Online Signature Verification Based on the Hybrid HMM/ANN Model

Zhong-Hua Quan[1,2], *Kun-Hong Liu*[1,2]
1 Hefei Institute of Intelligent Machines, Chinese Academy of Science. Hefei, China
2 Department of Automation, University of Science and Technology of China. Hefei, China

Summary
This paper presents a new approach based on HMM/ANN hybrid for online signature verification. The hybrid HMM/ANN model is constructed by using a type of time delay Neural Networks as local probability estimators for an HMM, where a posterior probability of the model is worked out by the Viterbi algorithm, given an observation sequence. The proposed HMM/ANN hybrid has a strong discriminant ability i.e, from a local sense, the ANN can be regarded as an efficient classifier, and from a global sense, the posterior probability is consistent with that of a Bayes classifier. Finally, the experimental results show that this approach is promising and competing.

Keywords
Hidden Markov Model, Artificial Neural Networks, Online signature verification, Viterbi algorithm

1 Introduction

Signature verification is a biometrics method. Well known biometrics methods include voice and fingerprint identification, face recognition, retina scan, signature verification, etc. They are being increasingly adopted in the personal authentication and identification. Although attributes like iris, fingerprint, and retina do not change overtime, they require special and relatively expensive instrument to acquire the image. While the device for signature acquisition is much cheaper. Furthermore, the most important advantage of signature verification is that it has been accepted widely because of its long tradition in many commercial fields, such as e-business, access control, and so on.

Generally speaking, signature verification can be divided into two groups: online and offline. In early off-line cases, signatures are captured once the writing process is over, thus only static images are available. Recently, more researches are carried on with the focus on the online signature verification, where signatures are acquired during the writing process with a special instrument, such as digital tablet. In fact, there is always dynamic information available in the case of online signature verification, such as velocity, acceleration and pressure which is more difficult to imitate than the static shape of signature. So, online signature verification can usually achieve better performance than the offline instance [1].

For online signature verification, so far there have been many widely employed methods, for example, Artificial Neural Networks (ANN)[2,3], dynamic time warping (DTW)[4,5], the hidden Markov models (HMM)[6,7], etc. Generally, the DTW is regarded as a popular method, but it usually suffers from the following two drawbacks: i) Heavy computational load and ii) Warping forgeries [8]. The first one can make the DTW time-consuming while the second will make the verification more difficult. As an alternative, the HMM is of capability to perform stochastic matching for a model and a signature using a sequence of probability distributions of the features along the signature. Practically, the HMM has been employed in the filed of online signature verification for two decades and has achieved some success. However, the HMM also has its intrinsic limitations [9]. Among these limitations, its poor discriminative power is fatal which limits its application on the signature verification. Based on this consideration, in this paper we propose an HMM/ANN hybrid approach to online signature verification. To the best of our knowledge, it is the first time for this approach to be applied to the online signature verification. In the proposed model, the probability is estimated by an ANN so as to construct the HMM/ANN hybrid model, which leads to the following improvements: i) Higher model accuracy: ANN based estimate of probabilities does not require detailed assumptions about the form of the statistical distribution to be modeled, so as to guarantee the building of more accurate probability models; ii) Discrimination: ANN can easily accommodate discriminate training [20]; and iii) Context sensitive, etc.[10]. Further more, most of the HMM based approaches for online signature verification apply a type of left-right HMM directly, but scarcely consider the consistent between the handwriting process and the model. It is adapted in this paper by correspond each state with a class of strokes which go ahead with a determined direction, and consequently a type of ergodic model with explicit state duration is constructed for signatures.

This paper is organized as follows: Section 2 describes the signature data used in this paper and the preprocessing method, and the HMM/ANN hybrid approach is presented in Section 3. Section 4 presents the verification method and Section 5 gives the experimental results. At last, Section 6 concludes this paper with some conclusive remarks.

