Finger-Touch Direction Feature Using a Frequency Distribution in the Writer Verification Base on Finger-Writing of a Simple Symbol

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Abstract. In this study, individuals were asked to draw a symbol by using their fingertips on a digital device screen. This study focused on finger-touch direction information that can be extracted from a smartphone screen. To suppress rapid changes in the detected direction data, preprocessing was introduced, and its effectiveness was confirmed by evaluating the verification performance. Finally, representing the direction data as a frequency distribution was introduced as a new feature, which was demonstrated to improve the verification performance.

Keywords: Biometrics · Writer verification · Simple symbol · Finger-touching direction · Frequency distribution.

1 Introduction

Recently, facial images, iris images, and fingerprints have been used for person authentication when using smartphones and tablet devices. These biometrics provide good usability and achieve a high authentication rate. However, they are constantly exposed, and thus, they can be acquired (stolen) easily. Furthermore, they cannot be changed like passwords, compounding their vulnerability.

Writer verification/identification, which authenticates individuals using information obtained from their writing actions [1], is attracting attention as it cannot be easily imitated. Signature verification has been employed for writer verification [2–4]. However, owing to the small displays of smartphones, smartphone users find it difficult to create a signature. In addition, signing is time consuming, and using a dedicated pen is inconvenient.

We have proposed an authentication method based on writing a simple symbol using a finger [5–7], as it is easy and fast for users to write simple symbols even on small displays of smartphones, and it does not require a dedicated pen. This is for achieving the most convenient way for writer verification. In addition, we have investigated the characteristics of finger-pressure and finger-touching areas in Ref. [8]. This information is completely private and not known to a third party or to the users themselves. Additionally, in Ref. [9], finger-touching direction has been used as a possible third authentication characteristic.

In this study, finger-touching direction was introduced as a feature in the writer verification method by writing a simple symbol with a finger and evaluating the verification performance. However, there were rapid changes in direction in the detected finger-touching direction data, which were caused by fluctuations in the touching area of the finger on the pad of a smartphone display. To suppress these rapid changes, preprocessing was introduced, and its effectiveness was confirmed by evaluating the verification performance. Furthermore, representing the finger direction as a frequency distribution was adopted as a method to improve the verification performance, and its effectiveness was also confirmed through an evaluation of the verification performance.

2 Writer Verification Based on Finger-writing of a Simple Symbol

In this section, writer verification based on finger-writing of a simple symbol proposed in Refs. [5–7] is briefly introduced. As candidates for a simple symbol, ◯, △, □ are considered. When writing a symbol, coordinate values of the fingertip position on a display, finger pressure, and finger touching area data are extracted from a device. Using the extracted coordinate values, the start and end points of writing and information on writing time, speed, and acceleration are calculated as individual features. The mean, maximum, and minimum values of finger pressure and finger-touching area are also used as individual features. During the enrollment stage, these features are extracted from regular users and their averaged values are stored as templates. During the test stage, features from a candidate who claims to be a regular user are extracted and compared with the user's templates. After that, Euclidean distance matching is used for verification. The applicant is regarded as genuine if the distance between the test and template data is smaller than a threshold.

Using 29 experimental subjects, Ref. [7] found that the equal error rate (EER) was approximately 30 %. EER is defined as the value which makes the false rejection rate (FRR) equal to the false acceptance rate (FAR) and is used for evaluating the verification performance. A smaller EER indicates better performance. However, the obtained EER was not satisfactory. Thus, new features are necessary for improving the verification performance.

3 Introduction of Finger-touching Direction Feature

In Refs. [6–8], pen-pressure and pen-touching area information were extracted and used as individual features. However, the finger-touching direction is also extractable [9] but has not been used as a feature in writer verification based on the finger-writing of a simple symbol. The finger-touching direction is the direction of the finger pad that touches the tablet screen and is detectable in some smartphones. In this study, we introduce the finger-touching direction feature into our writer verification method and examine the verification performance in finger-writing of a simple symbol.

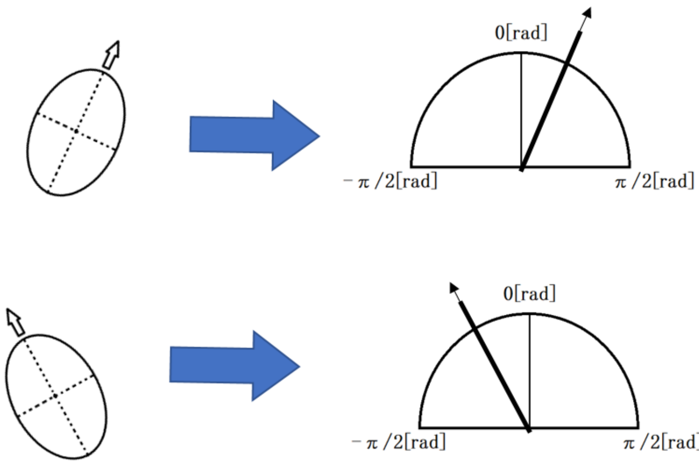

Fig. 1. Examples of detected finger-touching directions.

