Finger-Softness Feature for Writer Verification Based on Finger-Writing of a Simple Symbol

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***Abstract*—As a form of biometric authentication, we proposed writer verification based on finger-writing of a simple symbol on a smartphone screen. Because everyone writes the same one symbol, verification based on differences in handwriting shape cannot be expected. Therefore, it is desirable to extract features that are independent of handwriting shape. In this study, we investigate the relationship between finger contact area and finger pressure, which change when a finger is pressed against a smartphone screen. These are independent of handwriting shape. Specifically, time-series data of finger pressure and contact area is plotted on a two-dimensional graph, this relationship is approximated with a straight line, the slope and intercept are extracted from the straight line, and they are fused as a new two-dimensional finger softness feature. Via a comparison with two-dimensional features produced by fusing the finger pressure with the contact area, our results confirm that the proposed feature is superior to conventional features.**

***Keywords*—biometrics, writer verification, simple symbol, finger-softness feature**

I. Introduction

In recent years, research into biometric authentication has been active [1]. Biometric authentication can be divided into two types: those based on physical characteristics (body parts) and those based on behavioral characteristics (human habits). This study focuses on writer authentication, a type of behavioral biometrics. Writer authentication is a method of authenticating individuals using their writing habits [2–9]. Habits are difficult to steal, so the risk of theft or forgery by others is low, making it highly secure. There are three main categories of writer authentication: signature authentication [2–6], text-directed authentication [7], and text-independent authentication [8, 9].

In signature verification, users write their own signatures, which they are familiar with; therefore, users do not experience the unfamiliarity that comes from writing an unfamiliar pattern (shape). However, the most inconvenient point is that users must remember a writing pattern. In addition, writing a signature is time-consuming. Moreover, writing a signature on a small smartphone screen is difficult and inconvenient. Since each user writes the same pattern every time authentication is performed, the pattern is often known to others, making it easier for them to imitate it. Thus, the security of signature verification is low.

A text-indicated verification system specifies and indicates a writing pattern to a user. If writing patterns are different each time authentication is performed, then it becomes difficult for others to learn the writing pattern; therefore, the security of text-indicated verification is high. However, users must write specified patterns that are unfamiliar to them; therefore, the convenience of text-indicated verification is low.

Text-independent verification permits users to write any pattern; therefore, it is generally regarded as convenient for users. However, writing a different pattern every time authentication is performed is surprisingly inconvenient, as users must prepare and write different patterns to prevent others from learning them. Thus, text-independent verification has the highest security.

We have proposed a method for authentication by writing a simple symbol on a smartphone screen with a finger [10]. From the viewpoint of specifying a written pattern, the system is similar to text-indicated verification in that it specifies a writing pattern. However, it differs in that the same pattern (symbol) is always written. The proposed method requires users to finger-write a simple symbol that is known by everyone, familiar to everyone, and unlikely to be forgotten; therefore, it is expected to be more convenient than conventional writer verification methods. However, in practice, subjective evaluations will be necessary. Moreover, because everyone knows the writing pattern and writes the same pattern, the proposed system has the lowest security.

This study proposes a “finger-softness feature” to improve the verification performance. In Ref. [11], we have already examined the extraction method. In this paper, we demonstrate the effectiveness of finger-softness feature by comparing them with other two-dimensional features.

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II. Writer Verification Based on the Finger-Writing of a Simple Symbol

In Ref. [10], we proposed a method to realize a more convenient writer verification method, which can verify a person by writing a simple symbol with a finger on a smartphone screen. Examples of symbols include a circle, triangle, or square. With this system, it is not needed to remember what to write or use a dedicated pen for writing.

A. Features and Verification

In this study, all users write the same symbol on the small screen of a smartphone; therefore, the written shapes of the symbol will be similar, making it difficult to distinguish them using pattern matching, which compares a written shape with a template. Thus, we aim to extract individual features that are independent of handwriting shape from handwriting actions. Finger pressure and contact area are candidates for such features and are shown in Fig. 1. We have made it possible to detect them at regular intervals from a smartphone [12]. As a result, each measurement is obtained as a single time series from the start to the end of writing. Therefore, we need to extract features from each time series. In Ref. [10], the starting and ending coordinates, maximum value, average value, and minimum value of each data point were extracted as independent features of the handwriting shape. These are all one-dimensional features. We also used Euclidean distance for verification. The features extracted in advance and stored as templates are compared with the features extracted for verification to calculate a distance. If the distance is below a threshold, the user is determined to be the user, and if it is above the threshold, the user is determined to be someone other than the user.

