Online Signature Verification System for Kaisyo Script Based on Structured Learning and Segmentation of HMM

Dapeng ZHANG *, Shinkichi INAGAKI *, Tatsuya SUZUKI *, and Naoki KANADA *

Abstract: This paper presents a new Hidden Markov Model (HMM) for the online signature verification of oriental characters such as Japanese and Chinese. These oriental characters usually consist of many individual strokes such as dots and straight lines. Taking into account of this characteristic, a new HMM is proposed, which is composed of many sub-models each of which corresponds to an individual stroke. In addition, the ‘pen-up’ state which represents the movement between strokes is explicitly introduced. Then, a parameter re-estimation scheme for this special class of HMM is derived exploiting the structure of the proposed HMM. Thanks to the structured learning mechanism, the proposed HMM not only can drastically reduce the computational time necessary for the learning process but also shows higher recognition performance for the rejection of the skilled forgery. Finally, the usefulness of the proposed scheme is demonstrated by comparing it with conventional models.

Key Words : signature verification, HMM, oriental character, anti-forgery, structured learning.

1. Introduction

The demand for high level authentication system is now growing in order to realize the safe and reliable society. One of the promising ideas is to exploit biometrics, such as fingerprint, retina, blood pattern on the palm of the hand [1]. However, aiming at privacy-proof authentication solutions, authentication methods relying on personal motion trajectories like signature or gait are better than those requiring clients (legal users of the system) to submit more private information [2]. Previous studies in cybernetics, in particular the human motion analysis, have shown that handwriting strokes are a specific class of the rapid human movements, similar to pointing and reaching movements in two dimensions [3],[4]. In addition, in the forensic science, the authenticity of the signature is often grounded on a tiny variation in the stroke [5].

When we look at the oriental characters, they usually consist of many individual strokes such as dots and straight lines. Moreover, in the oriental character, five basic movement types exist, which are denoted as 5 basic stroke types: Horizontal, Vertical, Dotted, Solidus-like, Backslash-like. This implies that each individual stroke has specified dynamic information in it. In addition, there exist ‘pen-up’ states of a certain time duration between strokes. These features must be fully exploited for the design of the authentication system focusing on the oriental character.

Inspired by these backgrounds, a new signature verification system for the oriental characters, which is based on a Hidden Markov Model (HMM), is investigated in this paper. As for the signature data, the full motion profiles of signing behavior including dynamic data sequence composed of pen-tip’s position, pressure, and pen’s inclination are considered. These data can be captured and processed online. In many practical situations, the online signature verification is better than offline method [6].

Traditional HMMs as statistical representations of the temporal human behavior have good performance on voice and western handwriting recognition applications. The oriental handwriting, however, possess more complex structures such as discontinuity resulted from separated strokes and radicals. The examples of the ‘Kaisyo (regular) script’, the most popular script in Japan and China, are shown in Fig. 1. In Fig. 1, two people’s signatures are depicted. Each signature consists of two characters. In addition, each character can be divided into many individual strokes like the first stroke, the second stroke, and so on. The signer often spends much time in pen-wielding movement particularly at the beginning and the end of the stroke. In the traditional HMMs, to capture the precise information of the oriental characters, it results in huge number of hidden states and output symbols obtained from the vector quantization. Al-
though to enlarge the scale of parameter matrices of HMMs is an efficient way to attain the precise modeling, it generally causes unbearable computational load.

In order to overcome this difficulty, a new HMM is proposed in this paper, which is particularly useful for the signature verification of Japanese or Chinese signature [7],[8] written in ‘Kaisyo script’. Considering the structure of the Kaisyo script, the proposed HMM is composed of many sub-models, each of which represents an individual stroke in the signature, and which are connected sequentially. In addition, there is a special state called the ‘pen-up’ state at the end of each sub-model except the last one. This state is introduced to explicitly represent the movement between strokes. Then, the complete parameter re-estimation scheme is derived, which should be called a ‘structured learning’. In the proposed learning scheme, first of all, the signature is segmented according to the observed zero-tool-force state (pen-up state), and later sub-HMMs derived from the segmentation are integrated by state-transition parameters. The number of sub-HMMs is the same as the number of strokes segmented by pen-up states in the Kaisyo signature. The proposed HMM can not only drastically reduce the computational time necessary for the learning process but also can achieve higher recognition performance against the skilled forgery.