3.1 Finger-touching Direction

In the development environment, Android Studio on a Fujitsu ARROWS NX F-04G smartphone was used to extract the finger-touching direction data. As illustrated in Fig. 1, an ellipse is fitted to the finger-touching area on a tablet screen and the long axis of the ellipse is detected as the direction of the finger-touching area using "getOrientation" in Android Studio [9]. This is called the finger-touching direction. When the touching areas are assumed to be on the left side of Fig. 1, their directions are detected as originating from the right side. When vertical, the direction of a smartphone screen is defined as 0, and the detection ranges from $-\pi/2$ rad to $\pi/2$ rad.

However, during actual writing, the finger-touching direction was never constant. Thus, the mean of the detected direction values was calculated as an individual feature. In addition, the directions at the start and end points of writing and the mean values of the directions of several points near the start and end points of writing are used as features. The reason for using them as features is that they are influenced by the user's way of holding a smartphone, which emphasizes individualities in finger writing. In addition, finger pressure and finger touching area data are also detectable; thus, the directions at the point of maximum and minimum pressure and area are also recorded. The features using the finger-touching direction are summarized in Table 1.

3.2 Evaluation of Verification Performance

Ten subjects were asked to write three simple symbols ten times, using their finger only. Among the 10 data obtained from each subject, five were used for

Table 1. Features using finger-touching direction.

Mean of directions (MD)
Direction at the start point (DS)
Direction at the end point (DE)
Mean of directions near the start point (MDS)
Mean of directions near the end point (MDE)
Direction at the maximum pressure (DmaxP)
Direction at the minimum pressure (DminP)
Direction at the maximum area (DmaxA)
Direction at the minimum area (DminA)

making their template and the remaining five were used for testing. In addition, cross-validation was performed ten times. This reduced the influence of selecting data for the creation of a template and testing the verification performance. The averaged EERs in the 10 cross-validations performed for each direction feature and symbol are listed in Table 2. The smallest EER of 24.7 % was obtained when

Table 2. EERs (%) of finger-touching direction features.

	○	△	□
MD	24.7	35.8	39.3
DS	31.2	42.6	45.2
DE	29.5	46.5	43.2
MDS	27.8	42.8	42.0
MDE	32.0	41.7	39.9
DmaxP	40.4	51.5	42.6
DminP	37.5	43.8	46.0
DmaxA	35.4	51.4	40.4
DminA	36.6	41.8	41.8

drawing a circle and using the mean of directions. In other symbols, the mean of the direction feature achieved better performance. By averaging the direction data, differences in the finger-touching directions between individuals could be detected.

Compared with the EERs of drawing a circle, EERs when drawing a triangle and square were clearly larger. This was because when drawing a triangle and square, the drawing motion must change direction at the corners, while a circle can be drawn as a single stroke. When changing the drawing motion, such as at corners, the finger-touching direction is significantly changed, which might degrade the verification performance.

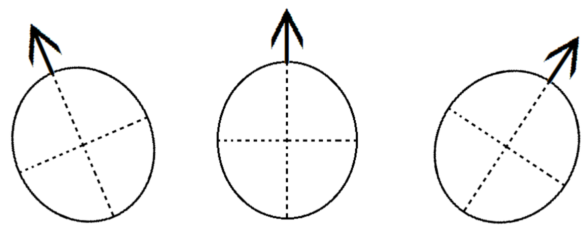

Fig. 2. Fluctuation of detected finger-touching direction.

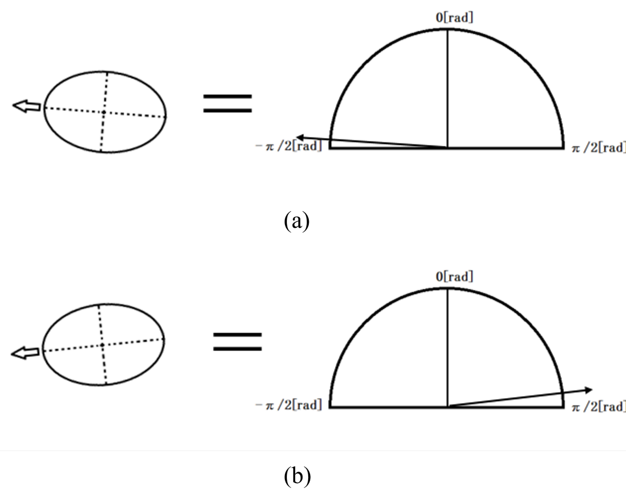

Fig. 3. Detected large change in detected finger-touching direction.

