# Investigation of Detection Characteristics of Finger Pressure and Touch Area and Their Application to Pre-Classifiers in Writer Verification 

Yohei Masegi and Atsushi Takahashi<br>Graduate School of Sustainability Sciences, Tottori University, 4-101 Koyama-minami, Tottori-shi, Tottori, 680-8552, Japan<br>Email: \{m19j4045m, m18j4013b\}@edu.tottori-u.ac.jp<br>Isao Nakanishi<br>Faculty of Engineering, Tottori University, 4-101 Koyama-minami, Tottori-shi, Tottori, 680-8552, Japan<br>Email: nakanishi@tottori-u.ac.jp


#### Abstract

We propose a highly convenient authentication system, that requires a user to write a simple symbol on a touch-panel display of a smartphone and/or tablet terminal. The detection characteristics of the finger pressure and finger touch area on a touch-panel display are investigated since they are expected to be individual features that are independent from the written shapes. As a result, the exact pressure and contact area values are not detected but it is confirmed that the values corresponding to the pressure and the contact area are measured on the touch panel screen. Moreover, we propose to use the extracted features as preclassifiers and apply them to writer verification. The verification performance is confirmed to be improved by the proposed classifier.


## I. Introduction

Most people own a smartphone or tablet terminal for using the internet and communicating with other people. In most cases, those terminals contain key personal information. Therefore, security technologies are required to prevent unauthorized access and illegal use of this information. Currently, fingerprint and face authentication are the personal authentication applications installed in these devices. They are convenient and have a high authentication rate. However, they offer low-level security because fingerprints and faces, being the external body parts, are exposed. Biological information cannot be changed like a password.

Accordingly, we focus on written authentication, a method of making authentication based on writing habits. An individual's writing habits are difficult for others to acquire and the risk of theft or imitation is low. Particularly, online signature verification, in which a signature is written using a pen on a tablet screen, is suitable [1]-[4].

However, it is time consuming to write a signature. Furthermore, it is difficult to write on a small screen, such as that of a smartphone, using a special pen. Therefore, we proposed a system that requires a simple symbol to be drawn with a finger on a smartphone or
tablet screen for authentication [5]. It was also confirmed that finger pressure and the finger touch area are effective as individual features [6].

Even though the detection characteristics of finger pressure and finger touch area on the touch panel screen used were not disclosed, it was unclear how they were not disclosed. This paper, a cylindrical weight is placed on the screen of a smartphone, and the weight and touch area detected are investigated. Apparently, finger pressure and touch area cannot be read by other people. Furthermore, if they are independent of the handwriting shape, they can be used as individual features in free handwriting verification.

## II. Person Verification Based on FingerWriting of Simple Symbols

Person verification based on finger-writing of simple symbol is proposed [5]. We propose writing a symbol (for example Circle, Triangle, and Rectangle) on a touch panel screen of a smartphone or tablet which nobody needs to remember. The symbol is directly drawn with a finger without using a pen. Our conventional research, as shown below, from writing data extracted 41 features from writing data and evaluated the verification performance using the Euclidean distance.

## 41 features

-Average of $X$ and $Y$ coordinates
-Maximum of X and Y coordinates
-Minimum of X and Y coordinates
-Difference between $X$ and $Y$ coordinate
-Distance between start and end points
-Drawing area
-Start and end points coordinates
-Average of finger pressure and touch area
-Maximum value of finger pressure and touch area, and their coordinates
-Minimum of finger pressure and touch area, and their coordinates
-Average speed and acceleration
-Maximum speed and acceleration. and their coordinates
-Minimum speed and acceleration, and their coordinates
-Velocity near start and end points
-Start and end points peripheral acceleration
-Start and end points finger pressure
-Start and end points finger touch area
-Writing time
As a result of measuring 20 sets of 3 symbols (Circle, Triangle, and Rectangle) for 19 subjects, the smallest EER (equal error rate) of $18.4 \%$ was obtained using the end point coordinates of the symbol Rectangle.

