Authentication Model of Dynamic Signatures using Global and Local Features

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Abstract

We consider a stochastic model for signature verification using dynamic signatures. For verification of dynamic signature data, we will use both global features and local features. Global features are such as the signature drawing time, average pen speed, the signature size, and so on. Local features are the signature shape and pen pressures evaluated locally. The stochastic model is given from the principal components of the feature vector, and two measures are defined to evaluate the distance from the center of the distribution. In the experimental study, we got a good result for authentication.

1. Introduction

Dynamic signature(e.g. [1],[2],[3]) is the one written on the tablet with an electronic pen. For the signature verification problems, we considered a two-stage method [5, 6, 7, 8]: the first stage is to match the signatures of the whole signatures point-wise, and the second stage is to compare the points where some special features of the signature holder appear.

In this paper, we propose to use mean values and primal eigenvectors both for global features and local features. We consider a stochastic model for signature verification using dynamic signature available from tablets and electronic pens. For verification of dynamic signature data, we will use both global features and local features. Global features are such as the signature drawing time, average pen speed, the signature size, and so on. Local features are the signature shape and pen pressures evaluated locally. To use local features is essential in criminal investigation [4]. To adjust two signatures, we use DP (Dynamic Programming) matching. The stochastic model is given from the principal components of the feature vector, and two measures are defined to evaluate the distance from the center of the distribution.

Section 2 explains the data and methodologies we use in this paper. Section 3 describes the treatment and experimental result of global features. Section 4 describes the treatment and experimental result of local features. Section 5 is the conclusions.

2 Data description

Here we define the mathematical description of the data. The available data comes every 10ms approximately.

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

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

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 0 at the pressure element are included before the pressure becomes positive.

3 Eigenspace of global features

3.1 Global features

The global features available from dynamic signatures are worth considering for verification.

Lee *et al.* [1] 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.

We here develop another method that also uses the same kinds of global features, and is valid even if the number of signatures is only one in the extreme case.

Now we define the feature vector of a signature by $\boldsymbol{x}^i \in \mathbf{R}^n$ where i denotes the signature number. We define these features by our intuitive consideration, but they can be defined in more systematic ways, *i.e.* by using genetic algorithm or other soft computing methods.

Table 1. 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 direction
8	the minimum of the pen direction
9	the width of the signature (*)
10	the height of the signature (*)

(*) these features are applicable only when the frame for the signature is the fixed standard size

3.2 Eigenspace of global features

The eigenspace is composed from the covariance matrix R of $\boldsymbol{x}^{(i)}, i = 1, \ldots, m$. The matrix R can be diagonalized as

$$P'RP = \Lambda \tag{2}$$

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

Since the intrinsic dimension of the vector $\boldsymbol{x}$ 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.*

$$P = [U_1 \; U_2] \tag{3}$$

and take

$$\boldsymbol{y} = U_1'(\boldsymbol{x} - \bar{\boldsymbol{x}}) \tag{4}$$

also, we define the submatrices of Λ as

$$\Lambda = \begin{bmatrix} \Lambda_1 & 0 \\ 0 & \Lambda_2 \end{bmatrix} \tag{5}$$

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

$$F = \{U_1\boldsymbol{\theta} | \boldsymbol{\theta} \text{ is arbitrary}\} \tag{6}$$

The parameter $\boldsymbol{\theta}$ that gives the minimum distance between the data point $\boldsymbol{x} - \hat{\boldsymbol{x}}$ and the subspace F minimizes $\|\boldsymbol{x} - \bar{\boldsymbol{x}} - U_1\bar{\boldsymbol{\theta}}\|$, where the $\hat{\boldsymbol{\theta}}$ is given by

$$\hat{\boldsymbol{\theta}} = (U_1'U_1)^{-1}U_1'(\boldsymbol{x} - \bar{\boldsymbol{x}}) \tag{7}$$

3.3 Probabilistic comprehension and criteria

The covariance matrix of $\boldsymbol{y}$ is

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

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

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

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

$$\boldsymbol{y}\Lambda_1^{-1}\boldsymbol{y} = \sum_{i=1}^{L} y_i^2/\lambda_i \tag{10}$$

There are two ways to evaluate the distance. They are

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

$$error1 = (\boldsymbol{x} - \bar{\boldsymbol{x}})'U_1\Lambda_1^{-1}U_1'(\boldsymbol{x} - \bar{\boldsymbol{x}}) \tag{11}$$

