Design and Evaluation of EdgeWrite Alphabets for Round-Face Smartwatches

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ABSTRACT
This study presents a project aimed at designing and evaluating a unistroke gesture set of alphanumeric characters targeting round-face smartwatches. We conducted a user study with 10 participants to generate the basic gesture design for 40 characters. For each character, we measured the preference and agreement scores and uncovered any challenges faced in designing unistroke gestures for round-face smartwatches. We developed a gesture recognizer using machine learning, which used a backpropagation mechanism to evaluate the designed gestures. Using the gesture recognizer, we collected 80,000 gesture data, and evaluated them with 5-fold cross-validation. The obtained mean recognition rate was 92.14%.

Author Keywords
Text entry; unistrokes; edges; smartwatches.

ACM Classification Keywords
H.5.2. Information interfaces and presentation (e.g. HCI): User Interfaces.

INTRODUCTION

Text entry is a basic interaction but cumbersome task in the contemporary urban life. In particular, small devices such as smartwatches make it difficult to type with tiny keys on a small touchscreen keyboard and require several actions. Smartwatches are now used in daily life. Entering text while conducting another task such as walking usually happens at a slower rate because the watch face shakes and the user cannot focus on the task. This situation is a typical example of a situationally induced impairment and disability (SIID) [1].

EdgeWrite [2] is a prominent approach in SIID situations. Compared with other small-screen text-entry methods such as ZoomBoard [3], with EdgeWrite, the user draws a unistroke gesture with his/her finger pressed on the physical screen edges of an input device. Because the corners and edges have physical boundaries, the user can enter text in two ways: without any visual contact and with an unstable device and unsupported hands. For these reasons, EdgeWrite is suitable for text entry on small devices. However, with the original design of the alphanumeric characters for EdgeWrite, a rectangular input area was employed, i.e., differently shaped input areas were not supported. This provides us with an opportunity to investigate different design space for EdgeWrite from the viewpoint of form factor: the use of rounded spaces.

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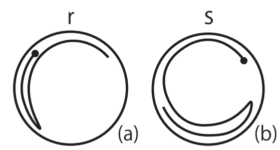

Figure 1. Input gestures

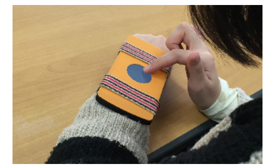

Figure 2. Experimental device

METHOD

Approach

In our approach, the user traces the edge of a circular input area with a finger. Precisely, the user enters an alphanumeric character with a unistroke gesture similar to the shape of the intended character. The following example shows the input procedure for entering the letter "r": (1) Imagine the shape of the letter "r", and place his/her finger on the screen at the starting point for drawing; (2) Draw the "r" shape by tracing the edge with the finger; (3) completed drawing the letter, and release the finger from the screen edge; and (4) The letter "r" is displayed on the screen. The resulted gesture is expected to form a shape similar to that the letter "r" (Figure 1a).

User generated gestures

The purpose of this investigation was to determine whether users can draw gestures using the proposed method. We recruited 10 participants aged from 21 to 23 (M = 22.1) years. All of them were right-handed. An Android Nexus 5 (4.95 inches, 1080×1920 pixels) was used as the input device. Its display was covered with a 1-mm-thick polypropylene plate with a 1.3-inch hole in the center imitating the edge of a round-face smartwatch (Figure 2).

The participants were asked to draw a unistroke gesture to best fit the shape and the drawing order for a presented character, tracing the edge of the round-shaped input area. They were also asked to distinguish between the gestures of characters that were similar in shape; it was assumed that some characters could create the same unistroke gestures, such as "h" and "n." Forty characters, including alphanumeric characters and punctuation marks (comma, period, space, and backspace), were presented, and their presentation order was randomized. Each participant conducted 12 trials. Using a 7-point Likert scale (7 = strongly agree), participants rated their preference for the gesture they created.

