# *Introducing Feature Selection Fusion into Person Verification Based on Finger-writing of a Simple Symbol*

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***Abstract*—Handwriting verification is one form of biometrics. Among its various approaches, finger-writing verification of a simple symbol is the most convenient, in which a user is verified by writing a simple symbol with a finger on a smartphone screen. In a previous study, an error rate of 11.9% was achieved. Furthermore, by selecting and fusing individually high-performing features, an equivalent error rate was obtained, even though the number of used features was reduced. In this study, we propose a new feature selection method focusing on individuality, and a fusion method that combines this with three other selection methods. By using the proposed method, we finally achieved the error rate of 5.8%.**

***Keywords*— Biometrics, Writer Verification, Finger-writing, Feature Selection Fusion**

## I. INTRODUCTION

In 2024, the household penetration rate of information and communication devices in Japan reached 97.4% for mobile terminals overall, of which smartphones accounted for 90.6%, and the smartphone usage rate for personal Internet access exceeded that of personal computers by 25.5% [1]. As a result, Internet connectivity and communication have shifted from personal computers to smartphones, enabling anyone to easily use a wide variety of services such as online banking, social networking, and online shopping. While the world has become more convenient, the increase in cybercrime has become a serious concern. Consequently, the demand for more secure person authentication has grown, and biometrics has attracted particular attention in recent years [2].

Biometrics can be broadly classified into verification methods based on body parts (physical features) and those based on human habits (behavioral features). We focus on handwriting verification, which belongs to the category of behavioral features. Handwriting verification is a method of verifying individuals based on their writing habits. Currently, signature verification is the most common form of handwriting verification [3]. However, signing is time-consuming, and it is difficult and inconvenient to write a signature on the small screen of a smartphone. To address this issue, we proposed verification based on finger-writing of a simple symbol, in which a user writes a simple symbol with a finger on the smartphone screen for verification [4]. In addition, highly discriminative features were selected and fused for verification. Despite the reduced dimensionality, comparable verification performance to that obtained using all features was confirmed. Furthermore, we proposed a feature selection method robust to tracing attacks [5].

In this study, we propose a new feature selection method based on the ratio of intra-individual variance to inter-individual variance. Moreover, we propose a new verification approach that integrates the four feature selection methods.

## II. VERIFICATION BASED ON FINGER-WRITING OF A SIMPLE SYMBOL

Signature verification is the most common form of handwriting verification, but it is difficult to sign on a small screen such as that of a smartphone, and the need for a dedicated pen makes it inconvenient. Therefore, writer verification based on finger-writing of a simple symbol was proposed [4]. In this paper, we refer to this method as Person Verification Based on Finger-writing of a Simple Symbol (PV-FSS). In this method, the user writes a simple, globally known symbol directly on the smartphone screen with a finger for verification. Thus, no dedicated pen is required, and there is no need to memorize complex writing content. In addition, since the writing time is about one second, the method offers very high convenience. For classification, 55 features listed in Table I are used [4]. These features were fused at the feature level and verification was performed using Euclidean distance and a support vector

TABLE I. EXTRACTED FEATURES IN PV-FSS [4]

