Improvements in Writer Verification Based on Finger-Writing of a Simple Symbol

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Abstract. Studies on the authentication of users based on their finger writing are underway. Users are asked to draw or write a simple symbol on a smartphone display, which eases authentication from a user's perspective than the conventional verification method. In conventional studies, 40 individual features were extracted from the finger-writing motion. After normalization and polar-coordinate transformation, they were fused together and used to verify whether the users were genuine or imposters. However, the introduced polar transformation method has limitations and an efficient selection rule to fuse features is required. In this study, we overcame the limitations of the polar transformation method. Moreover, we proposed the fusion of features with low correlation and validated their efficiency.

Keywords: Biometrics · Finger-writing · Simple symbol · Smartphone · Polar coordinate transformation · Feature fusion · Correlation.

1 Introduction

Biometrics is convenient because users are not required to have and remember anything when authenticated. Two types exist: using physical characteristics such as fingerprints and face images and using behavioral characteristics such as gait (walking) and keystrokes (typing). Physical biometrics provide stable biometric information; thus, it achieves a high verification/identification rate. However, it can be observed (measured) by others, even if people are unaware of it. Authentication systems may be deceived by unconsciously obtained biometric data. Conversely, biometric information of the behavioral type is unstable; therefore, its verification performance is not high. However, it is difficult to steal biometric information of the behavioral type.

We focus on writing, which is a behavioral biometrics. Signature verification for authentication using writing has been studied [1–3]. Signature verification is based on pattern matching, where a written pattern is compared with the template of a genuine user. Two types exist: offline and online. In the offline type, a signature already written on paper is converted into digital data using a scanner. In the online type, the digital data of a signature is directly captured using a pen-tablet device. In general, the online type is used for authentication.

Some inconveniences are associated with the online signature verification. To use a dedicated electronic pen is required, writing a signature is time-consuming, and writing a signature on a small screen of a smartphone is difficult. In addition, signature verification is problematic in terms of confidentiality. A signature is easy to guess from a name or can be guessed by observing the writing process. Written signatures can also be seen by others.

However, another category of writing biometrics exists, writer verification [4], where users can write anything independent of them. In this case, a written pattern changes whenever a user writes it. Therefore, a written pattern cannot be compared with an already-written and stored pattern. The extraction of writing habits that are independent of written characters is required; however, a technique to extract writing habits has not been established and practically implemented.

In the aforementioned situation, writer verification based on the finger writing of a simple symbol was proposed [5, 6] for user authentication of a smartphone or table terminal. Users write a simple symbol, which is easy to write on a small screen, directly using a finger instead of a dedicated pen. This authentication method lays more emphasis on convenience. As simple symbols, such as circles, triangles, and squares, which are easy to write, well known, and never forgotten, are assumed, the proposed method is most convenient while there are few confidentialities in written patterns. In Ref. [5], forty features extracted from finger-writing motion, such as the maximum, average and minimum values of x and y coordinates, finger pressure, and finger-touch area are fused in the verification. In Ref. [6], normalization in fusing different features and coordinate transformation of features were examined.

However, in the proposed polar-coordinate transformation method, the detected angle difference at $\pm\pi$ rad did not represent the true angle. In addition, in fusing features, no criteria were laid regarding the type of features to be fused. Naturally, fusing all the features achieves better performance. However, when applying the proposed method to a smartphone, the computational load should be significantly reduced because computational resources are limited.

In this study, we improve the polar coordinate transformation introduced in Ref. [6]. Next, by investigating the correlation between features, we validated that the fusion of features with a small correlation achieves better verification performance than those with a large correlation.

2 Writer verification based on the finger-writing of a simple symbol

This section briefly introduces writer verification based on the finger writing of a simple symbol proposed by Takahashi et al. [5, 6].

2.1 Assumed Scenario

The writer verification based on finger writing of a simple symbol is a convenient method to authenticate users of a system; therefore, it is not suitable for high-security systems. When using information devices for personal use such as smartphones, tablet terminals, and tablet computers, the proposed method is used for login authentication. Recently, some smartphones have adopted authentication using fingerprints, face images, and iris images; however, other smartphones use authentication using a conventional password or pattern lock, which requires users to remember it, resulting in the degradation of usability. However, the proposed method assumes that everyone can write, for example, a circle; therefore, it is not necessary to remember it.

