

Deriving a Subspace Model for Personal Authentication in Biometrics —Dynamic Signature Case—

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Abstract— This paper deals with personal authentication by biometrics, specifically signature verification. In biometrics, most common case is to register one set of data for authentication. In this sense, we cannot apply popular pattern recognition methods which requires sufficient amount of positive and negative training data. We propose a new recognition method by using a subspace obtained from a set of data prepared in the test experiment. By applying the subspace centered to the point obtained as the registered data, we can use the subspace for authentication of new registered person.

Keywords— Biometrics, dynamic signature authentication, principal component analysis, subspace.

I. INTRODUCTION

Biometrics has been attracting attention in personal authentication problems [5], [11]. Among various biometric methods, signature authentication [6], [7] is a kind of methods often used in daily life. Unlike the methods using such as iris, vein of palm or fingers, and fingerprints, the error rate of signature authentication is not always low. However, since signatures have been used for personal identification with credit cards or many kinds of documents, it can be easily accepted in various cases of daily life when writing characters.

In signature authentication, two categories of features are used: global and local features. An example of research using global features can be seen in Lee *et al.* [3]. They developed a method to use a number of global features, then extracting the statistical parameters such as mean and the standard deviation, and finally to make a judgment by voting based on the result whether each feature is within the normal deviation. However, the method requires sufficient amount of signatures of same person, which is not appropriate for signature verification problem.

In signature verification systems, a person is required to register a signature usually once. If a user has to sign more than once to register, he/she is not happy with it although it may increase the safety of the authentication. In other biometrics, same concept can be applied.

Considering this special feature of personal authentication, we will propose a method where a user does not have to register more than one set of data. Here we will restrict ourselves in data of dynamic signatures. In signature authentication, two kinds of source of authentication is used: what string to write and how to write them. However, in this paper, we will use the same string of characters as a more difficult situation. In the experimental work, we will use the signature Taro Yamada (in Kanji characters) in all

the cases. Our experimental works [10] shows that global features are not enough to authenticate; local features are also necessary in discriminating signatures among persons. Once features are extracted, the treatment of global and local features are the same, or more or less very similar. So, we will treat the global features only in the remaining part of this paper.

II. AUTHENTICATION POLICY

In pattern recognition, statistical methods[2] or neural networks [1] are often used. For example, Multilayer Perceptron has a potential to construct a nonlinear decision boundary, but it requires a sufficient amount of positive and negative cases, which is not the case for signature authentication problem.

Kernel methods [8] that have a radial or oval acceptance region seem more appropriate to express the acceptance region rather than the methods mentioned above, but it still needs a good amount of positive cases, and the acceptance region shape may not be satisfactory.

In the environment where we can use only a single signature, various pattern recognition methods such as linear discrimination or Perceptron are not appropriate, because the signature is a singleton in the feature space and data is not enough to construct a boundary or discrimination rule of the positive case.

Actually, an authentication using only a single registered case is a very difficult problem, and we have no idea how other data of the same person vary. Hence signature authentication is sometimes called “art”. However, we will pursue the authentication problem in this framework.

Fortunately we are able to get many signatures of the same persons engaged in the experiment, and it is possible to compute and compare subspaces of the feature vectors of various persons, accordingly.

Our experiment in this paper is two folds. One is to check whether the distributions of the feature vectors of the signatures similar or distinct by using 25 signatures each written by several persons. The other is to apply the subspace derived from those test signatures for a new registered signature. Figure 1 shows how to apply the subspace information of person A to apply to the new registered signature (person B).

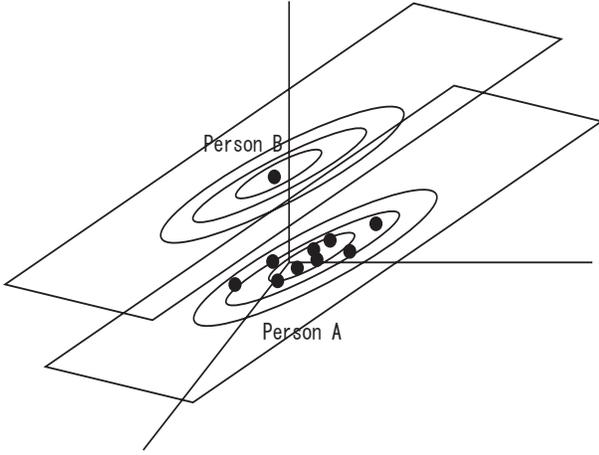


Fig. 1. Model building for a new registered data.