Finally, three different models are established to explore their performance against skilled forgery. A segmentation-integration procedure is adopted in two of these models to exploit specific characteristics in the oriental signature. The usefulness of the proposed recognition system is demonstrated through some comparative studies.

2. Data Corpus and Data Acquisition

2.1 Data Corpus

In this work, Japanese and Chinese signature samples were specifically collected. First of all, examinees are asked to write their own signature in Kaisyo (regular) script maintaining the rotation-invariant, size-invariant characteristics of the signature as possible as they can via a controlled signature acquisition interface. Then, examinees are requested to pretend ‘forgers’ by providing the forged signature of other examinees after some practice referring to the image of the original signature. This corpus consists of 25 sets of signatures written by 25 examinees. Each set contains 40 genuine signatures from one contributor and 40 skilled forgeries from 4 other contributors. The structure of the whole data corpus is shown in Table 1. The whole data corpus is divided into two sets, $D$: consists of original signatures; $\hat{D}$: consists of skilled forgery. Each of 25 examinees contributes to provide 40 original samples and 40 skilled forgeries. When a sample is claimed as some client’s identity, other clients’ samples in $D$ are considered as random forgery (a total of $24 \times 40$ samples for each test), and samples in $\hat{D}$ of that client are considered as skilled forgery. Skilled forgery of one client are contributed by several selected examinees who are good at signature imitation. Generally speaking, in practice, the skilled forgery are produced by people who have access to the original instance of signature and try to imitate it as closely as possible [9]–[11].

2.2 Data Acquisition

In this paper, Only three dimensional raw data is processed ($\dot{x}$: velocity along $x$ axis, $\dot{y}$: velocity along $y$ axis, $p$: tool-tip pressure) although five dimensional data ($\dot{x}$, $\dot{y}$, $p$, $\theta_1$: altitude angle respect to $z$ axis, $\theta_2$: azimuth angle respect to $x$-$y$ tablet plane) can be observed. This is because the results including additional inclination information is too unstable to be used to improve the system’s performance. The same effect is reported

![Fig. 2 Imitated signature data samples.](image)

<table>
<thead>
<tr>
<th>Signatures of Examinee-1</th>
<th>Signatures of Examinee-2</th>
<th>...</th>
<th>Signatures of Examinee-25</th>
</tr>
</thead>
<tbody>
<tr>
<td>40 original samples: $D_1$</td>
<td>40 original samples: $D_2$</td>
<td>...</td>
<td>40 original samples: $D_{25}$</td>
</tr>
<tr>
<td>40 samples imitated by others: $\hat{D}_1$</td>
<td>40 samples imitated by others: $\hat{D}_2$</td>
<td>...</td>
<td>40 samples imitated by others: $\hat{D}_{25}$</td>
</tr>
<tr>
<td>$D = \bigcup_{i=1}^{25} D_i$</td>
<td>$\hat{D} = \bigcup_{i=1}^{25} \hat{D}_i$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1 Contents of the data corpus.
The data are collected by Intuos3 PTZ-430/G made by Wacom. The examples of 3-dimensional raw data are shown in Fig. 2. Though they are carefully imitated by skilled imitators, there are many minor differences between characters in Fig. 2 and Fig. 1. In regular script of the oriental characters, the pressure of pen-tip becomes to zero at the end of each stroke. It can be seen in the pressure profile that there are 13 strokes in the lower signature in Fig. 2. In addition, large number of stokes are helpful for the model to detect the periodic pattern in signing behavior. Some signature contains more than 25 strokes like ‘urahama’. And there are many signatures in our database with characters which are similar or the same to each other, however the experiments results show that the proposed method is not deteriorated in this case because the model relies on the online dynamical trajectories in writing rather than the static appearance of characters to authenticate the writings. These characters are shown in Figs. 3 and 4.

Then, the raw data are normalized. Based on the normalized data, the Competitive and Selective Learning (CSL) algorithm [13] generates representative vectors as the output symbols of the HMMs. We defined 250 representative vectors using the CSL algorithm.

3. Segmented HMM and Structured Learning

To represent discontinuous characteristics of oriental signatures in statistical models and shorten the computation duration in learning phase, a segmented HMM and structured learning algorithm are proposed. In addition, this algorithm can naturally derived from the conventional Baum-Welch learning algorithm.