2.2 Simple Symbol

No character is suitable for the proposed method because it depends on the language of the user. Symbols are candidates for written content that is independent of language. However, assuming finger writing on a small smartphone screen, symbols with complicated shapes are unsuitable. In addition, symbols that take a long time to write are unsuitable. Therefore, a circle, triangle, or square that is widely known, never forgotten, and never misspelled is used as a symbol.

2.3 Individual Features

In verification, pattern matching based on the writing shape, such as a signature, cannot be applied because the shape of a symbol is very simple, and everybody writes the same shape. Therefore, the following features, which may be independent of the symbol shape, were used:

- Offline-type:
  - **SP**: coordinate values at the start point
  - **EP**: coordinate values at the end point
  - **MinX**: the minimum value in the x coordinate
  - **MinY**: the minimum value in the y coordinate
  - **MaxX**: the maximum value in the x coordinate
  - **MaxY**: the maximum value in the y coordinate
  - **DX**: distance between the maximum and the minimum x
  - **DY**: distance between the maximum and the minimum y
  - **MC**: the means of coordinate values
  - **DSE**: distance between the start and end points
  - **WA**: writing area
- Online-type:
  - **MinP**: coordinate values at the minimum pressure
  - **MaxP**: coordinate values at the maximum pressure
  - **MinT**: coordinate values at the minimum touching-area
  - **MaxT**: coordinate values at the maximum touching-area
  - **MinS**: coordinate values at the minimum speed
  - **MaxS**: coordinate values at the maximum speed
  - **MinA**: coordinate values at the minimum acceleration

- **MaxA**: coordinate values at the maximum acceleration
- **WT**: writing time
- **MP**: the mean of pressure
- **Pmin**: the minimum of pressure
- **Pmax**: the maximum of pressure
- **MT**: the mean of touching-area
- **Tmin**: the minimum of touching-area
- **Tmax**: the maximum of touching-area
- **MS**: the mean of speed
- **Smin**: the minimum of speed
- **Smax**: the maximum of speed
- **MA**: the mean of acceleration
- **Amin**: the minimum of acceleration
- **Amax**: the maximum of acceleration
- **PS**: pressure at the start point
- **TS**: touching-area at the start point
- **SS**: speed at the start point
- **AS**: acceleration at the start point
- **PE**: pressure at the end point
- **TE**: touching-area at the end point
- **SE**: speed at the end point
- **AE**: acceleration at the end point

For convenience, they are categorized into offline and online types. The online type can only be extracted using a pen-tablet device, whereas the offline type can also be extracted from a scanned image. The "coordinate values" are two-dimensional: x and y. The "speed" feature is extracted by calculating the distance between two successive sampled points assuming a sample period to detect finger-writing data on a screen of a smartphone or tablet device is constant and one. The " acceleration" feature is derived from calculating the distance between two successive speed features.

2.4 Coordinate Transformation

Generally, coordinate values x and y on a smartphone screen are extracted based on the origin, which is on one of the four corners of the screen. However, even if the same user writes the same symbol in different places on a screen, the extracted coordinate features are regarded as coming from different users. Thus, the coordinate origin was transformed into the center of the screen. Furthermore, the coordinate values are represented as angles and distances from the origin in polar coordinates.

In Ref. [6], the coordinate transformation was examined and the best performance was achieved in many features when using the polar transformation. However, the type of transformation, including no transformation, was suitable depending on the features.

2.5 Normalization

The number of dimensions in the aforementioned coordinate features is two and that of the other features is one. Therefore, their verification performance is not very high [5]. Thus, to fuse the features, multidimensionalizing is required to improve the verification performance. The simplest multidimensional method connects several one-dimensional or two-dimensional features as a multidimensional feature. This is known as feature-level fusion [7].

However, these features had different units. If such features are directly connected, large features become dominant in the characteristics of the fused feature, and this reduces the effect of fusing features. Thus, normalization is introduced before fusing the features. Some normalization methods include min-max, MAD, and Z-score. In Ref. [6], the verification performance using the min-max and Z-score methods was superior to that using the MAD method.

2.6 Fusion

As earlier mentioned, the multidimensionalization of features is achieved by simply connecting one or two-dimensional features. In Ref. [6], fusing not only all forty features (AL) but also offline (Of) and online (On) features, features that have a relation with the start (St) and end (Ed) points of writing, finger pressure (FP), finger-touching area (FA), speed (SP), and acceleration(AC) features, and features that achieved good performance (Gd) were examined.