III. DATA AND FEATURES

A. Data description

Here we define the mathematical description of the data. The available information is multi-dimensional time-series data, where the interval of the sampling time is based on the hardware, but it is approximately 10ms in the configuration such as using Wacom tablet, Wintab driver, Windows XP operating system and programmed with Visual C++.

One signature is denoted by $p^{(i)}(k), k = 1, \dots, n_i$, where i indicates the trial (sample) number, and k is the discrete-time of the pen information. Note that $p^{(i)}(k)$ is a vector that includes various pen information shown below.

$$p^{(i)}(k) = \begin{bmatrix} x \text{ (horizontal)} \\ y \text{ (vertical)} \\ \text{pressure} \\ \text{angle} \\ \text{direction} \end{bmatrix} \quad (1)$$

The data is recorded when the pen is close enough to catch the position even when the pen is not touching the tablet. Hence vectors with pressure=0 exist in the data before and after the pen touches the tablet.

B. Global features

We can consider various features from a stream of signature vectors $p^{(i)}(k), k = 1, \dots, n_i$, where the real time between the discrete-integer suffices is constant.

It is possible to extract a number of global features that are values coming from all or most of the data stream. On the contrary, we can also extract numerous local features that are available from subsets of each data stream. The shape of parts, the manner of turning a stroke, the difference in speed in each stroke, and huge amount of such kinds of personal manners can be considered.

Table I shows the global features we will use in the following discussion. Now we define the feature vector of a signature by $\mathbf{x}^{(i)} \in \mathbf{R}^n$ where i denotes the signature number. Note that, although we defined these features heuris-

tically, they can be found in more systematic ways, *i.e.* by using genetic algorithm or other soft computing methods.

TABLE I
THE GLOBAL FEATURES

1	the total signing time(*)
2	the number of strokes
3	the maximum pen pressure
4	the maximum speed of the pen
5	the maximum of the pen angle
6	the minimum of the pen angle
7	the maximum of the pen angle
8	the minimum of the pen angle
9	the width of the signature
10	the height of the signature

(*) The time when the pen is in the air is eliminated from the signing time.

IV. EIGENSPACE OF FEATURE VECTORS

A. Deriving Eigenspace

Here we discuss the eigenspace used in pattern recognition [2] in general.

Suppose R is the covariance matrix of $\{\mathbf{x}^{(i)}, i = 1, \dots, m\}$. Then the matrix R can be diagonalized as

$$P'RP = \Lambda \quad (2)$$

where P is an orthonormal matrix, and Λ is a diagonal matrix whose diagonal elements $\lambda_i (i = 1, \dots, n)$ are non-negative monotonically decreasing values.

Since the intrinsic dimension of the vector \mathbf{x} is substantially low, it is presumed that the dimension to construct the feature space should be a low value. Here, we take an integer L that is sufficiently small and let U_1 be a matrix whose columns are the first L -columns of P , *i.e.*

$$P = [U_1 \ U_2] \quad (3)$$

also, we define the submatrices of Λ as

$$\Lambda = \begin{bmatrix} \Lambda_1 & 0 \\ 0 & \Lambda_2 \end{bmatrix} \quad (4)$$

A subspace is defined by the linear combination of the L -eigenvectors of U_1 given by

$$F = \{U_1\boldsymbol{\theta} | \boldsymbol{\theta} \text{ is arbitrary}\} \quad (5)$$

The parameter $\boldsymbol{\theta}$ that gives the minimum distance between the data point $\mathbf{x} - \hat{\mathbf{x}}$ and the subspace F is given by