| No. | Feature |
|---|---|
| 1 | Maximum X coordinate |
| 2 | Y coordinate at maximum X |
| 3 | Maximum Y coordinate |
| 4 | X coordinate at maximum Y |
| 5 | Minimum X coordinate |
| 6 | Y coordinate at minimum X |
| 7 | Minimum Y coordinate |
| 8 | X coordinate at minimum Y |
| 9 | Mean X coordinate |
| 10 | Mean Y coordinate |
| 11 | Difference between the maximum and minimum X coordinates (Difference X) |
| 12 | Difference between the maximum and minimum Y coordinates (Difference Y) |
| 13 | Distance between start and end points |
| 14 | Drawing area size |
| 15 | Writing time |
| 16 | Maximum finger pressure |
| 17 | X coordinate at maximum pressure |
| 18 | Y coordinate at maximum pressure |
| 19 | Minimum finger pressure |
| 20 | X coordinate at minimum pressure |
| 21 | Y coordinate at minimum pressure |
| 22 | Mean finger pressure |
| 23 | Maximum contact area |
| 24 | X coordinate at maximum contact area |
| 25 | Y coordinate at maximum contact area |
| 26 | Minimum contact area |
| 27 | X coordinate at minimum contact area |
| 28 | Y coordinate at minimum contact area |
| 29 | Mean contact area |
| 30 | Maximum acceleration |
| 31 | X coordinate at maximum acceleration |
| 32 | Y coordinate at maximum acceleration |
| 33 | Minimum acceleration |
| 34 | X coordinate at minimum acceleration |
| 35 | Y coordinate at minimum acceleration |
| 36 | Mean acceleration |
| 37 | Maximum velocity |
| 38 | X coordinate at maximum velocity |
| 39 | Y coordinate at maximum velocity |
| 40 | Minimum velocity |
| 41 | X coordinate at minimum velocity |
| 42 | Y coordinate at minimum velocity |
| 43 | Mean velocity |
| 44 | Start point X coordinate |
| 45 | Start point Y coordinate |
| 46 | Start point finger pressure |
| 47 | Start point contact area |
| 48 | Acceleration around start point |
| 49 | Velocity around start point |
| 50 | End point X coordinate |
| 51 | End point Y coordinate |
| 52 | End point finger pressure |
| 53 | End point contact area |
| 54 | Acceleration around end point |
| 55 | Velocity around end point |

TABLE II. EER[%] OF PV-FSS USING EUCLIDEAN DISTANCE AND SVM [5]

| Symbol | ○ | △ | □ |
|---|---|---|---|
| Euclidean distance | 9.9 | 12.1 | 11.9 |
| SVM | 32.3 | 32.5 | 32.1 |

machine (SVM), a representative supervised machine learning method [5]. The verification results are shown in Table II. The equal error rate (EER) was used to evaluate verification performance. The false rejection rate (FRR) is the rate at which genuine users are incorrectly rejected as impostors, while the false acceptance rate (FAR) is the rate at which impostors are incorrectly accepted as genuine users. When the decision threshold for determining whether a user is genuine is varied, FRR and FAR exhibit a trade-off relationship, and the point at which these two error rates are equal is called the EER. A smaller EER indicates better verification performance.

As a similar biometric verification system operating on smartphones, a method based on flick gestures has been proposed [6]. In this method, features were extracted from finger flick gestures in the displayed directions on the smartphone screen, and verification was performed using Euclidean or Manhattan distance. The dataset consisted of 16 flicks per subject (four in each direction), collected 11 times from 10 participants, and eight features used are the starting coordinates (x, y), trajectory length, curvature, velocity, angle, pressure, and contact area. As a result, an EER of 1.5% was achieved, which is a higher verification performance compared to the results shown in Table II. However, performing 16 flicks requires considerable effort and time. In contrast, PV-FSS requires writing only one symbol for verification, making the required time very short. Since convenience is an important factor in smartphone verification, which is used many times a day, PV-FSS has a clear advantage in terms of usability.

### *A. Feature Selection*

In general, SVM can achieve higher classification accuracy than Euclidean distance–based method; however, as shown in Table II, contrary to expectations, the use of Euclidean distance resulted in better performance for all symbols. One possible reason for this is overfitting caused by the excessive number of feature dimensions. As the dimensionality of training data increases, the amount of data required to build a highly accurate model grows exponentially [7]. As a result, the training dataset prepared in [5] was insufficient for adequate learning, leading to inappropriate classification of verification data and a decline in overall performance.

Therefore, it is considered important to perform dimensionality reduction while selecting features that include individual differences. Furthermore, selecting features from multiple perspectives and integrating them is expected to realize a more sophisticated verification system. While selecting highly discriminative features is effective for improving verification performance, choosing independent