3.3 Considerations

Compared with the EERs obtained using the individual features in Ref. [6], the verification performance was not high. The reasons for this are as follows:

"getOrientation" used for detecting finger-touching direction, fits an ellipse into a touching area. If the touching area is close to a circle, it becomes difficult to determine the direction of the long axis. Therefore, the detected direction easily fluctuated by slightly changing the touching area, as indicated in Fig. 2 and may have resulted in degradation of the verification performance.

Furthermore, as shown in Fig. 3, the detection range of the direction was $-\pi/2$ to $\pi/2$ rad. If the long axis of an ellipse fitted is around $-\pi/2$ rad, as shown in (a), but it is slightly changed to (b) by fingertip movement, the direction is supposed to be around $\pi/2$ rad and significantly changed from $-\pi/2$ to $\pi/2$ rad. Figure 4 shows the time variation of the detected finger-touching direction. The

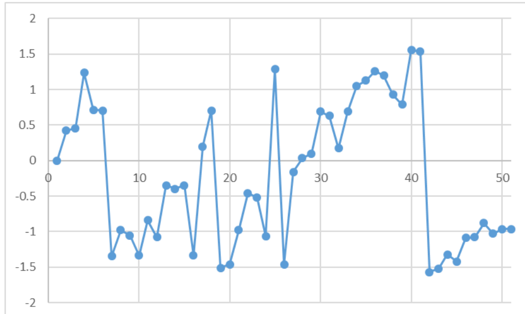

Fig. 4. An example of detected finger-touching direction.

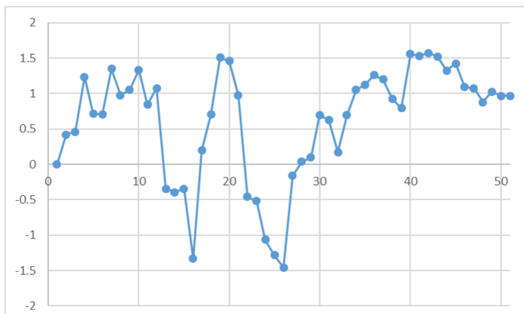

Fig. 5. An example of preprocessed direction data.

detected direction changes rapidly. For instance, a negative value is changed to a positive value at two successive sampled points. However, it is unlikely that such a rapid change in the finger direction occurs on a smartphone screen. This may degrade the verification performance.

4 Introduction of Preprocessing

To prevent rapid changes in the detected direction, preprocessing was introduced. As explained using Fig. 3, slight changes in the touching surface around $|\pi/2|$ rad cause quite large fluctuations, for instance, from $-\pi/2$ to $\pi/2$ rad in detected direction, which unlikely in practical situations. Thus, if the absolute difference between two successive direction data is larger than $\pi/2$, the detected direction is inverted, that is, multiplied by -1.

Figure 5 shows an example of the preprocessed direction data, where the original data are shown in Fig. 4. It can be confirmed that several rapid changes that occurred, as shown in Fig. 4, were suppressed. However, a few significant changes remained. Here, it is noted that the finger direction is never the same as the finger-touching direction. As mentioned above, "getOrientation", which is used for detecting the finger-touching direction, fits an ellipse into a finger-touching area. Depending on the touching condition of the finger pad, the shape of the touching area changes regardless of the physical finger direction. Therefore, even when the finger direction does not change, the finger touching directions can change. Large changes caused by touching-area changes occur naturally when detecting a finger-touching direction.

To evaluate the effectiveness of the proposed preprocessing method, its verification performance was evaluated. Table 3 lists the EERs with pre-processing in three symbols. Compared with EERs in Table 2, almost all EERs were reduced. Thus, the effectiveness of the preprocessing was confirmed. In particular, the reduction of EER was remarkable in the triangle and square symbols. EERs using DS features were not changed in any symbol, even when using the preprocessing, since the proposed preprocessing used the difference between two successive sampled data and was never performed at the start point. In contrast, EERs using MDS and DminP for some symbols were slightly increased. The proposed preprocessing forcibly changed the detected directions. However, there is no proof that the changed directions were optimal. In the future, the optimal direction should be investigated.

