Introduction of Finger-softness Feature into Writer Verification Based on Finger-writing of Simple Symbol

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***Abstract*—We proposed writer verification based on the finger-writing of a simple symbol on a smartphone screen for biometric authentication. Among the features used for authentication, the finger contact area and finger pressure features do not depend on the shape of the symbol. This study focuses on the relationship between finger contact area and finger pressure, which increases proportionally when the finger is pressed on a smartphone screen. Specifically, we plot the time-series data of finger pressure and contact area on a two-dimensional graph, approximate their relationship with a straight line, and use the slope and intercept as a new feature as the finger-softness feature. The best equal error rate (EER) of this new feature is 19.8%, and its average EER is approximately 23%. This new feature is considered superior to the direct use of conventional finger pressure and finger contact area features.**

***Index Terms*—Biometrics, Writer Authentication, Simple Symbol, Finger-softness Feature**

I. INTRODUCTION

Smartphones are widely used worldwide as they render life has more convenient; however, this is accompanied by an increase in cybercrimes. Hence, biometrics has been investigated extensively in recent years.

Two types of biometric verification methods exist: one is based on body parts (physical features), and the other is based on human habits (behavioral features). We focus on a writer verification method that uses behavioral features. Writer verification is the method of identifying a person based on his or her writing habits [1]–[5]. As habits are difficult to steal, the risk of theft or misrepresentation by others is low, thus rendering the method highly secure.

Signature verification is widely used in writer verification [6]. However, writing on the small screen of a smartphone is time consuming and difficult, which render it inconvenient. Therefore, in the previous study, a system that performs verification by writing a simple symbol on a smartphone screen with a finger was developed to realize the best writer verification in terms of convenience. In addition, the individual characteristics of finger pressure and contact area have been investigated and evaluated [7]. In this study, we propose a "finger-softness" feature was developed to further improve verification performance and as a shape-independent writing feature.

II. WRITER VERIFICATION BASED ON FINGER-WRITING OF SIMPLE SYMBOL

Writer verification based on the finger-writing of a simple symbol is the most convenient form of writing on the screen of a smartphone or tablet using just one symbol, for example ○, △, or □. It neither requires memorization nor the use of an additional instrument such as a pen for writing [7].

A. Features and Identification

In this study, all users write the same symbol; therefore, verification base on a pattern matching method cannot be applied. Thus, we aim to extract individual features from writing motion, which are independent of a writing shape.

The 41 features used in the previous study are listed in Table I. The coordinates are the values of the x- and y-coordinates, and each coordinate is counted as one feature. For example, in the case involving the maximum finger pressure value and its coordinates, three types of values are involved: the maximum finger pressure value and the x- and y- coordinates at which the maximum finger pressure value is observed. In addition, the fingertip position on the screen (two-dimensional coordinates), pressure (finger pressure), and contact area are observed at regular intervals using the smartphone used in Ref. [7]. Therefore, each measurement value is obtained as single time-series data from the start to the end of writing. Hence, the features must be extracted from each time series of the data. As independent features of writing shape, the start and end points, the maximum value, the mean value, and the minimum value are extracted as one-dimensional features in each dataset. In addition, the velocity and acceleration are calculated from the adjacent time-series data. The distance and area features are calculated from the coordinate values. Writing time is the time recorded from the starting point to the end point.

Euclidean distance is used for identification. The system compares the features of the person (template) with those for