3.1 Segmented HMM

The main subject of this study is the regular script signature in Japanese and Chinese, which can be segmented naturally by zero-tool-force state as shown in Fig. 2. Because each hidden state of HMM (Left-to-Right HMM is adopted in this work) has a probability distribution over the possible output symbols, we can define a ‘pen-up state’ (zero-tool-force state) with distribution $P(O_u|S_u)$ where $S_u$ is pen-up state, $O_u$ is the symbol associated with pen-up state. And it’s assumed that there are at least two $O_u$ generated by a single state. We call this HMM a ‘segmented HMM’. The following constraints must be met in the segmented HMM: (1) there are no common symbols (overlapped symbols) existed between pen-up states and pen-down states (states in which pen-tip pressure is not equal to zero); (2) $O_u$ is observable when collecting data. For example, a 3-stroke signature modeled by segmented HMM is shown in Fig. 5. The pen-up states in each sub-HMM are painted dark.

A complete specification of an HMM requires specification of several model parameters:

$N$: the number of state, and the set of all states is denoted as $S$;

$M$: the number of observation symbols, and the set of all observation symbols is denoted as $O$;

$A$: state-transition probability matrix, and $A = (a_{ij})$;

$a_{ij}$: the state-transition probability from $i$-th state to $j$-th state;

$P(O_u|S_u)$: the probability of observing symbol $O_u$ in state $S_u$.
B: probability matrix of the observation symbols, and \( B = (b_r(o_j)) \);
\( b_r(o_j) \): the probability of observation \( j \)-th symbol in \( i \)-th state;
\( \pi \): probability matrix of the initial state.

In the example of Fig. 5, the number of states \( N = 8 \), the number of representative vectors \( M = 5 \). For convenience, we use the compact notation \( \lambda = (A, B, \mathbf{S}, \mathbf{O}, \pi) \) to indicate the complete parameter set of the model. We also introduce the following definitions for the proposed segmented HMM:

\[ S_u: \text{the set of pen-up states}; \]
\[ S_d: \text{the set of pen-down states}; \]
\[ \mathbf{O}_u: \text{the set of symbols associated with pen-up state}; \]
\[ \mathbf{O}_d: \text{the set of symbol associated with pen-down state}. \]

So the proposed segmented HMM can be written as

\[ \lambda = (A, B, \mathbf{S}_u, \mathbf{S}_d, \mathbf{O}_u, \mathbf{O}_d, \pi). \]  

(1)

For simplification, only one \( \mathbf{O}_u \) is adopted in pen-up state. It should be noticed that one hidden state may generate many observation symbols according to its self-transition parameter. The probability measure of one of these symbols \( O_u \), is not trained from vector quantization, but is set to be 1 in \( S_u \). That is,

\[ b_u(O_u) = 1. \]  

(2)

So, the observation probability matrix B of the segmented HMM is given by

\[
B = 
\begin{bmatrix}
0 & b_1(o_1) & b_1(o_2) & b_1(o_3) & b_1(o_4) \\
0 & b_2(o_1) & b_2(o_2) & b_2(o_3) & b_2(o_4) \\
0 & b_3(o_1) & 0 & 0 & 0 \\
0 & b_4(o_1) & b_4(o_2) & b_4(o_3) & b_4(o_4) \\
0 & b_5(o_1) & b_5(o_2) & b_5(o_3) & b_5(o_4) \\
0 & b_6(o_1) & b_6(o_2) & b_6(o_3) & b_6(o_4) \\
0 & b_7(o_1) & b_7(o_2) & b_7(o_3) & b_7(o_4) \\
0 & b_8(o_1) & b_8(o_2) & b_8(o_3) & b_8(o_4)
\end{bmatrix}.
\]  

(3)

### 3.2 Structured Learning

The learning algorithm for the proposed segmented model consists of two stages: (1) run small-scale Baum-Welch algo-

\[ a_{i+1} = 1 - a_i. \]  

(4)

Then

\[
\gamma_i(t) = \sum_{j=1}^{N} \xi_j(t) = a_i(i) \cdot a_j \cdot b_r(o_{i+1}) \cdot \beta_{i+1}(i+1), \\
\alpha_i(i) \cdot a_{i+1} + b_r(o_{i+1}) \cdot \beta_{i+1}(i+1). 
\]  