Table 3. EERs (%) with preprocessing.

	◯	△	□
MD	22.2	29.4	30.1
DS	31.2	42.6	45.2
DE	27.4	35.2	32.2
MDS	26.6	43.0	42.3
MDE	31.4	39.5	35.5
DmaxP	36.7	42.7	42.5
DminP	38.9	45.8	44.0
DmaxA	34.5	40.6	39.9
DminA	35.5	41.1	40.8

5 Frequency Distribution as a New Feature

The finger-touching direction feature evaluated in the previous sections is a one-dimensional feature. The smaller number of feature dimensions is not effective for pattern matching. Thus, we propose that the direction feature should be multi-dimensionalized. However, to directly use finger-touching direction data in pattern matching makes the direction feature dependent on the written shape (content). The aim of this study is to authenticate users using features independent of the written shape. Thus, we introduce a frequency distribution into the direction feature.

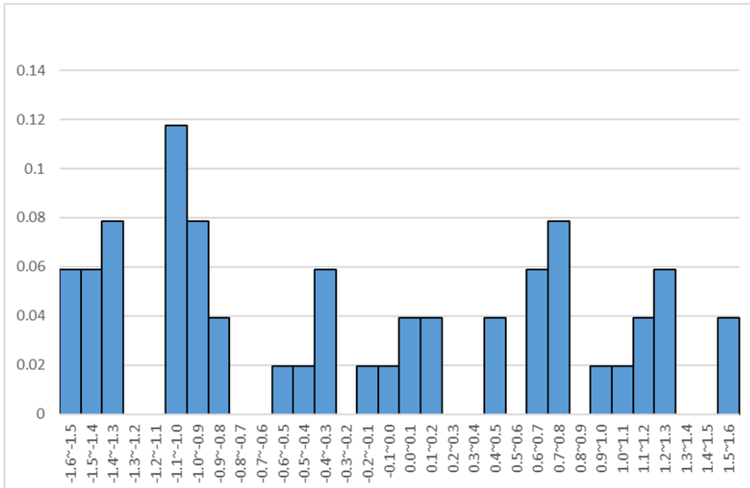

Fig. 6. A histogram of frequency distribution in direction data.

The frequency distribution of the finger-touching direction data is calculated and then the distribution is represented as a histogram, where the total frequency is normalized to one, since each histogram has a different total frequency. The number of bins and bin widths are determined empirically. Figure 6 shows an example of a histogram in which the bin width is 32.

In the enrollment stage, a histogram is obtained by processing each template for the direction, and then the obtained histograms are ensemble-averaged, that is, the frequencies in each class are averaged, resulting in a template histogram. In the test stage, the histogram of an applicant is compared with the template histogram using Euclidean distance matching, which is defined in Eq. (1).

$$d = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}, \tag{1}$$

where a_i is the frequency of the template data and b_i is the frequency of the test data. n denotes the number of classes. Using the Euclidean distance, dissimilarity (%) is defined as follows:

$$\text{Dissimilarity} = \frac{d}{\sqrt{2}} \times 100. \tag{2}$$

If two histograms are the same, the dissimilarity is 0, and on the other hand, if they are completely different, the dissimilarity becomes 100. When dissimilarity is smaller than a threshold, the candidate is regarded as a regular user.

We evaluated the verification performance using the frequency-distribution feature. The results are presented in Table 4. Compared with EERs in Table

Table 4. EER(%) using the frequency distribution feature of direction.

○	△	□
22.0	25.3	24.7

3, that is, the one-dimensional case, the smallest EERs were obtained for all symbols. Thus, the effectiveness of multi-dimensionalization was confirmed.

However, the obtained EERs were 22 % to 25 % and it is difficult to use the proposed frequency distribution feature of the direction alone for verifying individuals. Thus, it is required to fuse the proposed feature with conventional features.

6 Conclusions

In this paper, we focused on finger-touching direction and introduced it into the writer verification method based on the finger-writing of a simple symbol. However, it was found that rapid changes occurred in the detected finger-touching direction data. To prevent the rapid changes in the finger-touching direction data, preprocessing was introduced, which disallowed extremely large changes in two successive sampled points. In addition, for multi-dimensionalizing the direction feature, the frequency distribution of the direction data was proposed to be used as a new feature. The effectiveness of the method was confirmed by the evaluation of the verification performance. However, the obtained verification performance was insufficient and could be improved by fusing the direction features with conventional ones.

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