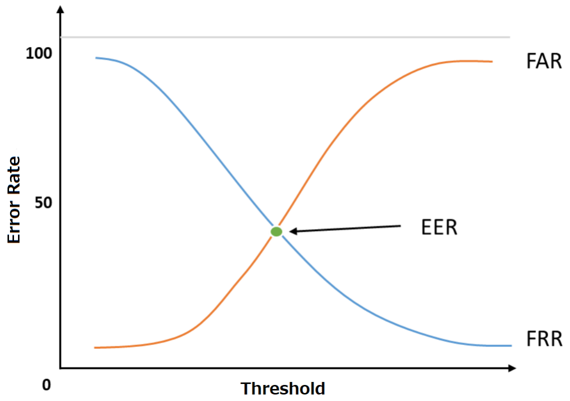


Fig. 1: Errer rate curves

TABLE I: Extracted features

X Max	Y Max
X min	Y min
X diff	Y diff
Start CIE	End CIE
Start-End CIE	Drawing Area
Finger Pressure avg	Finger Contact area avg
Finger Pressure Max and CIE	Finger Contact area Max and CIE
Finger Pressure min and CIE	Finger Contact area min and CIE
Speed avg	Acceleration avg
Speed Max and CIE	Acceleration Max and CIE
Speed min and CIE	Acceleration min and CIE
Start Finger Pressure	End Finger Pressure
Start Finger Contact Area	End Finger Contact Area
Start Circumference Speed	End Circumference Speed
Start Circumference Acceleration	End Circumference Acceleration
Time	

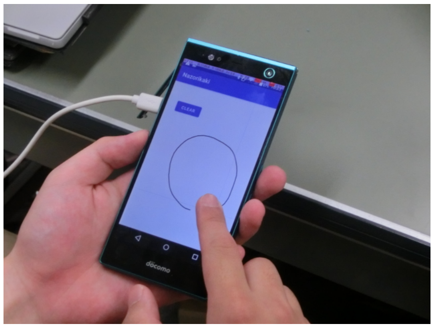


Fig. 2: Measuring Scene

TABLE II: Spec of ARROWS NX

OS	Android 5.0
CPU	MSM8994 2.0GHz
RAM	3GB
ROM	32GB
Display	about 5.2 inch in Plane Switching
Size	about 146 × 70×8.8mm
Mass	about 155g

identification, judges the person as a stranger if the distance exceeds the threshold, and judges the person as a person himself/herself if the distance is below the threshold.

B. Evaluation Method

As an evaluation index of the authentication performance, the equal error rate (EER) is used, which is equal to the false rejection rate (FRR) and the false acceptance rate (FAR). The FRR and FAR exhibit a trade-off relationship, and the EER is the intersection of the FRR and FAR, as shown in Fig. 1. Generally, the lower the EERs, the better is the verification performance.

C. Measurement Environment

The measurement scene is shown in Fig. 2. The smartphone used for the measurements was the ARROWS NX produced by Fujitsu. To acquire the finger-writing data, we developed an environment using Android Studio. From the smartphone, the time, coordinates (Cartesian coordinates), finger pressure, and finger contact area information was measured when users wrote on the screen with their finger.

The dataset used was the one from a previous study [7], in which 30 subjects were asked to write each symbol (○, △, □) 20 times. The test data was the average of 10 data from each subject. The number of comparisons was 10 for each person and that was 29 × 10 for other persons. Moreover, to improve the reliability, the cross-varidation was conducted 10 times. In total, 3000 comparisons were performed.

D. Verification performance of single features

The EERs for each finger pressure and contact area features of interest in this study are listed in Table III. The purpose of this study is to identify features with better verification performance.

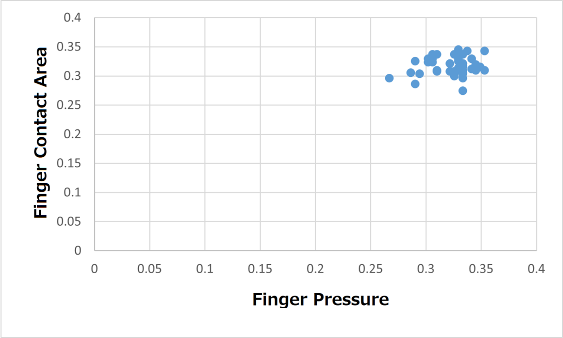
TABLE III: EER[%] of features

	○	△	□
Finger Pressure avg	27.7	28.8	25.8
Finger Contact area avg	25.1	25.0	22.1
Finger Pressure Max	26.3	22.9	21.5
Finger Contact area Max	24.4	23.6	22.3
Finger Contact area Max CIE	26.8	35.3	30.0
Finger Pressure min	38.9	40.9	41.4
Finger Contact area min	35.0	34.2	32.4
Finger Pressure min CIE	32.6	29.5	28.4
Finger Contact area min CIE	32.6	31.5	34.1