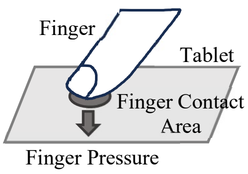

Fig. 1. Finger pressure and contact area.

B. Experiments and Results

We introduce the experimental conditions and evaluation results of the conventional verification method [10]. An ARROWS NX (Fujitsu) smartphone was used for the measurements. The environment for acquiring finger writing data was built using Android Studio. Using a smartphone, data was collected on the time, Cartesian coordinates, finger pressure, and finger contact area as subjects wrote a simple symbol on the screen with their finger.

Thirty subjects were asked to write each symbol, that is, a circle, triangle, or square, 20 times. Templates were obtained by averaging 10 data sets from each subject. There were 10 comparisons with each person and 29×10 comparisons with other subjects.

The Equal Error Rate (EER) was used as an evaluation index for verification performance. There is a trade-off between the False Rejection Rate (FRR) and the False Acceptance Rate (FAR), and the EER is when they are equal. Generally, a lower EER value indicates a better verification performance. To further improve reliability, we performed cross-validation 10 times. Therefore, the following EER is an averaged value of the EER values from the 10 cross-validations. Table I shows the EER of features related to finger pressure and contact area.

TABLE I. EER [%] OF FEATURES [10]

Feature	Circle	Triangle	Square
Finger Pressure Max.	26.3	22.9	21.5
Finger Pressure Avg.	27.7	28.8	25.8
Finger Pressure Min.	38.9	40.9	41.4
Finger Contact Area Max.	24.4	23.6	22.3
Finger Contact Area Avg.	25.1	25.0	22.1
Finger Contact Area Min.	35.0	34.2	32.4
Finger Pressure at Start Point	38.8	42.2	41.6
Finger Pressure at End Point	29.9	31.0	26.3
Finger Contact Area at Start Point	33.6	37.3	37.3
Finger Contact Area at End Point	28.4	30.8	28.3

III. Introduction of the Finger-softness Feature

We introduce a novel finger-softness feature to improve the verification performance.

A. Relationship between Finger Pressure and Finger Contact Area

In Ref. [13], the relationship between finger pressure and finger contact area was investigated, and it was reported that the contact area increases exponentially as the pressure increases. We therefore plotted the time series data of finger pressure and contact area in two-dimensional space to verify whether the exponential relationship could be observed in our measurement results.

Fig. 2 shows the relationship when one subject wrote a circle symbol. When writing on a smartphone screen, no exponential relationship was observed between finger pressure and contact area. The reason for this is that, while measurements were taken under a wide range of pressure (1–10 N) in Ref. [13], excessive pressure was not applied when writing on a smartphone screen, and data could not be measured in the high-pressure region where the relationship between finger pressure and contact area changes nonlinearly.

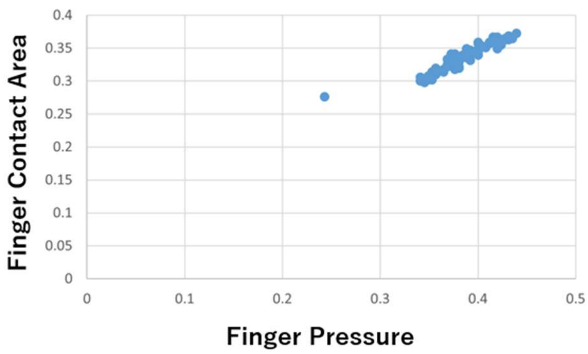

Fig. 2. Relationship between the finger pressure and finger contact area for a subject.

On the other hand, in the low pressure range, the relationship between finger pressure and contact area was linear, and the correlation between the two was very high. Therefore, the relationship between finger pressure and contact area was linearly approximated, and the slope and intercept values were simply concatenated into one two-dimensional vector, resulting in a finger-softness feature [11].

B. Feature Extraction

Now, we explain the specific feature extraction method. Using the smartphone employed in this study, we confirmed that the finger pressure and finger contact area data were obtained in normalized forms and that the values of the pressure were larger than those of the contact area. When the finger pressure and contact area are assigned to the horizontal and vertical axes, respectively, according to Ref. [13] as shown in Fig. 2, the angle of an approximated line to the horizontal axis is always less than 45 degrees ($\theta < 45°$), as shown in Fig. 3(a). The angle θ and slope α of an approximated line to the horizontal axis have the relation of $\alpha = \tan\theta$, as shown in Fig. 3(c). For example, if the angles of two different users, namely, User1 and User2, are θ_1 and θ_2 in Fig. 3(a), respectively, then their slopes are α_1 and α_2 and the difference between them is small, as shown in Fig. 3(c), which makes it difficult to distinguish between the users.