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \arg \min_{\boldsymbol{\theta}} \|\mathbf{x} - \bar{\mathbf{x}} - U_1\boldsymbol{\theta}\| \\ &= (U_1'U_1)^{-1}U_1'(\mathbf{x} - \bar{\mathbf{x}}) \end{aligned} \quad (6)$$

B. Probabilistic comprehension and criteria

Let \mathbf{y} be a projection of \mathbf{x} onto the feature space by defining

$$\mathbf{y} = U_1'(\mathbf{x} - \bar{\mathbf{x}}) \quad (7)$$

The covariance matrix of \mathbf{y} is

$$\begin{aligned} E[U_1'(\mathbf{x} - \bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})'U_1] &= U_1'RU_1 \\ &= U_1'U_1\Lambda_1U_1'U_1 + U_1'U_2\Lambda_2U_2'U_1 = \Lambda_1 \end{aligned} \quad (8)$$

because of the normal orthogonality of U_1 and U_2 . Hence the first and the second moments of the distribution of \mathbf{y} is clear. If we assume \mathbf{y} is Gaussian, the PDF (probabilistic distribution function) is

$$p(\mathbf{y}) \propto \exp\left(-\frac{1}{2}\mathbf{y}\Lambda_1^{-1}\mathbf{y}\right) \quad (9)$$

thus the possibility of \mathbf{y} belonging to this signature writer is due to this value. Equivalently we can measure the possibility by using the Mahalanobis distance

$$\mathbf{y}\Lambda_1^{-1}\mathbf{y} = \sum_{i=1}^L y_i^2/\lambda_i \quad (10)$$

There are two ways to evaluate the distance. They are

- the square distance to the center within the feature subspace given by

$$\text{criterion1} = (\mathbf{x} - \bar{\mathbf{x}})'U_1\Lambda_1^{-1}U_1'(\mathbf{x} - \bar{\mathbf{x}}) \quad (11)$$

- the square distance to the feature space given by

$$\begin{aligned} \text{criterion2} &= \|\mathbf{x} - \bar{\mathbf{x}} - U_1\hat{\boldsymbol{\theta}}\|^2 = (\mathbf{x} - \bar{\mathbf{x}})' \\ &\times (I - U_1(U_1'U_1)^{-1}U_1')(\mathbf{x} - \bar{\mathbf{x}}) \end{aligned} \quad (12)$$

C. Proposed Method

Here we propose a new method for signature authentication. Suppose we have M persons who wrote p -standard signatures, where standard signature is the specified character string as a signature. In our experiment, a very popular Japanese name ‘‘Taro Yamada’’ in Kanji will be used.

For the signatures by person i , derive the feature space matrix, mean vector and the eigenvalue matrix which are termed as $U_1^{(i)}$, $\bar{\mathbf{x}}^{(i)}$ and $\Lambda_1^{(i)}$, respectively.

Next we will compute the angles between each pair of subspaces by M persons. Note that the angle α between spaces S_1 and S_2 is defined as the maximal angle between vectors $\mathbf{v}_1 \in S_1, \mathbf{v}_2 \in S_2$.

By investigating the angle matrix obtained above, we will find a person whose feature space of signature is typical to the majority of M persons’ signatures. Suppose person j was selected as the most standard writer of signatures. Then, for a new person q who wrote only one signature whose feature vector is $\mathbf{x}^{(j)}$, we define criteria given as follows.

Model 1

$$\text{criterion1} = (\mathbf{x} - \bar{\mathbf{x}}^{(q)})'U_1^{(all)}\Lambda_1^{-1}(U_1^{(all)})'(\mathbf{x} - \bar{\mathbf{x}}^{(q)}) \quad (13)$$

$$\begin{aligned} \text{criterion2} &= \|\mathbf{x} - \bar{\mathbf{x}}^{(q)} - U_1^{(all)}\hat{\boldsymbol{\theta}}\|^2 \\ &= (\mathbf{x} - \bar{\mathbf{x}}^{(q)})' \left(I - U_1^{(all)}((U_1^{(all)})'U_1^{(all)})^{-1}(U_1^{(all)})' \right) \\ &\quad \times (\mathbf{x} - \bar{\mathbf{x}}^{(q)}) \end{aligned} \quad (14)$$

where the superscript *all* means that the matrix is computed based on all the data of all persons.