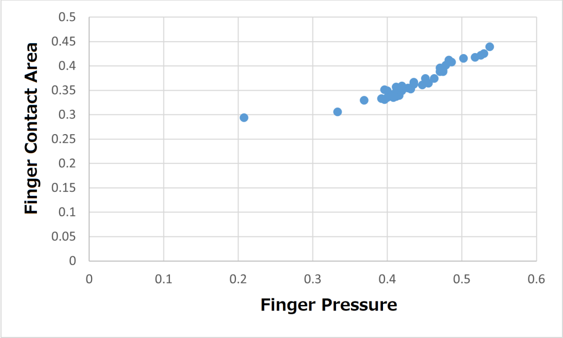
III. INTRODUCTION TO FINGER SOFTNESS FEATURE

A. Relationship between finger pressure and finger contact area

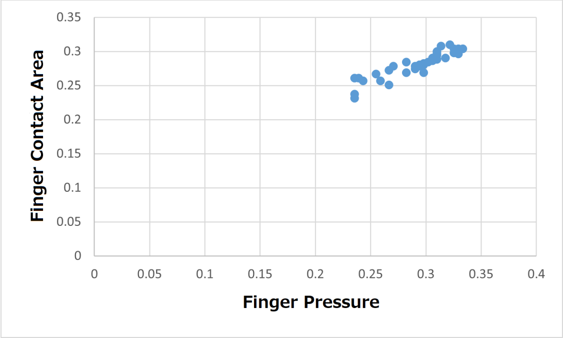
In Ref. [8], the change in finger contact area in response to force exertion was investigated, which revealed that an exponential relationship existed between finger pressure and finger contact area. Thus, we plotted the time-series data of finger pressure and contact area on a two-dimensional space to verify whether the exponential relationship between finger pressure and contact area applies for our findings. As an example, Fig. 3 shows the results of three subjects writing the symbol ○.



(a) Subject 1



(b) Subject 2



(c) Subject 3

Fig. 3: Relationship between finger pressure and finger contact area for three subjects

As shown, an exponential relationship was not indicated between finger pressure and finger contact area when writing on the smartphone screen. We consider that this is because, in Ref. [8], measurements were performed under a wide range of pressure (1–10 N), whereas when writing on a smartphone screen, excessive pressure was not applied; thus, data could not be measured in high-pressure areas where the relationship between finger pressure and contact area changes abruptly.

However, in the low-pressure range, linearity was indicated between the finger pressure and contact area, and their correlation was extremely high. Therefore, we perform a linear approximation of the relationship between finger pressure and contact area, extract the slope and intercept as the feature values, and concatenate them to create a two-dimensional feature. We call it the finger-softness feature.

B. *Feature Extraction*

Specifically, the measured finger pressure and contact area time-series data are plotted on the two-dimensional x- and y-axes, respectively, and a linear approximation is realized using the following equation:

$$y = \alpha x + \beta, \tag{1}$$

where the x- and y-axes represent the finger pressure and contact area values, respectively; and the constants α and β are the slope and intercept, respectively. These are one-dimensional.

C. *Verification performance of slope and intercept*

First, we evaluated the verification performance of the slope as independent two features. Table IV shows their EERs. The template is the average of 10 data points of the person.

TABLE IV: EERs[%] of slope and intercept

	○	△	□
Slope	43.0	39.7	37.9
Intercept	39.0	37.8	35.6

The lowest EER (i.e., 35.6%) was obtained for the symbol □. However, this result is not comparable to those obtained under the conventional finger pressure and contact area shown in Table III.