RESULT

Preference

On the first trial, the mean preference scores for the characters “c,” “o,” “u,” “0,” and “9” with the standard deviation given in parentheses were 6.90 (0.30), 6.70 (0.64), 6.30 (1.00), 6.40 (0.80), and 6.20 (0.60), respectively. These are all higher than a score of 6. Because these characters contain curvy lines, users naturally fitted them to the circular edge being used. In contrast, the scores for “f,” “m,” “t,” “x,” “4,” and “8” were 3.50 (1.20), 3.90 (0.70), 3.20 (1.33), 3.00 (1.10), and 3.10 (1.70), respectively. They are all lower than a score of 4 for the first trial. These characters comprise crossed lines (“f,” “t,” “x,” “4,” and “8”) or three parallel lines (“m”), which makes them more difficult to fit to the circular edge. Furthermore, a Wilcoxon signed-ranks test indicated that the preference was stronger in the final trial (Mdn = 6) than in the first trial (Mdn = 5), Z = 9.62, $p < 0.001$, and r = 0.34. This means that the participants adjusted their drawing behavior and attitude during the trials.

Agreement

We classified gestures drew by the participants in the final trial into groups with similar shapes as agreed by the participants. Classification was conducted by two researchers including the first author. If the two researchers found difficulties in judging a certain gesture, two more researchers were asked to judge. We then calculated the agreement score (A_r) based on the study by Wobbrok et al. [4] using the formula: $A_r = \sum_{P_i \subseteq P_r} (\frac{|P_i|}{|P_r|})^2$, where r is any character (e.g., the letter “a”) in the set of all characters R, P_r is the set of proposed gestures for the character, and P_i is a subset of identical gestures from P_r. The agreement score runs from 0 to 1, with score is equal to 1 indicating that all the participants drew the same gesture.

Among the higher preference group (“c,” “o,” “u,” “0,” and “9”), the characters “c,” “o,” “0,” and “9” obtained higher agreement scores; however, “u” had a slightly lower score (0.52). As we did not restrict characters to being either capitalized or in lowercase, it is possible that the participants might have imagined different shapes (e.g.,“u” or “U”). In other words, even if a participant marked a higher preference score for a gesture of a certain character, its agreement score can be lower than that obtained when each participant created a unique gesture. Interestingly, while the character “s” demonstrates a lower preference score, its agreement score is 1.0; all the participants created the same gesture. The character “s” is seemingly hard to draw in the circular input area because its shape comprises two opposite semicircular arcs with vertical displacement. Nevertheless, drawing it was easy for the participants who successfully traced it in the circular input area by running his/her fingertip counterclockwise from the upper right to the lower right and then going clockwise to the lower left (See Figure 1b).

The basic gesture design

Based on the gestures created in the final trial, we designed the basic gestures of alphanumeric characters for round-face smartwatches. The designed gesture of the character “r” is shown in Figure 1a and the complete list can be seen at http://www.golab.org/p/redgewrite.html. To design the basic gestures, we selected gestures with higher agreement scores unless they had no overlapping gestures. However, if they had an overlapping gesture, we decided on the gesture based upon the preference scores: the one with the highest score was selected. All the participants were unable to create distinguished gestures for the alphabetical character “o” and the numerical character “0.” Thus, we artificially designed a gesture for “0” similar to that of original EdgeWrite. As the basic gesture design works in the default setting, we developed a recognizer to conduct user tests of the design.

GESTURE RECOGNIZER AND EVALUATION

To validate the gesture design, we developed a gesture recognizer with machine learning using a backpropagation mechanism. The gesture recognizer was written in Java using the Android NDK, which calls a method of Fast Artificial Neural Network Library. Using the gesture recognizer, we conducted a gesture recognition test and considered the same participants as those who had participated in the gesture generation test. We collected training data including 20 sets of 40 characters per participant. Subsequently, we evaluated them with 5-fold cross-validation. The resulted mean recognition rate was 92.14% and is largely accepted as a default value even though further adjustment will be required.

CONCLUSION

In this study, we investigated basic gestures for EdgeWrite targeting round-face smartwatches with the goal of expanding the design space for text-entry methods in SIID situations. Based on the participants preferences and agreement scores, we designed basic designs for gestures of alphanumeric characters in addition to highlighting the challenges when designing gestures for round-face smartwatches. We also developed a gesture recognizer to evaluate the designs. In our future study, we may consider designing online learning systems to achieve a higher accuracy of character recognition.

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