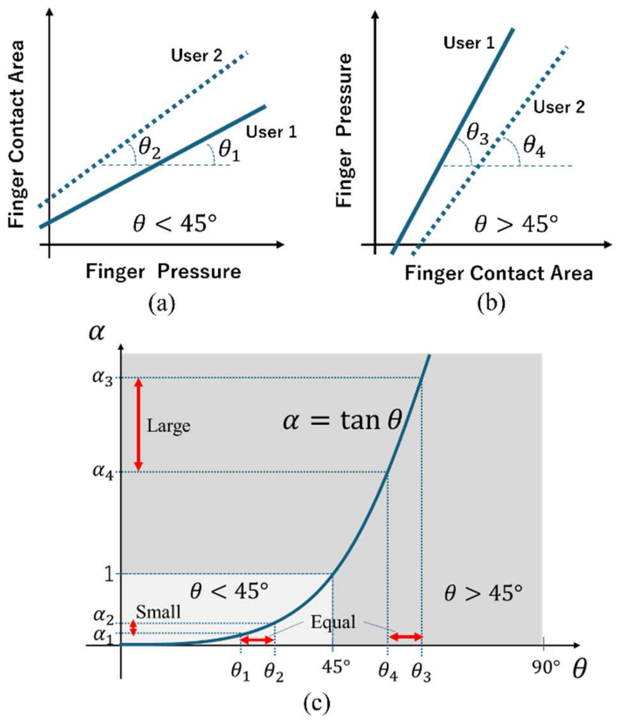

Fig. 3. (a) Case plotting the finger pressure and contact area data along the horizontal and vertical axes, respectively. (b) The reversed case. (c) Relation between angles and slopes.

However, if the two axes are swapped and the horizontal and vertical axes are used for the contact area and pressure, the angle of an approximated line to the horizontal axis always exceeds 45 degrees ($\theta > 45°$), as shown in Fig. 3(b). The difference between the two angles is the same as that in Fig. 3(a). However, their slopes are α_4 and α_3, and the difference between them is larger than that in the case of ($\theta < 45°$), as shown in Fig. 3(c), which makes it easier to distinguish between the users.

Therefore, we set the finger contact area and finger pressure to the horizontal and vertical axes, respectively, and performed a straight-line approximation. Its effectiveness was confirmed in Ref. [11]. However, this method is effective only when using a smartphone for which the values of pressure are larger than those of the contact area.

When using different smartphones, the finger pressure and contact area are measured in advance, and if the pressure is larger, the pressure data is plotted on the vertical axis and processed. On the other hand, if the pressure is not larger, the pressure data is plotted on the horizontal axis and the proposed effect is not obtained.

The specific linear approximation method is as follows: The measured time series data of finger pressure and contact area are plotted on the vertical and horizontal axes of a two-dimensional space, and approximated using the following equation:

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

where, the constants α and β represent the slope and intercept, respectively, as shown in Fig. 4. These are one-dimensional.

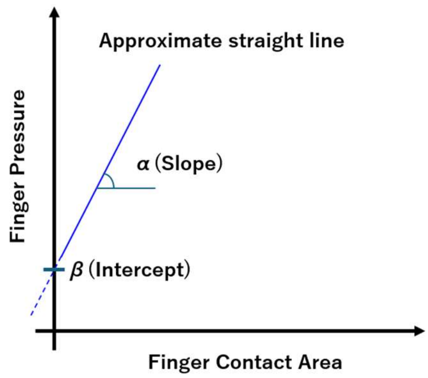

Fig. 4. Slope and intercept extracted from an approximated line.

Additionally, another way to improve verification performance has been applied. Looking at Fig. 2, it can be seen that the point with the lowest finger pressure is far away from the other points. This point also deviates significantly from the linear relationship shown by the other points. This is because finger pressure reaches its minimum and becomes unstable at the moment the finger touches the screen (starting to write) or the moment the finger is lifted (end of writing). If a linear approximation is performed including the minimum pressure point, this instability will degrade verification performance. Therefore, we propose to remove the minimum pressure point and then perform linear approximation. The effectiveness of removing the point with minimum finger pressure was confirmed in Ref. [11], for example, the EER of the slope when writing a circle was reduced by approximately 5%; therefore, it is introduced as a preprocessing step. After preprocessing, an approximately straight line, its slope, and its intercept are obtained.