D. *Pre-processing 1*

To investigate the cause of inferior verification performance, we compared the EERs of finger pressure and contact-area-related features, as shown in Table III. The results show that the EER of the minimam finger pressure exceeded other EERs for all the symbols. Fig. III (b) shows that the point with the lowest finger pressure was far from the other points. The point with the minimum finger pressure deviated significantly from the linear relationship indicated by the other points. Because the start and end points are the moments at which the finger establishes contacts with or detach from the screen, the finger pressure can easily attain at the minimum value, and the the value of the minimam finger pressure becomes unstable. Consequently, the approximate straight line is affected by such finger pressure minim, which increases intra-individual variability and degrades verification performance. Therefore, as a preprocessing step, the point with the finger pressure minimum is removed, an approximate straight line is obtained, and the slope and the intercept are obtained. This is referred to as Preprocessing 1.

Table V lists the EERs of the slope and intercept for Preprocessing 1. Compared with the EERs in Table IV, the EER

TABLE V: EER[%] of slope and intercept after Preprocessing 1

	○	△	□
Slope	37.3	38.7	38.2
Intercept	37.5	38.3	37.6

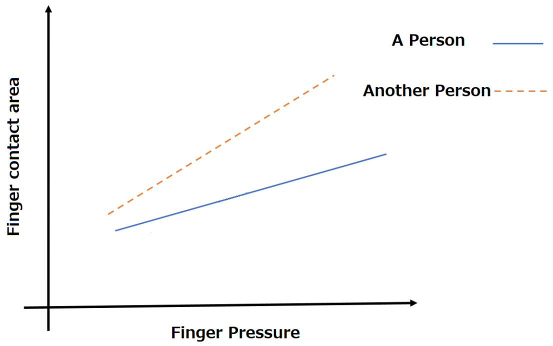


Fig. 4: Approximate straight lines based on finger pressure

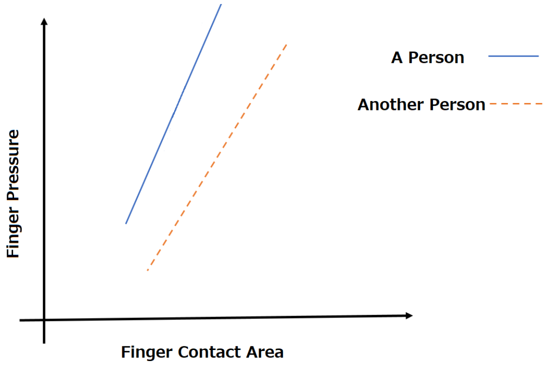


Fig. 5: Approximate straight lines based on finger contact area

of the slope under Preprocessing 1 reduced by approximately 5%, particularly for the symbol ○. The intercept decreased by approximately 2%. Meanwhile, the EER increased for certain cases in symbols △ and □.

E. Preprocessing 2

Next, we considered which should be set as the baseline (horizontal axis). As shown in Fig. 3 , we used finger pressure as the baseline, in accordance with Ref. [8]. Fig. 4 and 5 show the cases where finger pressure and finger contact area were used as the baselines, respectively. The solid line represents a straight-line approximation of two data points of the person, and the dotted line represents a strating-line approximation of one data point of another person, where the two individuals are assumed to exhibit different characteristics (slope and intercept). Even in these figures with interchanged vertical and horizontal axes, the relationship between straight-line segments is not changed.

In this study, the slopes of these line segments are extracted and expressed as angle. The relationship between the slope (α) and angle (θ) is expressed as a tan function as follows:

$$tan(\theta) = \alpha \tag{2}$$

Fig. 6 illustrates the tan function, with the vertical axis representing the slope and the horizontal axis representing the angle in degrees. The relationship between the slope and angle is shown in (a), where the change in the slope is gradual when the angle of the approximate line segment is 0°∼45°. However, as shown in (b), the slope changes abruptly as the angle changes from 45° to 90°. In the tablet device used in this study, both finger pressure and contact area are detected as normalized values. In addition, the finger pressure indicates higher values compared with the contact area. Therefore, as shown in Fig. 4, when the finger pressure is set on the horizontal axis, the angle of the line segment is within 0°∼45°. However, when the finger contact area is set on the horizontal axis, the angle exceeds 45°, as shown in Fig. 5. The change in the angle results to a large difference in the slope and the difference results in a significant difference between individuals; consequently, the verification performance is improved. The axis inversion is denoted as Preprocessing 2.