(5)

The second constraint is

\[
\xi_j(t) = a_i(i) \cdot a_j \cdot b_r(o_{i+1}) \cdot \beta_{i+1}(j) = 0, \]

if \( t \notin \{t_{d}^{(i)}, t_{d}^{(i+1)} + 1, ..., t_{d}^{(i)} - 1\}, S_j \in S_u^{(i)} \),

or \( t \notin \{t_{u}^{(i)}, t_{u}^{(i+1)} + 1, ..., t_{u}^{(i+1)} - 1\}, S_j \in S_u^{(i+1)} \).  

(6)

This can be observed in Fig. 8, which can be viewed as Markov chains. White dots represent pen-down states while black dots represent pen-up states generated by all states at certain time. Each column represents an observation. All the possible state-transition paths are depicted in straight lines. The re-estimation
procedure is to estimate and modify “the line weight of the links” (state-transition probability).

In the following paragraphs, the parameter re-estimation equations for \( a_{i|v} \) are derived in the cases of \( S_i \in S_d \) and \( S_i \in S_u \), respectively. In the case of \( S_i \in S_d^{(r)} \), the re-estimation equations are re-written in the time sequence \( t_d^{(r)}, ..., t_d^{(r)} = 1 \),

\[
\bar{a}_{i|i+1,S_d^{(r)}} = \frac{\sum_{t_d^{(r)}} \xi_{i|i+1}(t) \cdot \sum_{i_d^{(r)}} [\xi_{ij}(t-1) + \xi_{ji+1}(t-1)]}{\sum_{t_d^{(r)}} \xi_{ii}(t) + \xi_{i|i+1}(t)}.
\]

(7)

The key characteristics of Fig. 8 is that if at certain time \( S_u \) is transited to \( S_d \), there will be only one path between strokes, and this path is absolutely via the state \( S_d \). The following equations are fulfilled because at least two \( O_u \) are assumed to be generated by one single state. Since we have

\[
\alpha_{i|i+1}^{(r)}(t) = \alpha_{i|i+2}^{(r)}(t) \cdot a_{ii} \cdot b_{i}(\alpha_{i|i+1}^{(r)}),
\]

(9)

and

\[
\beta_{i|i+1}^{(r)}(t) = a_{ii} \cdot b_{i}(\alpha_{i|i+1}^{(r)}) \cdot \beta_{i+1}^{(r)}(t + 1),
\]

(10)

so we obtain that

\[
\xi_u(t^{(r)}(t_d^{(r+1)}) = 2) = a_{ii} \cdot b_s(\alpha_{i|i+1}^{(r)}) \cdot \beta_{i+1}^{(r)}(t_d^{(r+1)}).
\]

(11)

Similarly, the following holds:

\[
\xi_d(t^{(r)}(t_d^{(r+1)}) = 1).
\]

(12)

In the case of \( S_i \in S_u^{(r)} \), the re-estimation of \( a_{i|i} \) can be simplified as

\[
\bar{a}_{i|i+1,S_u^{(r)}} = \frac{\xi_{i|i+1}(t_d^{(r+1)} - 1)}{\sum_{t_d^{(r)}} \xi_{ii}(t) + \xi_{i|i+1}(t_d^{(r+1)} - 1)}.
\]

(13)

We can acquire \( T_u^{(r)} \) through counting the number of zero-tool force observations, and the variance of \( T_u^{(r)} \) in different samples of one client is relatively small. That is to say, in regular script of oriental signature, a pattern, that the duration in which individuals hold up their pen to draw a certain stroke is almost invariable, can be easily extracted. In this work, the mean of \( 1/T_u^{(r)} \) is used to replace \( a_{ii+1}^{(r)} \) of \( r \)-th stroke. Actually, when \( S_i \in S_d^{(r)} \), the expected value of the duration of each state can be calculated as follows,

\[
E(T_u^{(r)}(i)) = \frac{\sum_{i=1}^{\infty} d_{ii}^{(r)}(1 - a_u)}{1 - a_u} \cdot t = \frac{1}{1 - a_u}.
\]

(14)

This coincides with the result derived in (13).