TABLE III. TOP 10 INDIVIDUALLY DISCRIMINATIVE FEATURES AND THEIR EER[%] [8]

| ○ | EER | △ | EER | □ | EER |
|---|---|---|---|---|---|
| Difference Y | 24.2 | Maximum finger pressure | 22.9 | Maximum finger pressure | 21.5 |
| Drawing area size | 24.2 | Maximum contact area | 23.6 | Mean contact area | 22.1 |
| Maximum contact area | 24.4 | Mean contact area | 25.0 | Maximum contact area | 22.3 |
| Mean velocity | 24.7 | Drawing area size | 26.8 | Mean finger pressure | 25.8 |
| Writing time | 24.7 | Mean velocity | 27.4 | Drawing area size | 26.3 |
| Mean contact area | 25.1 | Writing time | 27.7 | End point finger pressure | 26.3 |
| Difference X | 25.6 | Mean finger pressure | 28.8 | End point contact area | 26.8 |
| Mean finger pressure | 26.3 | Difference Y | 29.4 | End point X coordinate | 27.3 |
| Minimum Y coordinate | 27.6 | Difference X | 30.4 | Mean velocity | 27.4 |
| Mean acceleration | 27.6 | End point contact area | 30.8 | Difference Y | 27.9 |

TABLE IV. EER[%] BY FUSION OF THE TOP 10 INDIVIDUALLY DISCRIMINATIVE FEATURES [8]

| ○ | △ | □ |
|---|---|---|
| 10.2 | 11.0 | 10.3 |

features is preferable for enhancing fault tolerance. There is no single perspective for feature selection.

*1) Individually DisCRiminative Features*

In [8], features that exhibited high verification performance individually were selected. Hereafter, the group of features selected by this method is referred to as "individually discriminative features." Table III lists the top ten features with the highest individual verification performance along with their EER. Furthermore, Table IV shows the results of verification using Euclidean distance after fusing the top ten features. Although a small number of features were used compared to the fusion of all features shown in Table II, nearly the same verification performance was achieved. This suggests that features with low discriminative performance contributed little to the Euclidean distance-based verification.

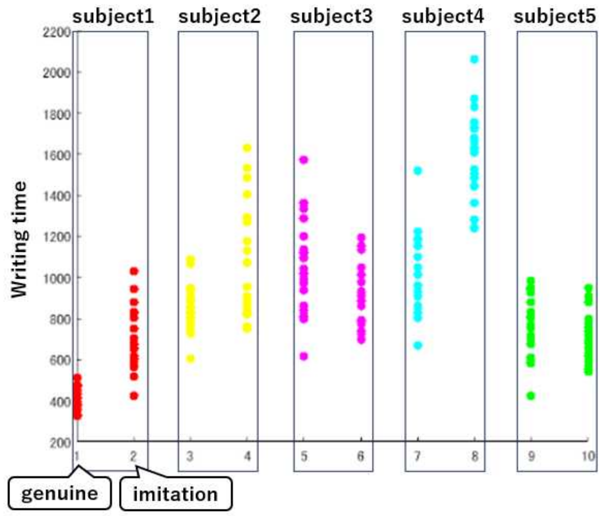


Fig. 1. Variance of Writing Time [5]

TABLE V. IMITATION-RESISTANT FEATURES [5]

| |
|---|
| Minimum contact area |
| Maximum contact area |
| Mean contact area |
| Start point contact area |
| End point contact area |
| Minimum finger pressure |
| Maximum finger pressure |
| Mean finger pressure |
| Start point finger pressure |
| End point finger pressure |

*2) Imitation-resistant Features*

Since PV-FSS utilizes handwriting motion, it is more resistant to theft and forgery compared to biometric verification based on physiological traits. However, this does not mean that it is completely free of vulnerabilities. Potential vulnerabilities include duplication and difficulty in concealment. Therefore, in [5], features were selected that were robust even when a malicious person attempted to impersonate a user by imitating his/her handwriting shapes and motions. Specifically, the variance between genuine handwriting data and the variance between imitation handwriting data were analyzed.

As an example, Fig. 1 shows a plot of writing time value for genuine and imitation handwriting, which was originally presented in [5]. Here, the odd numbers on the horizontal axis represent genuine handwriting, while the adjacent even numbers represent the corresponding imitation handwriting. If the variance of imitation data is larger than that of genuine data