C. Verification Performance of the Finger-softness Feature

We evaluated the verification performance using Euclidean distance matching and the dataset used in Ref. [10]. Table II shows the EER values for the slope and intercept [11]. The EER values for the slope and intercept are smaller than those of several conventional features related to finger pressure and contact area shown in Table I, and vice versa. The verification performance of the slope and intercept was comparable to that of conventional features.

TABLE II. EER [%] OF SLOPE AND INTERCEPT [11]

Feature	Circle	Triangle	Square
Slope	31.5	31.2	31.1
Intercept	35.9	36.9	37.6

Next, we combined the slope and intercept values into a single two-dimensional feature, the finger softness feature, and evaluated its verification performance. Table III shows the EER values of the finger softness feature for each symbol [11]. The lowest EER, 19.8 %, was obtained when writing a square. Furthermore, as can be seen by comparing with the EER values of the slope and intercept in Table II, the EER was reduced by approximately 10% by combining them into two dimensions.

TABLE III. EER [%] OF THE FINGER-SOFTNESS FEATURE [11]

Circle	Triangle	Square
22.6	23.2	19.8

IV. PERFORMANCE COMPARISON WITH CONVENTIONAL TWO-DIMENSIONAL FEATURES

In this section, we evaluate the verification performance of the finger-softness feature, which is two-dimensional, by using the two-dimensional features produced by fusing the one-dimensional finger pressure and contact area features. Table I shows that there are 10 conventional features related to the finger pressure and contact area. The verification performance was evaluated for all combinations consisting of two of these patterns, that is, 45 patterns in total. The slope and intercept, which are components that characterize the softness of the fingers, are not normalized during fusion. To make the comparison conditions the same, the finger pressure and contact area features used for comparison were also not normalized during fusion.

Table IV shows the results. Only the top two feature combinations are listed owing to space limitations. The verification performance of the finger-softness feature was superior for all combinations of each symbol. Since the contact area increases with increasing pen pressure, it is thought that there is a correlation between pen pressure and contact area. On the other hand, there is generally no correlation between the slope and intercept of a line. Even if the slope is the same, the intercept will vary, and vice versa. Although we have not actually confirmed the correlation between the slope and intercept of the approximated line, which constitutes the finger softness feature, it is considered weaker than that between finger pressure and contact area. During verification, fusing uncorrelated features, which have different opinions (decisions) enhances robustness and improves performance more than does fusing correlated features, which have the same opinion (decision). Therefore, the verification performance of the finger-softness feature is superior to those of conventional features related to the finger pressure and contact area.

TABLE IV. EER [%] OF THE FINGER PRESSURE-AND CONTACT AREA-RELATED FUSION FEATURES

Symbol	Fused Features	EER
Circle	Finger Contact Area at End Point Finger Contact Area Max.	23.0
	Finger Pressure at End Point Finger Pressure Max.	23.7
Triangle	Finger Contact Area Avg. Finger Contact Area Max.	23.4
	Finger Pressure Max. Finger Contact Area Avg.	24.2
Square	Finger Contact Area Avg. Finger Contact Area Max.	22.3
	Finger Pressure Max. Finger Contact Area Avg.	23.0

Even if normalization is performed, the slope and intercept values only change independently, and the correlation between them does not change. Therefore, this result will remain unchanged.

V. CONCLUSION

A finger softness feature was proposed as a new feature for writer verification based on finger-writing of a simple symbol. The slope and intercept were extracted from the approximate line obtained from the relationship between finger pressure and contact area, and these were combined as a two-dimensional vector.

Verification performance experiments confirmed that the proposed finger softness feature was superior to conventional features related to finger pressure and contact area. Using finger softness as a feature is more effective at improving verification performance than using features related to finger pressure or contact area.

In the future, we plan to fuse it with other features and evaluate its verification performance. Another challenge is to introduce more powerful classification methods, such as a support vector machine, which is a supervised learning-based classification method.

In this study, the superiority of the proposed finger softness feature was evaluated by measuring the difference in verification performance. To do this, we used verification based on simple Euclidean distance. Furthermore, to evaluate verification performance from multiple perspectives, we evaluated it using FRR and FAR, and used EER, where FRR and FAR were equal, as the performance index. We also performed cross-validation to reduce the effects of random variations in the measurement data. However, to improve the reliability of the results obtained, evaluation using a larger dataset is necessary, which is a future challenge. It would also be interesting to elucidate the mechanism behind the superiority of the proposed features using various analytical methods.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

TF devised the main conceptual ideas and carried out the experiments; IN managed the project, evaluated the results, and wrote the paper; all authors had approved the final version.

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This study was conducted with the approval of the Non-Medical Research Ethics Committee at the Faculty of Engineering, Tottori University.

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