- the square distance to the feature space given by

$$\begin{aligned} error2 &= \|\boldsymbol{x} - \bar{\boldsymbol{x}} - U_1\hat{\boldsymbol{\theta}}\|^2 = (\boldsymbol{x} - \bar{\boldsymbol{x}})' \\ &\times \left(I - U_1(U_1'U_1)^{-1}U_1'\right)(\boldsymbol{x} - \bar{\boldsymbol{x}}) \end{aligned} \tag{12}$$

Figure 1 shows the errors in error1-error2 plane. The circles denote the errors for the true signatures and dots denote those for the forgeries. We can see that they are basically Pareto optimal, but we cannot separate them by standard nonlinear curves. This means we should use local features as well.

4 Eigenspace of local features

The local features include various local information such as the speed of certain bending point, the pen direction when the signature finishes, etc. The objective of this subsection is to create a “standard” signature as well as the distribution model from signatures of the same person.

First, we normalize the signatures in such a way to confine the signatures to a same rectangular which is derived from the specified signature.

Next, we use DP matching to make correspondence between the given signature and the sample one, and make the number of points the same among all the signatures.

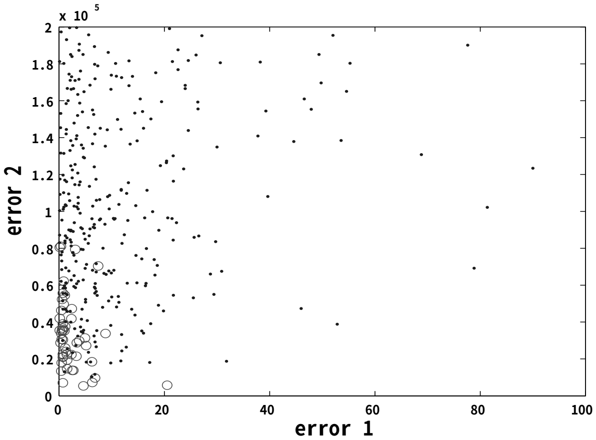

Figure 1. Errors of global features

Finally we will calculate the mean values of the adjusted signatures and the eigenspace obtained from the primal orthogonal eigenvectors of the covariance of the signatures.

In the following, we will explain the procedure in detail for each step.

4.1 Normalization of signatures

It is necessary to normalize signatures for extracting eigenspace. The data is automatically recorded when the pen approaches the tablet. However, it seems necessary to cut the points before and after the signatures.

The subspace extraction is the same as the global case if the time lengths of the signatures are the same. However, in the dynamic signatures, the time is not the same. Hence we should normalize the signatures in some ways.

In signatures of Japanese characters, for example, they consist of several characters, and most of the Japanese people write their signatures just as writing the characters separately. This situation seems more or less similar in East Asian countries. When a person finishes writing one character and moving the pen apart from the tablet, he/she sometimes takes a break, and the idling time is not always very similar.

Hence we exclude the idling time part from the signature. The procedure is as follows.

1. Delete the points when the pen is in the air.
2. Confine a signature in a fixed size rectangular.

4.2 DP Matching

Here we will use a discrete time index k. In the following part of this paper, the model data $\{p(k), k = 1, \cdots, P\}$ kept in the system and the test data (the current data) $\{q(k), k = 1, \cdots, Q\}$ are used, where $p(k) \in \mathbf{R}^2$ and $q(k) \in \mathbf{R}^2$.

The detail of matching method is explained in [5].

4.3 Average signature

After DP matching, we are ready to have the corresponding points to each point in the model data $\{p(k), k = 1, \ldots, n_1\}$. According to the correspondence, we extract the points and renumber them from 1 to n_1 continuously. Then we have the signature data:

$$q_i(k), k = 1, \ldots, n_1; i = 1, \ldots, m$$

Hence we can compute the average signature by

$$\bar{q}(k) = \frac{1}{m} \sum_{j=1}^{m} q_j(k), k = 1, \ldots, n_1 \qquad (13)$$

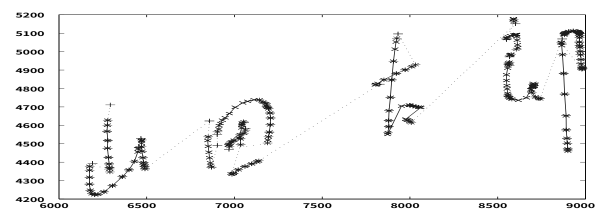

Figure 2. Average signature by person A

Figure 3 denotes the average signature emphasized by the pressure. Note that we have only the points whose pressure is positive. The points with positive pressure were categorized into three based on the magnitude of the pressure values where the range is equally divided into three. The points are expressed based on the pressure values: '+', 'x', '*' which are weak, medium and strong. Also, the connections between the points are denoted by solid lines, but the connection between points, one of which is '+' is expressed by a dotted line.