TABLE VI. NON-RESISTANT FEATURE TO IMITATION [5]

| |
|---|
| Difference X |
| Difference Y |
| Drawing area size |

TABLE VII. TOP 10 FEATURES AND THEIR VARIANCE RATIO

| ○ | | △ | | □ | |
|---|---|---|---|---|---|
| Writing time | 18.7 | Mean contact area | 15.6 | Writing time | 18.1 |
| End point acceleration | 17.4 | Writing time | 15.2 | Maximum contact area | 15.8 |
| End point velocity | 17.2 | Maximum contact area | 14.7 | Maximum finger pressure | 14.7 |
| Mean velocity | 15.1 | Drawing area size | 14.3 | Drawing area size | 14.5 |
| Drawing area size | 15.1 | End point velocity | 13.1 | Difference Y | 13.4 |
| Difference Y | 13.2 | End point acceleration | 13.0 | Mean contact area | 12.0 |
| Difference X | 13.1 | Mean contact area | 12.0 | Mean velocity | 11.5 |
| Mean contact area | 10.8 | Mean velocity | 11.4 | End point velocity | 10.5 |
| Maximum contact area | 9.2 | Difference X | 11.1 | End point acceleration | 10.1 |
| Mean Y coordinate | 9.1 | Difference Y | 10.9 | Difference X | 10.1 |

for a given feature, the feature is considered robust to imitation.

## III. NEW FEATURE SELECTION

### A. High-individuality Features

In the selection of individually good features, those with high verification performance were chosen in descending order. For imitation-robust features, the focus was on vulnerabilities, and features resistant to imitation of handwriting shapes and motions were selected. In this study, we consider individuality strength as a different perspective for feature selection. A feature with strong individuality is defined as one with small intra-individual variation and large inter-individual differences. Specifically, we propose to calculate the ratio of inter-individual variance to intra-individual variance of each feature and select features with large ratios, referred to as "high-individuality features." Hereafter, this ratio is simply referred to as the "variance ratio."

#### 1) Variance Ratio

The calculation of the variance ratio is shown as follows. Let there be $M$ subjects, and denote the intra-individual variance of the $k$-th subject ($k = 1$ to $M$) as $V_k$. For a given subject, let the measurement data be $x_N$ ($n = 1$ to $N$), and their mean be $\bar{x}_k$ The intra-individual variance $V_k$ is defined as

$$V_k = \frac{1}{N}\{(x_1 - \bar{x}_k)^2 + (x_2 - \bar{x}_k)^2 + \cdots + (x_N - \bar{x}_k)^2\} \tag{1}$$

Then, the average intra-individual variance ($V_I$) is expressed as

$$V_I = \frac{1}{M}\sum_{k=1}^{M} V_k \tag{2}$$

Next, let $x_k$ be the mean value of the measurement data of the $k$-th subject, and $\bar{\bar{x}}$ be the overall mean of all subjects. The inter-individual variance $V_{ALL}$ is then defined as:

$$V_{ALL} = \frac{1}{M}\{(\bar{x}_1 - \bar{\bar{x}})^2 + (\bar{x}_2 - \bar{\bar{x}})^2 + \cdots + (\bar{x}_M - \bar{\bar{x}})^2\} \tag{3}$$

From these, the variance ratio $F$ can be obtained as

$$F = \frac{V_{ALL}}{V_I} \tag{4}$$

#### 2) Result

Table VII lists, in descending order of variance ratio, the top ten features for each symbol along with their values. As can be seen, features such as writing time, velocity/acceleration, finger pressure, and finger contact area features, that cannot be visually confirmed during writing, ranked high. These features are considered to exhibit large variance ratios because individuality unconsciously appears during writing, making them stable within individuals. Furthermore, while coordinate features did not rank high, difference between the maximum and minimum X coordinates, and the difference between the maximum and minimum Y coordinates did, likely because coordinate differences are relative values, unlike absolute values such as the maximum or minimum coordinate. The reason why end point velocity and acceleration had larger variance ratios than those at the starting point is that some subjects firmly stop their finger at the end, while others finish with a flicking motion. This makes individuality more apparent at the end of writing than at the beginning, resulting in larger variance ratios.

#### 3) Evaluation of Verification Performance

Table VIII shows the verification performance obtained by fusing the top ten and bottom ten features based on variance ratio and applying Euclidean distance for verification. When the top ten features were fused, the verification performance was better than that obtained using all features. In contrast, when the bottom ten features were fused, the verification performance worsened. These results indicate that feature selection based on variance ratio makes it possible to quantitatively identify features that are both stable within individuals and discriminative across individuals, thereby enabling the selection of effective features for classification. By eliminating features that did not contribute to verification, the overall accuracy improved, demonstrating the effectiveness of this feature selection method.