Second, it is obvious that small-scale re-estimation procedure executed in sub-HMMs can be combined with that executed in full scale. The results of this two-stage learning algorithm are the same as the results of conventional learning algorithm. At the initial state of the forward algorithm and at the trap state of the backward algorithm within sub-HMM,

\[
\alpha_{i|i}^{(r)}(t) = 1,
\]

(15)

\[
\beta_{i|i+1}^{(r)}(t) = 1.
\]

(16)

If equations (15) and (16) were replaced with other constants, the results of sub-HMM re-estimation (except joint parameter) will remain the same because the constant will be canceled out both from the numerator and denominator as shown in above equations.

4. Comparison of Three Types of Model

According to Section 3, it is feasible to simplify the parameter re-estimation process by deducting the state transition matrix partially from the pen-up state duration. In this paper, we compare three different types of model as shown in Fig. 9. The first model contains only one pen-up state and one pen-down state in each sub-model, and is denoted as ‘up-and-down HMM’ (Fig. 9(a)). According to (14), using pen-up state duration and pen-down state duration, the whole state transition matrix can be computed directly in this model. It implies that the up-and-down HMM can exploit more simple parameter re-estimation scheme wherein the transition probability \( a_{ij} \) is simply calculated from the observed pen-up and pen-down duration. The second model is denoted as the ‘segmented HMM’ (Fig. 9(b)). In this model, every sub-HMM has one pen-up state and several pen-down states for each stroke. The number of pen-down states in the segmented HMM is defined according to the duration of the stroke. And its pen-up states are replaced with corresponding pen-down states in the left-to-right HMM.
Therefore, the up-and-down HMM can be regarded as a special version of the segmented HMM. The third model is denoted as the ‘left-to-right HMM’, which is a standard left-to-right HMM without any pen-up states.

This kind of segmentation may degrade the model precision, i.e., the performance for discrimination. It is obvious that the left-to-right HMM is the most discriminative model in most cases. The computational load necessary for the parameter re-estimation, however, shows great advantage of the up-and-down models (a) and (b). Moreover, in these models, the parameter re-estimation algorithm can find a good local minima thanks to its simple structure. On the other hand, it is unlikely that the parameter re-estimation algorithm finds a good local minima in the case of large-scale left-to-right HMM because of complex shape of the cost function in the parameter space.

5. Experiments and Comparative Study

The first objective of experiments is to prove that the computational load for the parameter re-estimation algorithm in the segmented HMM is much smaller than that for the left-to-right HMM (conventional model), which does not utilize durations between strokes to segment the whole model. The second objective is to prove that the segmented HMM shows better performance in distinguishing skilled forgeries from original samples nevertheless its simple structure. Table 2 shows the number of parameters of these HMMs.

### Table 2 Parameters of HMMs.

<table>
<thead>
<tr>
<th></th>
<th>left-to-right HMM</th>
<th>segmented HMM</th>
<th>up-and-down HMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of states</td>
<td>$4 \times N$</td>
<td>$4 \times N$</td>
<td>$2 \times N$</td>
</tr>
<tr>
<td>Number of output symbols</td>
<td>250</td>
<td>251 (250+symbol of zero-tool-force)</td>
<td>251</td>
</tr>
</tbody>
</table>

Table 3 Computational load for re-estimation.

<table>
<thead>
<tr>
<th></th>
<th>segmented HMM</th>
<th>left-to-right HMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_{24}$</td>
<td>150 sec</td>
<td>9153 sec</td>
</tr>
<tr>
<td>$D_{30}$</td>
<td>95 sec</td>
<td>3405 sec</td>
</tr>
<tr>
<td>$D_{20}$</td>
<td>158 sec</td>
<td>8614 sec</td>
</tr>
<tr>
<td>Average</td>
<td>131 sec</td>
<td>7057 sec</td>
</tr>
</tbody>
</table>

5.1 Evaluation of Computational Load

The computational load of the re-estimation procedure of the segmented HMM and left-to-right HMM are compared using three data sets. The results are shown in Table 3. The CPU of the PC environment used in this experiment is Pentium 4 2.8GHz, with 1GB Memory.

We can see that the structured learning (parameter re-estimation) based on the segmentation by the pen-up durations is very efficient to reduce the computational load. In the up-and-down model, since the state-transition matrix is acquired only by the durations of pen-up and pen-down, the computational load is even shorter than the segmented HMM.