Model 2

$$\text{criterion1} = (\mathbf{x} - \bar{\mathbf{x}}^{(q)})'U_1^{(j)}\Lambda_1^{-1}(U_1^{(j)})'(\mathbf{x} - \bar{\mathbf{x}}^{(q)}) \quad (15)$$

$$\begin{aligned} \text{criterion2} &= \|\mathbf{x} - \bar{\mathbf{x}}^{(q)} - U_1^{(j)}\hat{\boldsymbol{\theta}}\|^2 \\ &= (\mathbf{x} - \bar{\mathbf{x}}^{(q)})' \left(I - U_1^{(j)}((U_1^{(j)})'U_1^{(j)})^{-1}(U_1^{(j)})' \right) \\ &\quad \times (\mathbf{x} - \bar{\mathbf{x}}^{(q)}) \end{aligned} \quad (16)$$

where the matrix U_1 is the one obtained by using the data of person j . The validity of this new method is based on the assumption that the variation of the features are done in similar ways because of the mechanism of the signing action. The validity of this assumption will be investigated in the following experimental results.

V. EXPERIMENTAL RESULT

We use signatures by 10 persons, 25 signatures each. First we computed the subspaces derived by the method shown in Section IV(A), where all the signature by 10 persons were used.

Next, we computed the angles between all the pairs of the subspaces, which is shown in Table II. Note that the angle between two subspaces is defined as the maximal angle of two vectors each of which belongs to the respective subspace.

Note that the angles heavily depend on the dimension of the subspaces. If L is large, all the angles approach 90 degrees. Here, L was set to 3 in all the cases.

We can see that the person 6 has a very different subspace, *i.e.* nearly orthogonal to other subspaces, while all the others are more or less facing to similar directions. Now we select $p0$ because the sum of the angles between this and every other person’s eigenspace is the smallest.

Figure 2 shows the squares of Euclidian distances between the registered signature and other test signatures. The horizontal axis denotes the distance in logarithm scale. The blue dots indicate the distance value, and those surrounded by the red circles denote the distance value where both data were written by the same person. The vertical value is only a random value so that the dots can be seen separately. In each figure, 20th signature among 25 ones is selected as the registered signature for the person 0

TABLE II
 ANGLES BETWEEN EACH GROUPS (DEGREES)

	p0	p1	p2	p3	p4
p0	0.00	9.82	12.22	26.43	7.23
p1	9.82	0.00	17.55	27.19	11.25
p2	12.22	17.55	0.00	24.86	12.82
p3	26.43	27.19	24.86	0.00	25.02
p4	7.23	11.25	12.82	25.02	0.00
p5	13.26	14.36	19.02	32.43	13.39
p6	82.44	88.48	74.01	84.11	85.22
p7	22.02	18.08	31.25	19.01	23.20
p8	6.89	10.71	14.74	29.99	8.07
p9	9.64	9.93	15.09	22.86	8.71
	p5	p6	p7	p8	p9
p0	13.26	82.44	22.02	6.89	9.64
p1	14.36	88.48	18.08	10.71	9.93
p2	19.02	74.01	31.25	14.74	15.09
p3	32.43	84.11	19.01	29.99	22.87
p4	16.22	85.22	28.86	8.07	8.71
p5	0.00	84.35	22.26	12.80	12.89
p6	84.35	0.00	84.84	83.53	87.18
p7	22.26	84.84	0.00	23.88	19.73
p8	14.72	84.38	22.68	0.00	12.45
p9	27.48	88.99	19.38	12.45	0.00

through 9, respectively. By these figures, we can see that it is impossible to classify the data by the nearest neighbor method.