TABLE VIII. EER[%] BY FEATURES BASED ON VARIANCE RATIO

| | ○ | △ | □ |
|---|---|---|---|
| Top 10 features | 9.7 | 11.2 | 9.7 |
| Worst 10 features | 36.6 | 32.5 | 33.8 |

TABLE IX. EER[%] FOR EACH SELECTION METHOD

| | ○ | △ | □ |
|---|---|---|---|
| Individually discriminative features | 8.4 | 8.2 | 7.7 |
| High-individuality features | 8.0 | 9.1 | 8.8 |
| Imitation-resistant features | 15.8 | 17.4 | 15.3 |

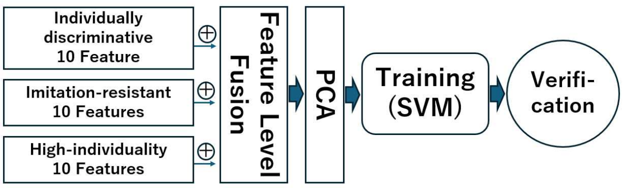


Fig. 2. Four Feature Selection Fusion

### B. Independent Feature Selection

In our previous study [9], we confirmed that fusing uncorrelated features could improve verification performance. However, while it is possible to examine the correlation between two features, it is difficult to evaluate correlations among three or more features simultaneously. In this study, the fusion of uncorrelated features is achieved by applying principal component analysis (PCA) to the multidimensional features after fusion. It is necessary to standardize the data when performing PCA. This can be accomplished through normalization. It was found that the min-max method was particularly effective in [9], we also adopt the min-max method in this study. After the normalization, the mean value is subtracted from each data point to set the mean to zero, which we define as standardization.

## IV. FEATURE SELECTION FUSION

Table IX shows the verification performance for each selected feature selection method. Specifically, the top ten features were fused for the individually good features [4] and the variance ratio method, while the ten features discussed in Table V were fused for the imitation-robust features [5], and SVM was used for verification. In all selection methods, verification performance improved compared to the conventional performance by fusing all features shown in Table II.

### A. Fusion Method

Fig. 2 shows the procedure of feature fusion. First, ten individually good features, ten imitation-resistant features, and ten high-individuality features, making a total of 30 features, are fused as a 30-dimensional feature. In this study, the features selected by three methods, as shown in Table X-XIII, are fused. At this stage, the same feature may be selected by multiple

TABLE X. SELECTED FEATURES (CIRCLE)

| Individually discriminative | Imitation-resistant | High-individuality |
|---|---|---|
| Difference Y | Minimum contact area | Writing time |
| Drawing area size | Maximum contact area | End point acceleration |
| Maximum contact area | Mean contact area | End point velocity |
| Mean velocity | Start point contact area | Mean velocity |
| Writing time | End point contact area | Drawing area size |
| Mean contact area | Minimum finger pressure | Difference Y |
| Difference X | Maximum finger pressure | Difference X |
| Maximum finger pressure | Mean finger pressure | Mean contact area |
| Minimum Y coordinate | Start point finger pressure | Maximum contact area |

TABLE XI. SELECTED FEATURES (TRIANGLE)

| Individually discriminative | Imitation-resistant | High-individuality |
|---|---|---|
| Maximum finger pressure | Minimum contact area | Maximum contact area |
| Maximum contact area | Maximum contact area | Writing time |
| Mean contact area | Mean contact area | Maximum finger pressure |
| Drawing area size | Start point contact area | Drawing area size |
| Mean velocity | End point contact area | End point velocity |
| Writing time | Minimum finger pressure | End point acceleration |
| Maximum finger pressure | Maximum finger pressure | Mean contact area |
| Difference Y | Mean finger pressure | Mean velocity |
| Difference X | Start point finger pressure | Difference X |
| End point contact area | End point finger pressure | Difference Y |