2.7 Verification

Authentication of users of a system is performed by verifying whether an applicant who wants to use the system is genuine. Before verification, a genuine user finger-writes a symbol several times, features are extracted, and their averaged values are enrolled as templates in an authentication system. In the verification stage, verification data from an applicant who claims to be a regular user are compared with templates of the regular user using Euclidian distance matching. If the distance is smaller than the threshold, the applicant is regarded as the regular user.

2.8 Verification Performance

In Ref. [6], a finger-writing database was created using thirty experimental subjects, who wrote three symbols (circles, triangles, and squares) twenty times. From twenty genuine data, ten were used to create a template and the others were used for testing (performance evaluation). Cross-validation reduces the influence of selecting data to create a template and changes the combination of data to create a template and test in each cross-validation. The number of cross-validations was ten. The verification performances presented in the following are averaged values of ten cross-validations.

For reference, the verification performance obtained in Refs. [6] are introduced in Tables 1 and 2, where the equal error rate (EER) is used to evaluate the verification performance of biometrics and defined as a rate where the false rejection rate is equal to the false acceptance rate. A smaller EER indicates a better verification performance.

Table 1. EERs (%) using min-max method [6].

Symbol	AL	Of	On	St	Ed	FP	FA	SP	AS	Gd
◯	11.0	14.2	13.0	20.0	15.7	18.0	17.2	16.7	18.5	10.6
△	14.9	17.5	16.7	22.1	19.0	18.9	18.8	23.6	26.1	12.3
□	12.8	16.7	15.0	20.0	16.4	15.4	17.2	21.5	25.1	11.4

Table 2. EERs (%) using Z-score method [6].

Symbol	AL	Of	On	St	Ed	FP	FA	SP	AS	Gd
◯	11.9	13.9	12.7	18.1	14.2	17.9	17.7	16.3	18.4	11.0
△	16.8	16.3	18.1	18.5	16.1	18.2	19.0	22.6	25.2	12.4
□	14.7	17.3	16.0	17.6	14.4	15.7	17.9	22.2	25.1	11.5

When writing a circle, the fusion of good features achieved the smallest EER of 10.6 % using the min-max method. In all the symbols and normalization methods, the fusion of all the features achieved a better verification performance. This is easy to understand because a more multidimensional space makes it easier to distinguish the targets.

3 Improvement of Coordinate Transformation

The polar coordinate transformation introduced in [6] had a problem as explained below. As illustrated in Fig. 1, the target angles, $\bullet$ and $\circ$ are near; thus, their angle difference must be small. However, when the angle was defined as $-\pi \leq \theta < \pi$, the angle difference was approximately 2π rad. Originally identical features located near might be regarded as different, resulting in degradation of the verification performance.

3.1 Relative Angle

Thus, we improved the polar transformation. First, when the angle $\theta < 0$, it is transformed into $\theta^{'} = 2\pi - |\theta|$. When $\theta \geq 0$, $\theta^{'} = \theta$.

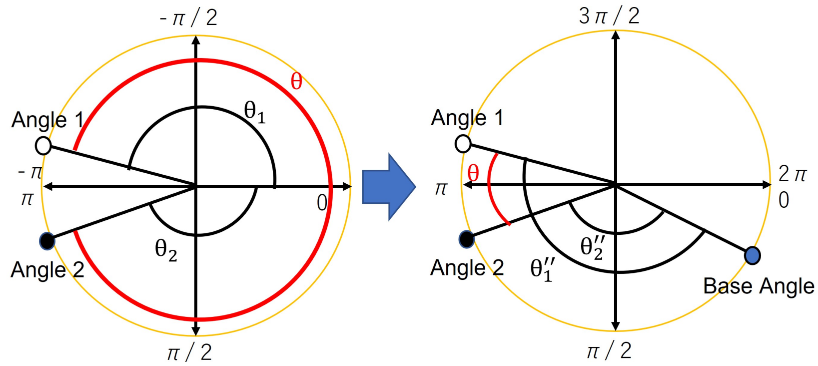

Fig. 1. Polar transformation before (left side) and after (right side) improvement.

Next, $\theta^{'}$ is transformed into a relative angle using a reference angle, which can be determined arbitrarily. In this study, the minimum value of the data to create a template was used. Assuming the reference angle is ϕ, when $|\theta^{'} - \phi| > \pi$, $\theta^{'}$ is transformed to $\theta^{''} = 2\pi - |\theta^{'} - \phi|$. Otherwise, $\theta^{''} = |\theta^{'} - \phi|$.