Figure 3 shows the criterion1-criterion2 space defined by 13-14, where the blue dots and the red circles mean the same as those in Fig. 2. Each sub-figure shows the distance in log scale (for both criteria), where the red one is the signature signed by the same person to the registered one, for the person 0 through 9, respectively. Since both criteria indicate small value if the two signatures are similar, it is desirable that the dots with red circles make a cluster in left-low area. Note that q is an integer $0, 1, \dots, 9$ in each sub-figure from left to right, top to bottom order.

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Compared to the case when the subspace was derived by using all the persons’ data in Fig. 3 (circled sub-figure), we can see that the signatures by the same persons are further located in the area close to the left-bottom point, and there are less number of signatures by other persons among the right person’s ones in the Pareto-optimal sense. This is

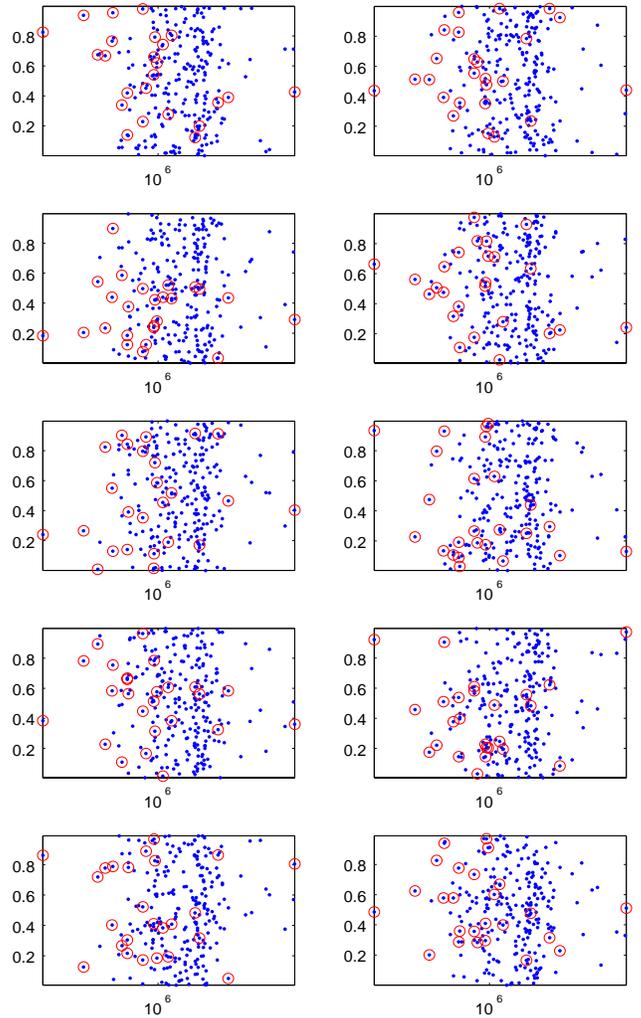


Fig. 2. Square error between the registered signature by person 0 and each test signature, respectively.

not only for signatures by person 0 but also the same for signatures by other persons.

VI. CONCLUSIONS

This paper proposed a new method for biometrics such as signature authentication. We experimentally got a very good result that the subspace computed from the signatures of one person was very suitable for other persons. This result prompts us to proceed to the next stage of experiment.