2 Signature Data and Preprocessing

2.1 Signature Data

The signature data used in this paper is from the MCYT-100 database, which is licensed for research and includes 100 subjects. For each subject, there are 25 genuine signatures and 25 skilled forgeries. Signatures are acquired using WACOM tablet (model INTUOS A6 USB) dynamically when the pen is moving on the tablet. This tablet provides the following discrete-time dynamic sequences: i) Position in x-axis, $x(t)$; ii) Position in y-axis, $y(t)$; iii) Pressure $p(t)$ applied by the pen; iv) Azimuth angle $\gamma(t)$ of the pen with respect to the tablet and v) altitude angle $\varphi(t)$ of the pen with respect to the tablet [18].

2.2 Preprocessing

There are many methods for preprocessing, most of which have been discussed in [12]. In this paper, each signature is normalized on the position and scale firstly, and then the extra time sequences such as curve velocity, tangent angle are computed.

Usually, the normalization is accomplished by the following equations:

$$x_1(t) = x(t) - \bar{x},\ y_1(t) = y(t) - \bar{y} \quad (1)$$

where $x(t)$ represents the x-coordinate sequence and $\bar{x}$ means the average of $x(t)$.

$$\begin{aligned} x_2(t) &= K \cdot x_1(t) \Big/ \left[\sum_t x_1(t)^2 + y_1(t)^2 \right]^{0.5} \\ y_2(t) &= K \cdot y_1(t) \Big/ \left[\sum_t x_1(t)^2 + y_1(t)^2 \right]^{0.5} \end{aligned} \quad (2)$$

K is a constant that equals 16 in this paper. Addition to the basic time functions acquired by the digital tablet, there are two other types of derived time sequences which can be computed by the following equations.

$$\begin{aligned} v_x(t) &= (x_2(t) - x_2(t-1)) \cdot 0.5 \\ &\quad + (x_2(t+1) - x_2(t-1)) \cdot 0.25 \\ v_y(t) &= (y_2(t) - y_2(t-1)) \cdot 0.5 \\ &\quad + (y_2(t+1) - y_2(t-1)) \cdot 0.25 \end{aligned} \quad (3)$$

computes the velocity on x and y direction respectively. Then

$$\theta(t) = \arctan(v_y(t) / v_x(t)) \quad (4)$$

gives the tangent angle of the trajectory on time t and

$$\theta(t) = \begin{cases} \theta(t), & x(t) \geq 0 \\ \theta(t) + \pi, & else \end{cases} \quad (5)$$

transforms $\theta(t)$ into $[-\frac{\pi}{2}, \frac{3\pi}{2}]$.

The line speed sequence can be computed as:

$$v(t) = \sqrt{v_x(t)^2 + v_y(t)^2} \quad (6)$$

In this paper, the line speed v, pressure $p(t)$, coordinates x and y are regarded as local dynamic features for comparison, they need no more preprocessing other than the normalization since the original points retain the difference in writing speed and writing rhythm[16]. However, the tangent angle sequence which is regarded as observed sequence for HMM/ANN model is re-sampled to T equidistant point along the signature curve, where T equals the point number before re-sampling.

3 The Hybrid HMM/ANN Model

3.1 HMM Description

A standard HMM can be defined by the following parameters[19]:

A set of N states $S = \{q_1, q_2, \cdots q_N\}$;

A state transition matrix $A = \{a_{ij}\}$ where a_{ij} is the transition probability from state q_i to state q_j:

$$a_{ij} = \Pr(q_j \ at \ t+1 \mid q_i \ at \ t), \quad 1 \le i, j \le N \quad (7)$$

Set of M discrete symbols $\{v_1, v_2, \cdots v_M\}$;

An observation probability matrix $B = \{b_{jk}\}$, where b_{jk} is the probability of generating symbol v_k from state q_j, and

The initial probability distribution for the states $\pi = \{\pi_j\}, j = 1, 2, \cdots N; \pi_j = \Pr(q_j \ at \ t = 1)$.