## III. Detection Characteristics of Finger Pressure and Touch Area

The coordinate values on the touch panel screen have been used in various studies on handwriting authentication, and their detection characteristics are widely known. However, since the finger pressure and touch area have not been used as individual characteristics until now, the features and detection characteristics were not clear. Therefore, we investigated the detection accuracy of the finger pressure and touch area of the smartphone touch panel that was used in the conventional research.

It is difficult to maintain a constant pressure and area while conducting experiments because the strength and size of the finger pressure and touch area change depending on the human beings are involved. Therefore, in this experiment a weight is used instead of a finger. Thus, it is possible to apply a constant pressure and touch area to the touch panel screen. Furthermore, since the weight and size of the weight are accurately determined by the standard, we can calculate the theoretical values of the pressure from weight and touch area. In addition, we can verify the detection accuracy by comparing the theoretical and measured values.

In the experiment, the smartphone (ARROWS NX) used in the conventional research [5] and four types of reference cylindrical weights (hereinafter referred to as weight) with different weights and sizes were used. Tables 1 and 2 show the specifications. Figure 1 shows model diagrams of the measurement method, whereas Fig. 2 shows actual measurement scenes. As shown in Fig. 1, each weight was put on the smartphone screen and measured until the measurement value was stabilized. To reduce measurement errors, the average value of 50 measurement results was used as the measurement value.

First, the weights were covered by an insulating tape to
TABLE 1. SPECIFICATION OF ARROWS NX.

| OS | Android5.0 |
| :---: | :---: |
| CPU | MSM8994 2.0 GHz |
| RAM | 3 GB |
| ROM | 32 GB |
| DISPLAY | About5.2in IPS liquid <br> crystal/ WQHD <br> $(1440 \times 2560)$ |
| SIZE | About $146 \times 70 \times 8.8 \mathrm{~mm}$ |
| MASS | About 155 g |

TABLE 2. DETAIL OF STANDARD WEIGHT TYPE CYLINDRICAL WEIGHT.

| Cylindrical Weight $[\mathrm{g}]$ | Bottom Area $\left[\mathrm{m}^{2}\right]$ |
| :---: | :---: |
| 5 | 0.0113 |
| 10 | 0.0133 |
| 20 | 0.0177 |
| 50 | 0.0314 |

Weight

## Display

Figure 1. Simple measurement method model.


Figure 2. Measurement scene.
remove the conductivity, followed by an aluminum foil for uniform conductivity. The change in weight and contact area covering the insulating tape or aluminum foil was negligible. Furthermore, sometimes it was difficult for smartphone sensors to report the weights; hence, "glove mode" was used on the smartphone to increase the sensitivity of the built-in sensors.

## IV. Measurement Results and Discussion

Table 3 shows the experimental and theoretical values obtained by the measurement and weights, respectively.

TABLE 3. EXPERIMENTAL RESULTS AND THEORETICAL VALUE.

|  | Pressure |  | Touch Area |  |
| :---: | :---: | :---: | :---: | :---: |
| Weight $[\mathrm{g}]$ | Experiment value | Theory value $\left[\mathrm{N} / \mathrm{m}^{2}\right]$ | Experiment value | Theory value $\left[\mathrm{m}^{2}\right]$ |
| 5 | 0.0805 | 4.4210 | 0.3469 | 0.0113 |
| 10 | 0.0952 | 7.5340 | 0.3729 | 0.0133 |
| 20 | 0.1152 | 11.3177 | 0.3980 | 0.0177 |
| 50 | 0.1417 | 15.9155 | 0.4785 | 0.0314 |



Figure 3. Relationship between experimental and theoretical values at the pressure.


Figure 4. Relationship between experimental and theoretical values at the contact area.

Clearly, the experimental values on the touch panel used are completely different from the theoretical values. Therefore, the exact pressure and contact area values are not detected.