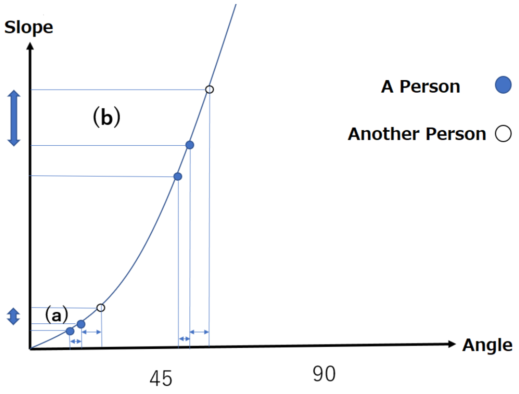


Fig. 6: tan fanction

We evaluated the verification performance by extracting the slope and intercept using Preprocessing 2. The results are listed in Table VI.

TABLE VI: EER[%] of slope and intercept after Preprocessing 2

	○	△	□
Slope	34.8	33.0	33.2
Intercept	32.1	31.1	31.7

The EER was reduced by approximatly 8% for all symbols, particularly for the slope of symbol ○, compared with the EER without preprocessing in Table IV.

Next, the EER was calculated combined with Preprocessing 1. The results are listed in Table VII. Compared with the case in which each preprosessing was performed alone, the EER was generally decreased. Furthermore, compared with the results in Table IV without preprocessing, the slope

TABLE VII: EER[%]of slope and intercept after Preprocessing 1 and 2

	○	△	□
Slope	31.5	31.2	31.1
Intercept	35.9	36.9	37.6

reduced by approximately 12%, particularly for the symbol ○. Therefore, the removal of the measured point with the minimum finger pressure and the exchange of the baseline for linear approximation were effective preprocessing.

F. Verification performance of finger-softness feature

Finally, the slope and intercept were merged into a finger-softness feature. Table VIII lists the EERs for the finger-softness feature. The lowest EER of =19.8% was obtained for the symbol □. Compared with the EERs of the slope and intercept in Table VII, the abovementioned lowest EER was approximately 10% lower. This is due to the two-dimensionality of the feature by fusion.