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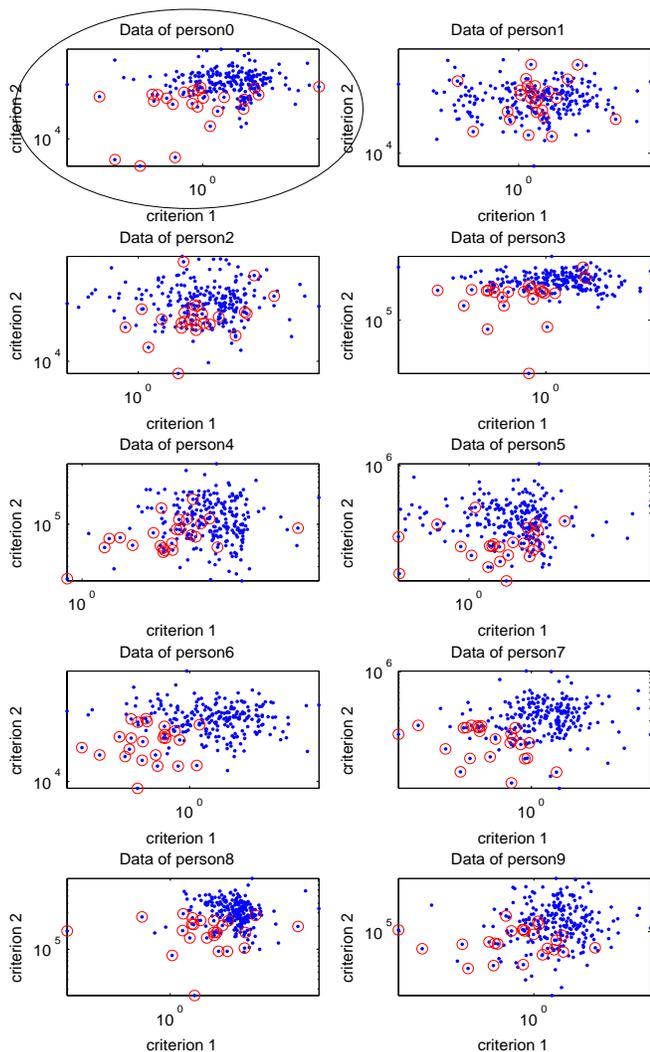


Fig. 3. Error criteria for registered person (circle) and all other persons (dot) using the subspace for all the signatures

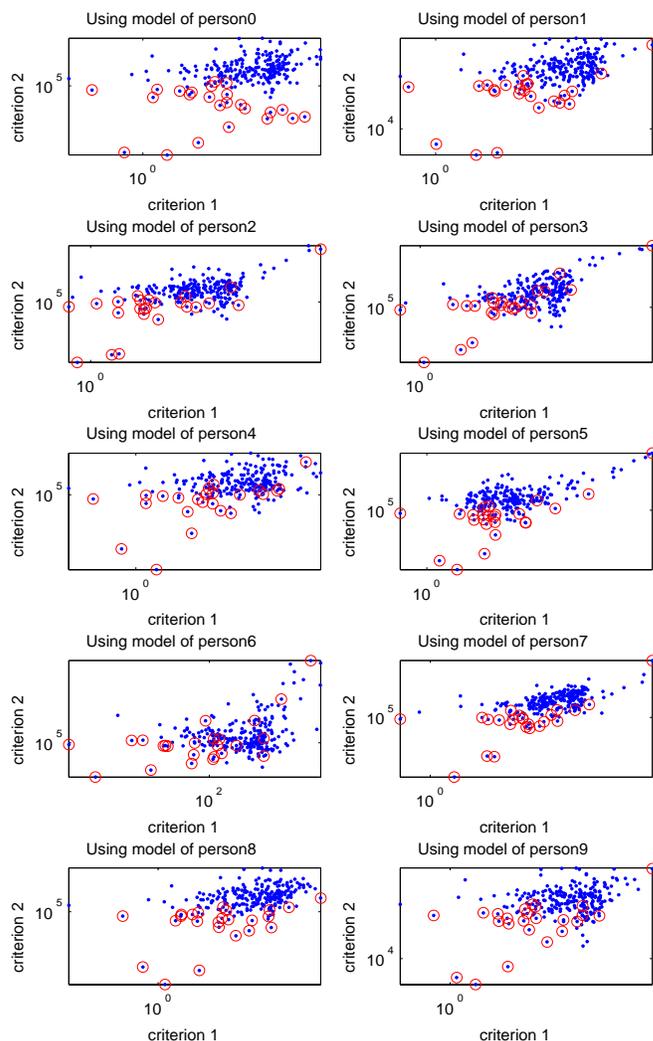


Fig. 4. Error criteria for registered person (Person 0: circle) and all other persons (dot) using the subspace for every 10 persons each.

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