Next, the experimental and theoretical values are normalized by the standard deviation. The horizontal and axes represent the experimental and theoretical values, respectively. In the case of the pressure shown in Fig. 3, the experimental and the theoretical values are almost linear; hence, the experimental value almost corresponds to the theoretical value.

For the contact area shown in Fig. 4, the experimental and theoretical values are almost linear, like pressure. However, when the contact area is small, it does not correspond to the theoretical value. Therefore, the detection accuracy deteriorates when the contact area is small. These findings confirmed that the values (information) corresponding to the pressure and the contact area could be measured on the touch panel screen.

TABLE 4. Features at the start and end points

|  |  |  | $\bigcirc$ | $\triangle$ | $\square$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Start <br> Point | Finger Pressure | Min | 18 | 19 | 19 |
|  |  | Max | 1 | 0 | 0 |
|  | Touch Area | Min | 19 | 19 | 19 |
|  |  | Max | 0 | 0 | 0 |
| End Point | Finger Pressure | Min | 8 | 3 | 6 |
|  |  | Max | 11 | 16 | 13 |
|  | Touch Area | Min | 8 | 0 | 4 |
|  |  | Max | 11 | 19 | 15 |



Figure 5. Three regions.

## V. Independent of Writing Shape Features

To authenticate by writing a simple symbol that is easily recognized, it is necessary to extract features that are independent of the writing shape. Unlike the conventional signature verification, the proposed features do not use the difference in handwriting shape. Therefore, we focus on the starting and the ending points in the finger pressure and touch area as features that do not depend on the writing shape.

Table 4 shows the number of subjects for which the finger pressure and touch area was minimum or maximum at the start and end points, according to the data used in the conventional research. Thus, at the starting point, most people wrote small. Conversely, at the ending point, many people wrote large, but there were a few who wrote small.

This confirms that the information about finger pressure and touch area at the start and end points is effective in classifying smart phone users. Thus, we propose to configure a three-classifier (hereafter 3classifier) which equally divides the region between the maximum and minimum values at the start or end point of finger pressure or finger touch area into three sections: max, mid, and min as shown in Fig. 5.

In the enrollment stage, the maximum and minimum values at the start and end points of the finger pressure and touch areas are collected from all users when writing a symbol. Next, the collected maximum values or minimum values at the start or end point of the finger pressure or touch areas for each user are averaged. Using the averaged values, the maximum-minimum areas are determined. Three sections are then determined for point and each feature for each user in advance. Information about these three-sections at both points and features is enrolled as templates in the authentication system.
TABLE 5. RESULTS OF 3 CLASSIFIER.

| a | FRR [\%] | FAR [\%] |
| :---: | :---: | :---: |
| $\bigcirc$ | 37 | 34 |
| $\Delta$ | 34 | 49 |
| $\square$ | 34 | 47 |
| b | FRR [\%] | FAR [\%] |
| $\bigcirc$ | 37 | 31 |
| $\Delta$ | 48 | 30 |
| $\square$ | 45 | 27 |
| c | FRR [\%] | FAR [\%] |
| O | 59 | 15 |
| $\Delta$ | 58 | 21 |
| $\square$ | 57 | 22 |



Figure 6. Distribution of 3classifier in finger pressure.

In the classification stage, the maximum and minimum values at the start and end points of the finger pressure and touch areas are detected and then examined, which section the detected each value is included.

In addition, we propose to combine two 3classifiers of the start end the end points (in total 9 combinations) and combine four 3classifiers (in total 81 combinations) of the start and end points of the finger pressure and touch are features. In these combinations, the user is determined to be genuine only when all results of the combined classifiers match.

Classification performance was evaluated using FRR (False Reject Rate) and FAR (False Acceptance Rate). The results are shown in Table 5. The lowest FRR was $34 \%$ was obtained when writing a square or triangle symbol in the case of "a", whereas the lowest FAR was $15 \%$, obtained when writing a circle symbol in the case of "c". The classification performance was not as sufficient as expected.