TABLE VIII: EER[%] of finger-softness feature

○	△	□
22.6	23.2	19.8

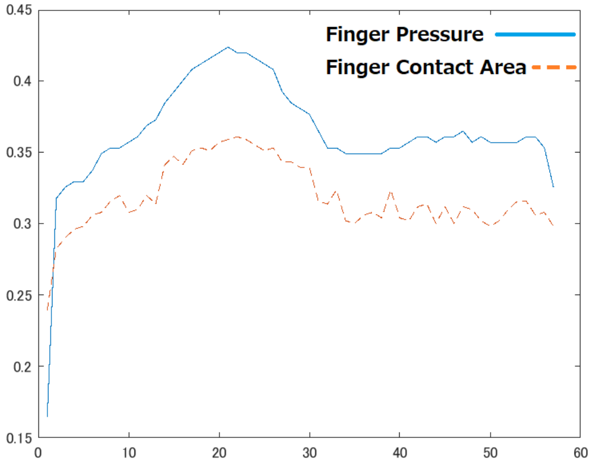
G. Consideration

We consider that the superior verification performance for the symbol □ compared with those for other symbols was due to the longer time required for writing and them the greater number of sample points was obtained, which increased the accuracy of the linear approximation. Additionally, we investigated the reason that caused the EERs increased for symbols △ and □ when Preprocessing 1 was performed. Fig. 7 shows the time- series data of finger pressure and contact area of a subject writing the symbols ○, △, and □. The solid and dotted lines represent the finger pressure and finger contact area, respectively. In the case of symbol ○, the finger pressure changed relatively smoothly. However, for the symbols △ and □, the finger pressure becames extremely high or low at the corners of the symbols. This is speculated to be caused by the abrupt change in the direction of the finger at the corner of the symbol, which resulted in removal of finger force. In the case of symbol ○, removing the sample point at which the finger pressure reached the minimum in Preprocessing 1 eliminated the unstable point at the moment the finger began to establish contact with the smartphone screen, thus improving the accuracy of the linear approximation. However, in the case of symbols △ and □, when force diminished at the corners during writing, if the finger pressure at the corners is lower than that at the starting point, then it is removed via Preprocessing 1, thereby resulting in the removal of points that may have been individual characteristics, which we assumed to have degraded verification performance.

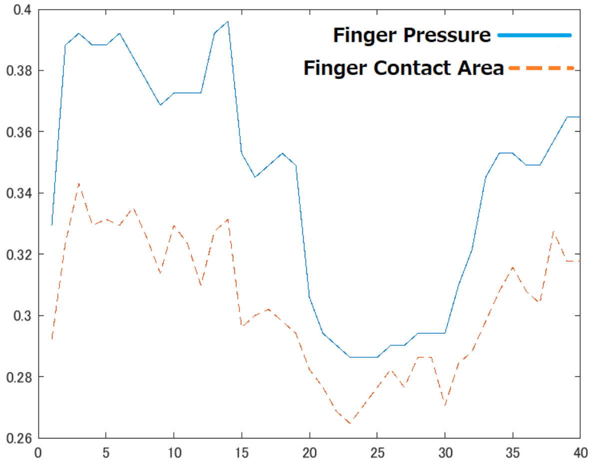
IV. CONCLUSION

In this study, we proposed the finger-softness feature as a new feature. The slope and intercept were extracted from the approximate line obtained from the finger pressure–contact area relationship and fused as a feature. In addition, we introduced the following preprocessing steps:

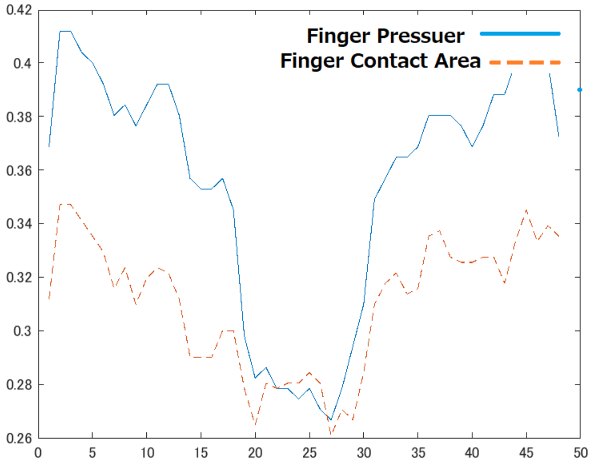
- The point containing the minimum finger pressure was removed from the two-dimensional graph for performing the liner approximation.



(a) ○ (57 samples)



(b) △ (40 samples)



(c) □ (48 samples)

Fig. 7: Time-series data of finger pressure and finger contact area for a subject

- A linear approximation was realized based on the finger contact area.

The finger-softness feature developed in this study showed better verification performance for all symbols than the conventional finger pressure and contact area related features. In particular, the lowest EER of 19.8% was obtained for the symbol □. Therefore, using finger softness as a feature is more effective than using the finger pressure or contact area feature for improving verification performance.

In the future, we plan to evaluate the verification performance using a support vector machine as a verification method as well as by performing fusion with other features. In addition, we plan to investigate whether other features behave in a peculiar manner, such as the minimum finger pressure observed in this study.

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