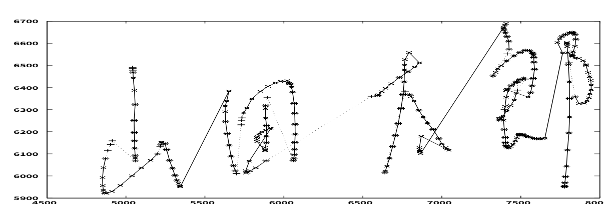

Figure 3. Average signature by person B

4.4 Eigenvectors and the cost function

Now we have a normalized data $q(1), \ldots, q(n_1)$ where $q(k) \in \mathbf{R}^2$. The data was normalized based on the coordinate, but we have the corresponding other information such as pressure, angle and direction. The orthogonalization can be done by concatenating all these vectors, but here we will use the data in the following sets:

1. coordinate $q(k) \in \mathbf{R}^2, k = 1, \ldots, n_1$
2. pressure $r(k) \in \mathbf{R}, k = 1, \ldots, n_1$
3. angle $s(k) \in \mathbf{R}, k = 1, \ldots, n_1$
4. direction $t(k) \in \mathbf{R}, k = 1, \ldots, n_1$

By putting the elements vertically, we have $2n_1$, n_1, n_1 and n_1-dimensional vectors respectively. From now, the procedure is the same for these four vectors, and it is also the same to the global case. Hence we omit describing the procedure in detail.

Thus we have the following two criteria for each of the above data.

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

$$error1 = (\boldsymbol{x} - \bar{\boldsymbol{x}})' U_1 \Lambda_1^{-1} U_1' (\boldsymbol{x} - \bar{\boldsymbol{x}}) \qquad (14)$$

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

$$error2 = \|\boldsymbol{x} - \bar{\boldsymbol{x}} - U_1 \hat{\boldsymbol{\theta}}\|^2 = (\boldsymbol{x} - \bar{\boldsymbol{x}})' \times \left(I - U_1 (U_1' U_1)^{-1} U_1'\right) (\boldsymbol{x} - \bar{\boldsymbol{x}}) \qquad (15)$$

Figure 4 shows the error1-error2 for local features. The circles denote the error values for the true person's signature (person A), and the crosses denote those for nine forgers. We can see the good property of this model.

5 Conclusions

This paper proposed a method to verify signatures based on the feature space for global and local features. The feature space is given by the primal components of the feature vectors, and the probabilistic measure was used both for distances within the feature space and the distance to the feature space from the observation.

Acknowledgment

The authors would like to thank R&D Division, Glory Ltd. for providing signature data. This work was supported in part by GRANT-IN-AID for ORC Project from the Japanese Government Structure for Education, Culture, Sports, Science and Technology.

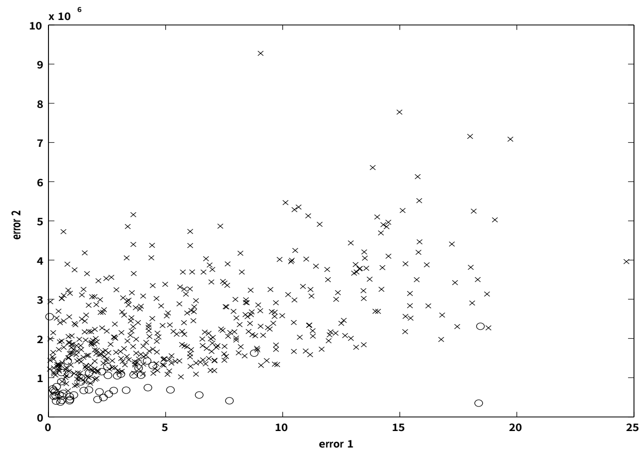

Figure 4. Errors in local features

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