TABLE XII. SELECTED FEATURES (SQUARE)

| Individually discriminative | Imitation-resistant | High-individuality |
|---|---|---|
| Maximum finger pressure | Minimum contact area | Writing time |
| Mean contact area | Maximum contact area | Maximum contact area |
| Maximum contact area | Mean contact area | Maximum finger pressure |
| Mean finger pressure | Start point contact area | Drawing area size |
| Drawing area size | End point contact area | Difference Y |
| End point finger pressure | Minimum finger pressure | Mean contact area |
| End point contact area | Maximum finger pressure | Mean velocity |
| End point Y coordinate | Mean finger pressure | End point velocity |
| Mean velocity | Start point finger pressure | End point acceleration |
| Difference Y | End point finger pressure | Difference X |

TABLE XIII. EER [%] BY 4 PROPOSED FEATURE SELECTION FUSION

| | ○ | △ | □ |
|---|---|---|---|
| Overlapping | 6.3 | 7.6 | 5.8 |
| Non-overlapping | 6.8 | 8.9 | 6.3 |

methods, resulting in duplication during feature-level fusion. Therefore, we propose two approaches: one where duplication is allowed and all 30 features are fused, and another where duplicate features selected by multiple methods are counted only once. Subsequently, PCA is applied to decorrelate the features, thereby realizing feature selection from four perspectives. Then, learning and verification are performed using SVM.

For the evaluation of verification performance, we used the dataset used in [4], in which 30 subjects wrote three symbols (circle, triangle, square) twenty times each. Of the 20 writing samples, 10 were used for learning SVM models and the remaining 10 were used as test data. The SVM was constructed in a one-vs-all scheme, using 10 genuine samples and 10 randomly selected samples from the remaining 29 subjects as training data. In a similar way, 10 genuine samples from each subject and 10 samples from other 29 subjects were used as test data. To eliminate dependency on specific learning-test data combinations, ten fold cross-validation was performed. EER presented hereafter is the average over the ten cross-validation runs. Cross-validation was performed by randomly selecting 10 out of 20 genuine samples for learning and using the rest for testing, while for impostor samples, 10 were randomly chosen, one from each of 10 different individuals among the 29 subjects. Here, the random selection of samples for learning and testing was not identical, meaning that impostors used in learning did not match those in testing. As a result, the evaluation results 10 include the cases where impostor data not used in learning were used in testing. Table XIII shows the results of verification using the proposed fusion method. These results outperformed the verification performance obtained using all features, as shown in Table II. Moreover, compared with the verification performance of the ten selected features from the three perspectives shown in Table IX, the proposed method achieved better results for all symbols. This demonstrates the effectiveness of combining multiple feature selection methods. In addition, the case allowing duplication yielded slightly smaller EERs than the case without duplication. This is because, when duplicate features were removed, the numbers of features were reduced to 20 for the circle, 17 for the triangle, and 18 for the square, while 30 for the duplication allowed case. The increase in EER can be attributed simply to the reduction in feature dimensionality. Since the fusion of identical features does not change separability in the verification space, the presence or absence of duplication was considered to have little impact on verification performance.

## V. CONCLUSION

In this study, we proposed a feature selection method based on high individuality in PV-FSS. By calculating the ratio of intra-individual to inter-individual variance and ranking features in descending order, features with higher individuality were selected. When the top ten features were fused at the feature level and verification was performed, comparable performance to that obtained with individually good features was achieved. Furthermore, we proposed a method that integrates four feature selection methods for verification. The selected features from each method were fused at the feature level, decorrelated by PCA, and then classified using SVM. Through comparisons of the proposed method with other methods, the superiority of the proposed method was confirmed.

For future work, we will investigate the optimal dimensionality and combinations of features to be fused in order to further improve verification performance. In addition, while PCA was applied for decorrelation in this study, it can also be used for dimensionality reduction, and its effect should be examined.

Note that the dataset used for evaluation in this study did not include imitation trials such as tracing, so robustness against imitation was not evaluated. Future research will evaluate robustness against imitation.

Furthermore, while the dataset used in this study was collected using a single device, differences in device (sensor) characteristics may affect verification performance. Evaluation using various devices is an interesting research topic.

Deep learning technology can also be used for verification, but the current dataset is insufficient to fully realize the potential of deep learning. Therefore, this study employed SVM, which demonstrates high verification performance even with small datasets. It is expected that deep learning technology will be introduced in the future once the number of subjects increases and the dataset is sufficiently expanded.

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