Figure 6 illustrates the number of experimental subjects classified into each combination in the case of " $a$ ", where, for example, " $\mathrm{min} / \mathrm{min}$ " indicates that a value at the start point of finger pressure was classified into the minimum section and a value at the end point was also classified into the minimum section. From this figure, it is clear that there is maldistribution in the classification results. Even if nine combinations were provided, more than half of them were not used in the


Figure 7. Process flow of the proposed method.


Figure 8. OR operation of 3classifier features.
classification. It could be assumed that people do not have completely distinct writing styles.

We tried to increase the number of sections (4 or more classifier) by subdividing each section. However, the classification performance did not improve.

## VI. Pre-Classifier

In this section, we introduce the produced 3classifier as a pre-classifier into a writer verification. The processing flow of the proposed writer verification with a 3classifier is shown in Fig. 7.

First, rough classification using the 3classifier in the finger pressure and touch area is performed. Next, only a user who is judged as genuine proceeds to the writer verification proposed in Ref. [5], in which the authenticity of the user is verified using writing features including finger pressure and touch area. Contrarily, a user who is judged as not genuine by the 3classifier is immediately rejected. Therefore, it is important to decrease the cases in which genuine users are mistakenly judged as not genuine. Hence, the FRR of the 3classifier as a pre-classifier should be as minimum.

To meet this demand, we propose to configure a preclassifier that fuses the results in three 3classifiers using finger pressure data at the start and end points and touch area data at the start point by a logical sum (OR) operation as shown in Fig. 8. These classifiers are chosen because that they independently achieved the lowest FRR. If one of three 3classifiers regards a user as genuine, then the user is processed in the writer verification.

Table 6 shows the classification performance when fusing the three 3 classifiers using finger pressure data at the start and end points and touch area data at the start point. Although the FRR was never 0 , it became reasonably small.

TABLE 6. CLASSIFICATION PERFORMANCE WHEN FUSING THREE
3CLASSIFIERS.

| Symbol |  |  |
| :---: | :---: | :---: |
| $\bigcirc$ | FRR [\%] | FAR [\%] |
| $\Delta$ | 1 | 89 |
| $\square$ | 1 | 93 |
| $\square$ |  |  |

## VII. Verification Performance Using the Proposed Pre-Classifier

We introduced the proposed pre-classifier into the writer verification method proposed in Ref. [5] and evaluated its verification performance. The evaluation was performed using EER. Smaller EER means better verification performance.

Table 7 display EERs when individually using a feature in three simple symbols and comparing with EERs by the conventional writer verification method. By introducing the proposed pre-classifier, EERs were never increased, that is, the verification performance never deteriorated. There were cases where the improvement of EER was insignificant, however, EER had improved by $1.9 \%$ when using the coordinates of the start point of the circle symbol. The smallest EER was $17.9 \%$ when using the end point coordinate data and writing a rectangle symbol. It was significant that the verification performance improved and never deteriorated introducing the proposed pre-classifier, which was realized by simple categorization of finger pressure and touch area information.

## VIII. Conclusions

Previous research has confirmed that the finger pressure and finger touch area are effective as individual features of handwriting authentication, but the actual detection characteristics on the touch panel screen used were unclear. As shown in Figs. 3 and 4, the detected writing features (pressure, contact area) differed from the theoretical values; however, values corresponding to the pressure and contact area could be measured on the touch panel screen.

Moreover, we proposed using the feature of the finger pressure and the touch area at the start and end points of an independent writing shape. Therefore, we tried to define and identify these differences in three regions: maximum, minimum, and middle. Primarily since the number of classifications in the 3classifier has a limit, and the distribution of features is biased, the use of only a 3classifier did not identify accurately identify.

Therefore, we proposed to use it as a pre-classifier in combination with the conventional authentication system. As a result, the authentication system was improved by EER of $1.9 \%$, confirming the effectiveness of the preclassifier.

In the future, we plan to investigate more features of independent handwriting shape.