5.2 Evaluation of Discriminative Performance

Generally speaking, the discriminative ability of the up-and-down HMM and the segmented HMM are worse than the left-to-right HMM due to their simple structure, i.e., the computational load and the discriminative ability are tradeoff. However, it is not strictly inverse-proportional as shown in this section.

Table 4 shows the result of another experiment which is run through the full scale of the data corpus. At first, when an arbitrary sample is claimed as a client’s identity, $D$ is used as on-questioned data sets: Second, $\hat{D}$ written by impostors are used as on-questioned data sets. We introduce below symbols to define different error types:

$N_A$: the number of original samples which are accepted;
$N_R$: the number of rejected samples which are not written by true client.
$N_D$: the number of samples in $D$.

It should be noticed that the threshold value to determine whether a sample is accepted or rejected is the logarithmetrical likelihood of certain chosen original sample, which can be denoted as $P(O_{\text{threshold}}|\lambda)$.

**AR**: Accepting Rate, e.g., AR of examinee-$i$ can be computed by

$$AR = \frac{N_A}{N_D};$$

(17)

**RR**: Rejection Rate, e.g., RR of examinee-$i$ on $D$ can be computed by

$$RR = \frac{N_R}{(N_D - N_A)}.$$  

(18)

The RR of examinee-$i$ on $\hat{D}$ can be computed by

$$RR = \frac{N_R}{N_D}.$$  

(19)

As shown in Table 4, although there is no significant difference between models in the case of using $D$ as on-questioned data sets, the discriminative performance of the segmented HMM is higher than that of the left-to-right HMM in the case of using $\hat{D}$. This is quite interesting characteristics of segmented HMM, and the reason of this can be considered as follows:

First of all, the features involved in the signature can be classified into the following three layers.

![Fig. 10 Two examples of signatures including imitations where the arrows indicate the directions of near strokes.](image-url)
Feature-1: common features. They can be easily imitated and be successfully imitated in most cases (common in both skilled forgery and original signature);

Feature-2: variable features. They can be imitated after training, however, they could be falsely percept in the imitation (common in skilled forgery, typical examples of these features are the order of strokes, the duration between strokes, tiny variations of the pen-tip glitches, etc.);

Feature-3: essential features. They can be hardly imitated, and only belong to the original signature (like dynamical features related to velocity and pressure profiles).

An example of Feature-1 is the overall structure (left-to-right or top-to-bottom) of characters. An example of Feature-2 is the order of strokes or the number of strokes.

Figure 10 shows several imitated signatures in which the same kanji ‘da’ are written at different orders. The left signature is pronounced as ‘terada’ in Japanese. The order of last 3 strokes of kanji ‘da’ in the original sample and the failed imitation is different. In the right signature (‘tazaki’), the number of strokes is different because the last stroke is separate from others in the failed imitation.

An example of Feature-3 is transitions between counterclockwise and clockwise movement [15], occurring frequently especially in trajectories at the ends of backslash-like or solidus-like strokes. It’s hard to be shown in figures but previous studies of handwriting movements known as ‘graphonomics’ have depicted these kinds of features related to kinematics, kinetics and dynamics of handwriting movements in detail and principle [16].

If it is assumed that the global optimum is always achieved in all models by Baum-Welch algorithm, then the left-to-right HMM must shows the best discriminative performance because it contains many features of the signing behavior. However, due to the complex structure of the left-to-right HMM, it often tends to be ‘overfitted’ by some unimportant features. On the other hand, this influence is comparatively small in the segmented HMM and the up-and-down HMM benefited from its unique structure with appropriate complexity. In particular, since the variable feature (feature-2) is dominant in the skilled forgeries, some skilled forged samples (unsuccessfully in imitating feature-2) are easily rejected by the segmented HMM. For example, in the case of unsuccessful forgery, the stroke order or the duration between strokes is different from that of the original user. These features can be successfully embedded in the segmented HMM with simple parameter re-estimate algorithm thanks to its segmented structure.