The reference angle was set to the minimum value because the features of a genuine user are distributed in a small-angle region, and each is represented as an absolute value based on zero degrees. By setting the minimum value as a base instead of using a zero degree, the angles of all features can be represented as differences from the minimum value; therefore, intra-individual variations are reduced, which could improve the verification performance. However, test data do not always fit within the distribution range of the template data but are distributed around the same range. Therefore, test data were also represented as differences from the minimum value of the template data and their intra-individual variations were also reduced.

Based on the aforementioned procedure, $\theta^{''}$ is given as $0 \leq \theta^{''} < 2\pi$ and the correct angle difference θ between the originally near features is calculated, as shown on the right side of Fig. 1.

3.2 Results

To validate the effectiveness of the improved polar transformation, we compared the averaged coordinate values before and after the improvement, using a finger-writing database obtained by Takahashi et al. [6]. An example is shown in Fig. 2. Ten genuine angle data points of a feature processed by the original polar transformation are distributed on the left side, and their mean value is indicated as a red point. Those obtained by the improved polar transformation are indicated on the right-hand side.

In the original method, the mean value was located outside the distribution of the genuine data. Originally, the mean value was in the middle of the distribution.

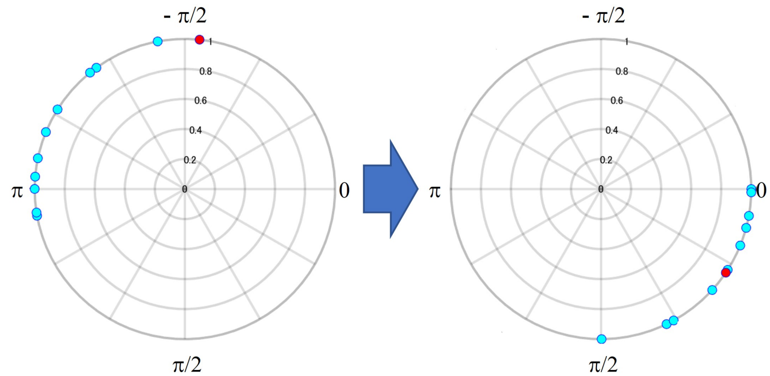

Fig. 2. Angles and their averages before and after improvement of polar transformation.

Therefore, each angle value was incorrectly represented by the original polar transformation. However, in the improved polar transformation, the mean value was located in the middle of the distribution of genuine data.

Examples of verification performance by introducing the improved polar transformation when writing a circle and using the min-max method are presented in Table 3. For reference, the EERs obtained from the original polar transformation (Org) [6] and those obtained by setting the minimum value to 0 degrees (0deg) are also presented. In the three methods, the smallest EER is colored.

Table 3. Examples of EER (%) by the improved polar transformation.

Feature	Org	0deg	Proposed
MaxX	27.3	29.3	28.4
MinX	25.9	27.5	24.4
MaxY	30.2	30.1	30.1
MinY	33.4	25.6	25.6
Amax	34.9	34.6	34.4
Amin	25.7	29.5	25.5
SP	25.8	29.0	24.7
Pmax	29.6	28.2	28.5
Pmin	27.5	30.4	28.7
Tmax	28.4	25.5	26.3
Tmin	28.2	30.3	28.5
EP	23.0	26.1	22.9
Smax	32.1	32.7	31.8
Smin	32.1	27.9	24.3

From this comparison, the verification performance was improved using an improved polar transformation. However, cases exist where the original method or the method using a zero-degree base achieved better performance. The equivalent results were obtained using other symbols and normalization methods. As shown in Fig. 1, the improved polar transformation is necessary to reduce misdetection caused in the original transformation. Although the original method achieved a higher verification performance, it was never used. However, in some cases, EERs obtained by setting the minimum value to 0 degrees were smaller than those obtained by the improved method. Therefore, determination of the base should be further examined.

Using the improved polar coordinate transformation, we re-evaluated the verification performance of features that are related to finger-pressure (FP), finger-touching area (FA), speed (SP), and acceleration (AC) features, features at the start (St) and end (Ed) points of writing, and miscellaneous features (MS), as well as the case of using all forty features (AL). The results are shown in Tables 4 and 5. Compared with the results in Tables 1 and 2, almost all EERs were reduced; therefore, the effectiveness of the improved polar coordinate transformation was validated.

Table 4. EERs (%) using min-max method.

Symbol	FP	FA	SP	AS	St	Ed	MS	AL
◯	18.3	17.1	16.3	18.4	20.0	15.7	15.7	9.9
△	17.6	17.7	20.0	25.5	26.3	19.0	14.0	12.1
□	15.1	16.6	21.8	25.7	20.0	16.4	15.0	11.9

Table 5. EERs (%) using Z-score method.