TABLE 7. AUTHENTICATION RESULTS FOR EACH SYMBOL.

| Feature Value | Symbol | EER(\%) |  |
| :---: | :---: | :---: | :---: |
|  |  | Previous research results | Proposed method results |
| Start point coordinate | $\bigcirc$ | 27.7 | 25.8 |
|  | $\triangle$ | 25.8 | 25.2 |
|  | $\square$ | 19.5 | 19.4 |
| End point coordinate | $\bigcirc$ | 28.9 | 28.3 |
|  | $\triangle$ | 28.4 | 27.2 |
|  | $\square$ | 18.4 | 17.9 |
| Drawing area | $\bigcirc$ | 25.7 | 24.2 |
|  | $\triangle$ | 27.3 | 26.8 |
|  | $\square$ | 27.9 | 26.3 |
| Average | $\bigcirc$ | 28.9 | 27.7 |
|  | $\triangle$ | 29.3 | 28.8 |
|  | $\square$ | 27.2 | 25.8 |
| Average of finger touch area | $\bigcirc$ | 25.8 | 25.1 |
|  | $\triangle$ | 25.2 | 25.0 |
|  | $\square$ | 23.1 | 22.1 |
| Maximum finger pressure | $\bigcirc$ | 27.2 | 26.3 |
|  | $\triangle$ | 23.1 | 22.9 |
|  | $\square$ | 22.4 | 21.5 |
| Maximum Finger touch area | $\bigcirc$ | 25.1 | 24.4 |
|  | $\triangle$ | 23.7 | 23.6 |
|  | $\square$ | 23.5 | 22.3 |
| Maximum finger touch area coordinate | $\bigcirc$ | 27.9 | 26.8 |
|  | $\triangle$ | 35.8 | 35.3 |
|  | $\square$ | 31.6 | 30.0 |
| Average writing speed | $\bigcirc$ | 25.7 | 24.7 |
|  | $\triangle$ | 27.9 | 27.4 |
|  | $\square$ | 28.2 | 27.4 |
| Average acceleration | $\bigcirc$ | 28.4 | 27.6 |
|  | $\triangle$ | 33.7 | 33.2 |
|  | $\square$ | 32.1 | 31.5 |
| Minimum acceleration coordinate | $\bigcirc$ | 28.9 | 27.9 |
|  | $\triangle$ | 44.6 | 43.7 |
|  | $\square$ | 42.4 | 40.9 |

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

IN devised the project, the main conceptual ideas and proof outline; YM carried out the experiments and proposed a three-classifier; AT contributed to introducing the proposed three-classifier into the conventional writer verification method; IN and YM wrote the paper; all authors had approved the final version.

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Yohei Masegi was born in Aichi, Japan on June 25th, 1996. He received B.E. degree in Electrical Engineering and Computer Science from Tottori University, Japan. He is now a master course student in Graduate School of Sustainability Sciences, Tottori University. His research interest is in writer verification.


Atsushi Takahashi was born in Hyogo, Japan on March 28th, 1996. He received B.E. and M.E. degrees in Electrical Engineering and Computer Science and Graduate School of Sustainability Sciences from Tottori University, Japan in 2018 and 2020, respectively. His research interest was in writer verification.
He joined KOTANI Corporation in 2020.


Isao Nakanishi was born on December 27, 1961 in Osaka, Japan. He received his B. E., M. E., and Dr. E. degrees in Electrical Engineering from Osaka Prefecture University, Japan in 1984, 1986, and 1997, respectively. He joined SANYO Corp. in 1986 and was a Researcher in computer research and development. He joined Tottori University, Japan in 1994 and was engaged in digital signal processing. He is now a Professor in the Faculty of Engineering, Tottori University. His research interests are in digital signal processing, speech signal processing, and biometrics.
Prof. Nakanishi is a senior member of the IEEE and the Institute of Electronics, Information and Communication Engineers (IEICE). He was a Chair of IEEE Hiroshima Section in 2017 and 2018 and is now an Adviser of Technical Committee on Biometrics of IEICE.