Such a model can be denoted as $\lambda = \{N, M, A, B, \pi\}$, or $\lambda = [A, B, \pi]$ sometimes. To adapt to the all of the kinds of applications, there are many types of HMMs proposed and employed nowadays, such as continuous HMM [19, 21], autoregressive HMM [22], HMM with inclusion of explicit state duration density [15], and so on. Now that there are so many types of HMMs, one must make several choices to design and apply a model for application.

The first one is the choosing of model structure that includes topology and number of states. To make such a choice, a preceding definition of the state is necessary. But unfortunately, most of the related works based on HMM just employed a left-right HMM for online signature verification and had no explicit consideration about the meaning of the states. There is only one can be used for reference that is proposed by Zou [13] where signatures are considered as composed of some stationary (or quasi- stationary) segments and the states are corresponded with these segments. However, there is a logical stigma for Zou's work that there are some segments with the same features observed but the states underlying are different, since the HMM is left-right topology. In this paper, a type of ergodic (or full connected) HMMs are employed, where the states are regarded as corresponding to a number of strokes which go ahead with a determinate direction. The rough direction of each state is displayed in the following figure.

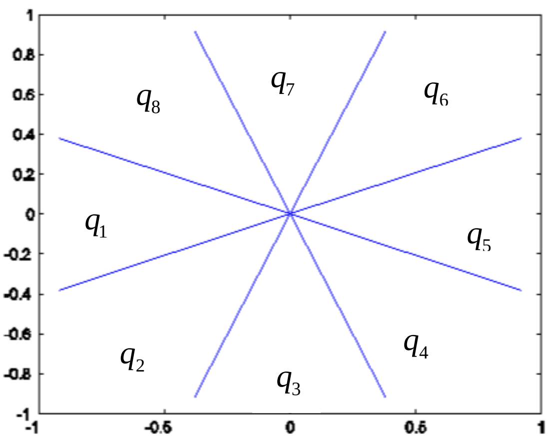

Figure 1. Bounds of direction for each state

As showed in Figure 1, there are 8 states defined in advance for all signatures, but for a special instance, e.g. signature displayed in Figure 2, there are not so many states. Moreover, the states should be hidden and not to be observed for HMM, so the exact states and number of states of a model would be determined according to the signatures which are modeled. The states defined in advance can be regarded as initialization for them.

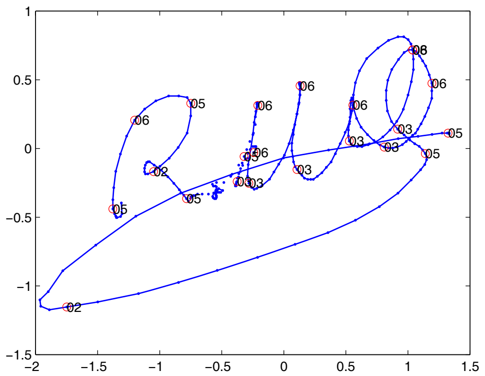

Figure 2. A sample recognized by the HMM/ANN hybrid model

The second choice is about the state duration. As can be observed in Figure 2, there are some segments where the state holds identical, and transitions between different states only take place at the ends of these segments. For such a configuration, the duration probability associated with state q_i , with self transition coefficient a_{ii} , is:

$$p_i(d) = (a_{ii})^{d-1}(1-a_{ii}) \qquad (8)$$

However, for the relatively small number of states that correspond to segments of a signature, this distribution of state duration is inappropriate [7]. To model the handwriting process more accurately we prefer to use the models with explicit bounded state duration [15], in which the self transition probabilities are set to zero, and a bound of state duration $[l_i, u_i]$ is assumed for each state. The duration probability for state q_i is assumed to be evenly distributed within the bound otherwise a very small value is assigned. Further more, as displayed in figure 2, the direction of signature trajectory changes gradually at the two ends of each state, so that, it is difficult to recognize the state correctly at the ends of segments based on the direction only. However, this puzzle can be readily solved if the state duration is considered.