Symbol	FP	FA	SP	AS	St	Ed	MS	AL
◯	18.6	13.9	24.5	18.0	23.9	15.3	15.6	11.6
△	17.5	18.0	22.3	32.4	21.6	18.7	13.7	13.0
□	17.9	16.8	35.8	37.8	19.8	16.0	15.7	16.1

The detailed reason why the obtained EERs depended on the symbols is not clear. However, it is certain that there are some differences among three symbols, such as writing time, with or without corners. If more complicated symbols or multiple symbols are written, the verification performance could be improved. However, the proposed authentication focuses on convenience. More complicated symbols may be less well known, forgettable, difficult to write and may not be written on a small screen of a smartphone. Writing multiple symbols is similar.

4 Effect of Fusing Uncorrelated Features

When applying writer verification based on the finger writing of a simple symbol to smartphones, less computational load is required because they have limited computational resources. It is important to examine a method to obtain better performance with less computational load (complexity). Several combinations of features were examined in Ref. [5, 6] and also in the previous section. However, no criteria exist for which combination of features is best for verification.

4.1 Correlation Coefficient

We refer to majority vote, a decision-level fusion method [7]. In the majority vote, even if many people have the same opinion, it results in one opinion; therefore, the majority vote does not work. However, although some people make an incorrect decision, the final decision may be corrected if other people make a correct decision. The robustness of the majority decision is exhibited and decision errors can be prevented. Therefore, it is better to gather people with different opinions on the majority vote. This suggests that different features should be fused to achieve robustness in the decision. Undoubtedly, fusing all features achieves better performance, although it is redundant in processing. However, it is efficient to obtain equivalent verification performance by fusing fewer features.

In this study, we regarded uncorrelated features as different. In biometric fusion, "physically uncorrelated traits are expected to result in better performance improvement than correlated traits " [7]. However, no method directly examines the correlation between three or more features. Thus, we calculated the correlation coefficient between the two features, and features with low coefficient values were fused.

To calculate the correlation, the Pearson product-moment correlation coefficient was used, which is defined as:

$$\frac{\text{Covariance of A and B}}{(\text{Standard Deviation of A}) \times (\text{ Standard Deviation of B})}, \tag{1}$$

where "A" and "B" are features for which correlations are examined.

Table 6 presents the general definition of the strength of the correlation. The correlation between the two features is evaluated by comparing the obtained correlation coefficient values with the definition of this table.

Table 6. Strength of Correlation.

Coefficient Value	Strength
0.0 - 0.2	no correlation
0.2 - 0.4	weak correlation
0.4 - 0.7	correlated
0.7 - 1.0	strong correlation

4.2 Correlation Results

Using the finger-writing database in Ref. [6], the correlation of all forty features was investigated. Some of the results are presented as a matrix in Table 7. Because diagonal elements correspond to the correlation coefficients of the same features, they have a value of 1 and are excluded. In the other elements, no element has a strong correlation (0.7-1.0). The selection of features with strong correlations is difficult.

Table 7. Part of correlation coefficient matrix.

	DX	MinX	MaxX	DY	MinY	MaxY
DX	1	0.14	-0.25	0.43	-0.23	-0.02
MinX	0.14	1	-0.43	0.48	-0.15	0.19
MaxX	-0.25	-0.43	1	-0.53	0.46	-0.08
DY	0.43	0.48	-0.53	1	-0.27	0.04
MinY	-0.21	-0.15	0.46	-0.27	1	-0.25
MaxY	-0.02	0.19	-0.08	0.04	-0.25	1

Thus, rather than using the general definition in Table 6, we use a modified definition in Table 8, where the strength of the correlation is evaluated as only two cases, with or without correlation, and the threshold to distinguish them is set to a low value. Based on the modified definition, it was found that the features that were uncorrelated with the DX feature were MinX and MaxY, and DX was correlated with only the DY feature in Table 7.

Table 8. Modified Strength of Correlation.

Coefficient Value	Strength
0.0 - 0.2	without correlation
0.3 - 1.0	with correlation

4.3 Comparison of Verification Performance

In this study, we focused on five features: DX, MinX, MaxX, DY, and MinY, and evaluated their correlation with other features. Consequently, we selected six correlated and uncorrelated features, as shown in Tables 9 and 10 and evaluated the verification performance of the fused features.

