strong correlation between the stroke length and inter stroke distance, with a Pearson correlation of 0.97. This means that users who execute large strokes also have to move their hands further between strokes. Because of the close relationship between these two factors it is practical to simply use stroke length instead of both stroke length and inter stroke distance.

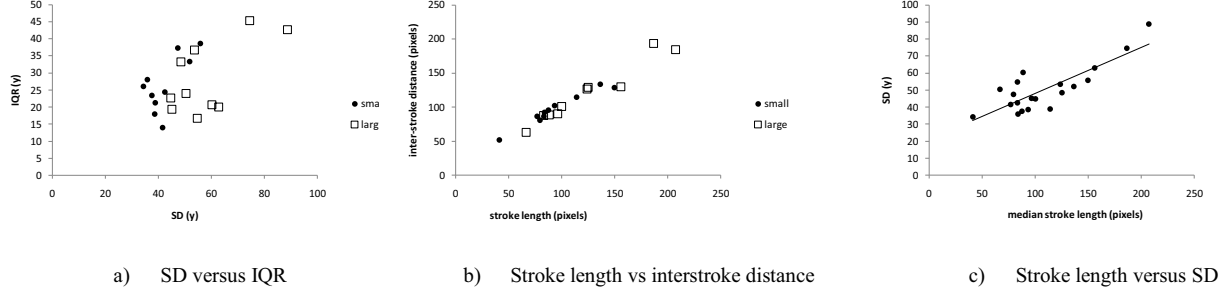


Figure 5. Size measures

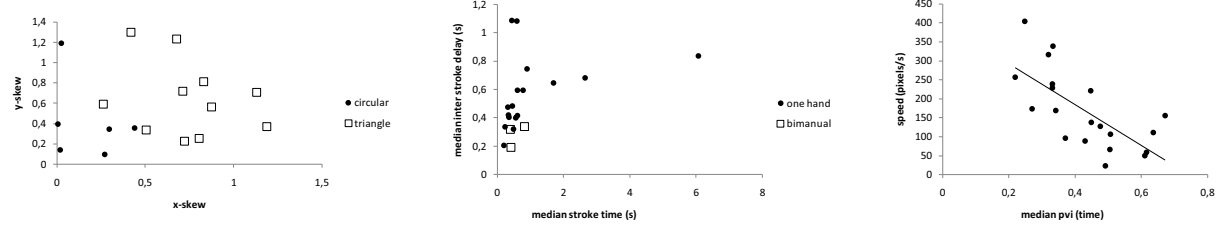


Figure 6. Symmetry

Figure 7. Timing

Figure 8. Regularity versus speed

Moreover, Figure 5b also shows that the manually classified sizes are partially classified. A majority of the large data points are populated at the high end of the scale, and a majority of those classified as small appear at the low end of the scale. However, there is much overlap, and this overlap is probably due to the imprecise and inaccurate manual classification of size according to eye-measurement of the plots in Figure 2.

The plots in Figure 5a are overall measures, and those in Fig 5b represent stroke level. Figure 5c combines these two as stroke length is plotted against the standard deviation of the y coordinates. The plot shows that there is a correlation between these two measures with a Pearson correlation of 0.82. This means that the size of the median stroke length correlates with the standard deviation of all the y measurements.

In conclusion, the size of motion is a feature that adds to establishing a distinct characteristic of users.

D. Symmetry

Figure 6 shows a plot of the data according to the absolute values of the x -skew and y -skew. The data points are manually classified according to the appearance of the touch trace signatures in Figure 2. The plot shows that the points manually classified as circular are clustered closer to the origin than those manually classified as triangular. Note that the bimanual users are omitted from this plot as their overall x -skew are not directly applicable. Figure 6 illustrate that the symmetry value s , that is, the length of the skew vector, is able to quantify the degree of symmetry. A t -test demonstrates that the s values for the manually classified points are statistically different ($t=3.3; df=15; p<0.005$).

In conclusion, the symmetry measures based on x -skew and y -skew are suitable for contributing to the unique feature of each user. In a practical application, a bimanual classification would first be applied to identify users employing a bimanual interaction strategy. To calculate an x -skew for these measurements the data points should first be mirrored to one side of the midpoint between the two hand centers, represented by the two modes, that is, one could apply a mirroring function as follows:

$$m(x) = \begin{cases} x & : x > x_{mid} \\ 2x_{mid} - x & : x \leq x_{mid} \end{cases} \quad (12)$$

where

$$x_{mid} = \frac{1}{2}(x_{mode1} + x_{mode2}) \quad (13)$$

E. Timing

Figure 7 shows the median stroke time plotted against the median inter stroke delay. The data shows that there is some correlation between the stroke time and the inter stroke delay. Moreover, the manually classified bimanual users appear close to the origins with small stroke times and inter stroke delays. This confirms that the bimanual users are fast.