In the results on $\hat{D}$ in Table 4, the accepting rate is arbitrarily fixed at 55%. The lower the accepting rate is chosen, the higher the rejection rate becomes. In order to evaluate the performance on the detection tasks that involve a tradeoff between error types, a so-called Detection Error Tradeoff (DET) plot [17] is used in this experiment. The threshold value to determine AR/FAR of certain client is changed from the highest log-likelihood to the lowest, to explore the whole data set. The average results on $\{\hat{D}_{i1}, ..., \hat{D}_{iS}\}$ are plotted in Fig. 11.

FAR: False Accepting Rate, occurs when an impostor is accepted as an true client. In Fig. 10, FAR of examinee-i can be computed by

$$\text{FAR} = 1 - \frac{N_A}{N_D};$$

(20)

FRR: False Rejection Rate, takes place when a true client is rejected by the model. In Fig. 10, FRR of examinee-i on $\hat{D}$ can be computed by

$$\text{FRR} = 1 - \frac{N_R}{N_D};$$

(21)

The Equal Error Rate (EER) table is shown in Table 5. EER occurs when FAR is equal with FRR [18]. It can be concluded that the segmented HMM is better than other models even when the threshold value determining the accepting criteria and the rejecting criteria is changed in a wide range.

5.3 Sequential Verification Using Imposters’ Data Set

If not only the client’s data set but also the impostor’s data set is available for the model development, the following two-stage authentication can be considered.

At the first step, a model trained by the original client’s samples chosen from $D_i$ is used to evaluate the samples on questioned (both $D_i$ and $\hat{D}$). The threshold value (often the average logarithmic likelihood of all samples of $D_i$) is chosen to decide whether the sample is accepted or rejected. At the second step, only those samples that are accepted in the first step are evaluated by a model trained by the impostors’ data set. Another
threshold value in this stage is chosen to decide whether the sample is accepted or rejected.

Figure 12 shows these two steps separately. In each step, there are two data sets, samples from $D_i$ (left) and $\hat{D}_i$ (right). Each block represents one sample. The blocks in higher position represent samples possessing higher logarithmic likelihood.

Equations (22) and (23) indicate that the logarithmic likelihoods of the accepted samples are higher than that of the rejected samples in the first step and the second step, respectively.

$$P(O \in N_2 \cup N_3 | \lambda_1) > P(O \in N_1 \cup N_4 | \lambda_1) \quad (22)$$

$$P(O \in (N_6 \cup (N_3 \cap N_5)) | \lambda_2) > P(O \in ((N_2 \cap N_6) \cup N_5) | \lambda_2) \quad (23)$$

$\lambda_1$: model trained by the client’s data set; $\lambda_2$: model trained by the impostors’ data set; $N_1$: samples of the client which is rejected in the first stage; $N_2$: samples of the client which is accepted in the first stage; $N_3$: samples of the client which is accepted in the second stage; $N_4$: samples of the client which is rejected in the first stage; $N_5$: samples of the client which is rejected in the second stage.

Changing the two threshold values will change the proportion of gray blocks. The final results in terms with FAR/FRR are shown in Fig. 13. This sequential verification strategy based on multi-model combination can drastically reduce the FAR while it will increase FRR a little. In practice, $N_6$ is often small, so the decrease of RR is also small. The computation of FAR and FRR are the same as (20) and (21). It shows that the sequential strategy is efficient to extract different features between original samples and imitated samples. The segmented HMM, however, does not show significant differences between the stand-alone and the two-stage sequential cases. This also implies the effectiveness of the segmented HMM.

6. Conclusion

In this paper, a segmented HMM particularly useful for the verification of the oriental characters has been proposed and analyzed. The segmented HMM is composed of many sub-models each of which corresponds to an individual stroke. In addition, the ‘pen-up’ state which represents the movement between strokes is explicitly introduced. Then, the parameter update scheme for this special class of HMM has been derived exploiting the structure of the segmented HMM. Thanks to its segmented structure, the segmented HMM drastically reduces the computational load for the parameter re-estimation compared with the conventional model. In addition, the segmented HMM shows better discriminative performance, in particular for the data set which contains many skilled forgeries.

Further improvements on the performance can be achieved by increasing the number of the representative vectors. Adding more knowledge in the pre-processing and integrating these rules in the re-estimation process may also be helpful to promote the verification performance against skilled forgery. For continuous script of the oriental signature, the model can also be segmented according to cursive curvature or velocity profile, which will be exploited in the authors’ future work.

References


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