The results are shown in Tables 11 and 12. Comparing the averaged values obtained using the uncorrelated features with those obtained using the correlated features in each symbol, EERs of the uncorrelated features are less than those of the correlated features. The fusion of uncorrelated features was confirmed to be more effective than the fusion of correlated features.

Table 9. Combinations of Uncorrelated Features.

DX	MinX	MaxX	DY	MinY
Ymax	MinA	MinA	MinA	MinA
MA	PS	Amax	SP	SS
SS	Pmin	MA	PS	Pmin
TE	EP	SP	TS	MS
MS	PE	PS	EP	WT
WT	Tmin	Tmin	MinS	WA

Table 10. Combinations of Correlated Features.

DX	MinX	MaxX	DY	MinY
MinY	MaxX	MinX	DX	MaxX
MinP	DY	DY	MinX	MinA
Tmin	SS	MinY	MaxX	EP
AE	MA	MinP	PE	SE
PE	Smin	Tmin	Smax	AE
WA	WA	Smin	WA	MinS

Table 11. EERs (%) by Uncorrelated Features.

	◯	△	□
DX	20.4	18.0	17.3
MinX	18.2	20.5	19.6
MaxX	16.2	19.6	19.6
DY	20.0	20.5	26.8
MinY	16.1	23.8	19.2
Ave.	18.1	20.5	20.5

Table 12. EERs (%) by Correlated Features.

	◯	△	□
DX	19.6	20.6	21.2
MinX	16.7	17.0	21.5
MaxX	19.6	28.0	16.3
DY	16.6	20.2	23.1
Dmin	22.3	20.8	25.0
Ave.	18.9	21.3	22.0

Table 13. EERs (%) by All Uncorrelated Features.

	◯	△	□
DX	10.8	12.8	10.0
MinX	12.0	15.0	13.3
MaxX	10.5	14.6	9.8
DY	11.8	14.4	11.3
MinY	12.3	16.1	14.2
Ave.	11.5	14.6	11.7

Next, we evaluated the verification performance of these five features by fusing all uncorrelated features. The results are shown in Table 13, where the number of fused features is 18, 26, 23, 20, and 18 for DX, MinX, MaxX, DY, and MinY, respectively. Compared with EERs in Table 11, increasing the number of fused uncorrelated features improved the verification performance. When writing a square symbol, the smallest EER of 9.8 % was obtained by fusing the MaxX feature with twenty-three uncorrelated features. In Table 4, EER = 9.9 % was obtained by fusing all the 40 features. An equivalent verification performance can be achieved using approximately half of the features. In the uncorrelated features, there are no characteristics other than being uncorrelated.

Notably, fusing correlated features does not degrade verification performance. Although many people may have the same opinion in the majority vote, they are redundant but never lead to wrong decisions. If the redundancy in fusing features is not a problem and all features obtained can be used in fusing, it is not necessary to consider whether the fusion of features is correlated. However, the fusion of uncorrelated features will be efficient when person authentication is performed in devices with limited computational resources, such as smartphones and better verification performance is required with minor computations.

In this study, the differences in features were examined based on the correlation between two features. Therefore, only the features of the row elements in Table 7 were examined. However, other combinations use the features of both rows and columns in Table 7. Not all combinations of the features were examined. In Ref. [6], it was confirmed that the fusion of "good" features achieved better performance than the fusion of all features. In a majority vote, people who not only have different opinions (robustness) but also can decide accurately (accuracy) should be assembled. The combination of uncorrelated and good features may be the best method to fuse features. In the future, the verification performance of these features will be evaluated.

5 Conclusions

As a novel person authentication method when using smartphones, studies on the finger writing of a simple symbol on a screen are underway, where user convenience has the highest priority. In Ref. [6], forty features, which were independent of written contents, were extracted from writing motion, normalized, sometimes coordinate-transformed, and fused to verify individuals. However, the normalization introduced was problematic in that the calculated angle values did not correspond to the true values. In addition, features that should be used for efficient fusion have not been discussed.

In this study, the polar coordinate transformation was improved and its effectiveness was validated. Furthermore, the correlation between the features was examined, and it was confirmed that the fusion of uncorrelated features achieved equivalent performance with fewer features. In an environment with limited computational resources, such as smartphones, this is effective for feature selection because a better verification performance is required with few features.

To achieve the best verification performance, the combination of uncorrelated and good features should be examined. For practical use, to examine the verification time is needed for evaluating the proposed authentication method. Evaluation of the usability of the proposed authentication method is also a topic for future research.

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