The data suggest that time can be used in combination with other factors to uniquely characterize users.

F. Speed and regularity

Speed is linked to time and distance and Figure 8 confirms that the users are distributed according to their median stroke speed ranging from 25 to over 400 pixels per

second. Thus, some users execute their strokes slowly and others in various degrees of higher speeds.

Figure 8 also shows that users are distributed according to the regularity of the stroke timings measured in terms of the median pair wise variability index. In other words, some users are characterized by regular stroke timings while others are irregular. Moreover, this plot shows that the speed and regularity are inversely correlated with a Pearson correlation ratio of -0.69 . This means that the faster a user is, the more regular the stroke timings are, while slower users have more irregular patterns. The former represent more skilled users while the latter represent less experienced users.

In conclusion, both speed and regularity can be used to classify characterize individuals.

G. Identification

Users can be identified according to the nearest neighbor principle where for a new user the exemplar with the smallest distance is determined as the user.

To assess the uniqueness of the features selected the Euclidian distance between each pair of users were computed. To obtain comparable results two of the features were normalized, namely the stroke length and speed as these are much larger than the other features in magnitude involving pixels. These were normalized by dividing by the largest measurement obtained for the respective feature. The results of the computation show that the mean distance between features is 1.8, the maximum is 7.0 and the minimum is 0.3. This the minimum distance is thus over 16% of the mean value. This large minimum distance means that each feature is distinct. In particular, users 2 and 8, and 14 and 15 where the most similar in the set, but yet sufficiently different to be unique.

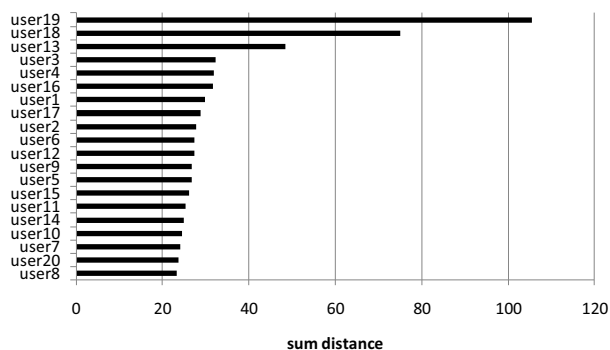


Figure 9. Uniqueness of the user feature vectors

Next, the sum of all distances to all other users was computed for each user to obtain a rank of total distance (see Figure 9). According to this figure user 8 has the smallest total distance to each neighbor with a total distance of 23.3. Moreover, the plot shows that user 19 is the most different from the other users followed by user 18 and user 13 with distances of 105.5, 75.1 and 48.4, respectively.

Four of the original members of the participants were approached three months after the original tests and the experiment was repeated with a different issue of the same

comic. The results, presented in Table I shows that the second test case did not match the original observations and none of the users could be uniquely identified. User 6 and 7 was closest to the original with a rank of 3, user 1 had a rank of 5 and user 12 had the largest distance with a rank of 7. This means that the user characteristics are similar for several users to a degree which they cannot be uniquely identified although the distances are relatively small. These results suggests that touch based habits alone are not sufficient to uniquely identify users. The results might have been better if the users were followed over time such that the learning effects could be minimized and the true traits would emerge. However, an identification system needs to work with little data to be effective.

TABLE I. USER IDENTIFICATION, RANK AND NORMALIZED DISTANCE

Participant	rank (distance)	dist.	min dist.	max dist.
User 1	5/20	0.8	0.5	5.2
User 6	3/20	0.9	0.7	5.7
User 7	3/20	0.6	0.4	5.4
User 12	7/20	0.8	0.4	6.0

VI. LIMITATIONS AND FUTURE WORK

This study is based on a moderate sample of users. It would be valuable to extend the study involving a broader set of user both in terms of age and other demographics. The current study only includes one participant with left-handed dominance and a large sample would probably lead to more left-dominant users. Moreover, it would be interesting to follow user across a longer time period with a broader range of tasks to assess effects of learning. In future work it would be interesting to also study the characteristics of the strokes at curve level. Another interesting avenue of further research is to explore other distance measures than the Euclidian such as angles.

VII. CONCLUSIONS

This study has explored strategies for detecting unique user characteristics based on touch dynamics. The study has shown that it is possible to successfully detect discrete characteristics such as whether a user is left-handed or right-handed and whether the user operates the device with one hand or two hands. Moreover, the study shows that users can be classified according to their general gesture size and gesture timing characteristics. And the results confirm that bimanual users are among the fastest users. Next, users can be ranked according to their interaction symmetry, gestures speed and gesture regularity. Users who perform fast strokes have also more regular stroke patterns and this is attributed to the users' level of skill.

The measures presented herein can be used for automatic customization of touch-based graphical user interfaces. However, more research into touch characteristics is needed before the approach can be used for identifying users, especially for self-locking of stolen handheld devices,

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