The last one of choice is about the global score for an observed sequence given a model. Usually the maximum likelihood (ML) is computed as the global score, but the ML is not appropriate to classification, since a post probability is preferred according to the Byes classification. So the discriminant HMM is employed in this paper which will be discussed in the following subsection.

3.2 The Discriminant HMM

Discriminant HMM was firstly proposed by H. Bourlard[11]. For standard HMM, the goal is to find a model which maximizes the likelihood function $P(O \mid \lambda_i)$ for the observed sequence O. Whereas the goal of the Discriminant HMM is to find a model λ_i that maximizes a posterior probability $P(\lambda_i \mid O)$ for a given sequence O. The Viterbi formulation of the posterior probability can be written as

$$P(\lambda_i \mid O) = \max_{l_1 \cdots l_T} P(q_{l_1}^1, \cdots, q_{l_T}^1, \lambda_i \mid O) \qquad (9)$$

where $q_{l_t}^t \in S$ with $l_t \in [1, N]$, $t \in [1, T]$ represents states sequence. The right-hand side of Eq. (9) can be factorized into:

$$P(q_{l_1}^1, \cdots, q_{l_T}^T, \lambda_i \mid O) = P(q_{l_1}^1, \cdots, q_{l_T}^T \mid O) P(\lambda_i \mid q_{l_1}^1, \cdots, q_{l_T}^T, O) \qquad (10)$$

which suggests two separate steps for recognition. The first step is to find the best state sequence given the observation sequence O. The second step is to find the model λ_i from the state sequence without the explicit dependence on O, so that

$$P(\lambda_i \mid q_{l_1}^1, \cdots, q_{l_T}^T, O) = P(\lambda_i \mid q_{l_1}^1, \cdots, q_{l_T}^T) \qquad (11)$$

For ASR, the first factor of Eq.(10) represents acoustic decoding, and the second one represents phonological and lexical meanings, which is estimated from phonological knowledge of the vocabulary. However, for online signature verification, there is no distinct meaning for the two factors. Currently, most of the related works assume one model for each signer, and the probability in Eq.(11) is usually simplified by regarding it as a constant, e.g., 1. Such a strategy is adopted in this paper also.

The other factor of Eq.(10) is immediately related to the local probability, which can be factorized into:

$$P(q_{l_1}^1, \cdots, q_{l_T}^T \mid O) = p(q_{l_1}^1 \mid O)\, p(q_{l_2}^2 \mid q_{l_1}^1, O) \cdots p(q_{l_T}^T \mid q_{l_1}^1, \cdots, q_{l_{T-1}}^{T-1}, O) \qquad (12)$$

Now each factor of Eq.(12) can be simplified by relaxing the conditional constraint; especially, in the following the factors of Eq.(12) are assumed to only depend on the previous state and on a signal window with width 2p+1. In fact, the local probability is simplified as

$$p(q_{l_t}^t \mid q_{l_1}^1, \cdots, q_{l_{t-1}}^{t-1}, O) = p(q_{l_t}^t \mid q_{l_{t-1}}^{t-1}, O_{t-p}^{t+p}) \qquad (13)$$

The following dynamic programming (DP) recurrence holds:

$$P(q_l \mid O_1^t) = \max_k [P(q_k \mid O_1^{t-1})\, p(q_l \mid o_t, q_k)] \qquad (14)$$

where k runs over all possible states before states q_l, and $P(q_l \mid O_1^{t-1})$ denotes the cumulated best path probability of reaching state q_l with emitting the partial sequence O_1^{t-1}.

3.3 TDNN as Probability Estimator

Many researchers have shown that the outputs of ANNs used in classification mode can be interpreted as estimates of posteriori probabilities of the output classes conditioned on the input [10, 11, 12]. In this paper a time delay neural network (TDNN) is employ as the local poster probability estimator for the discriminant HMM so a type of hybrid HMM/ANN model is established. The scheme of the TDNN is displayed in Fig.3.

As showed Fig.3, there are two layers of perceptrons (hidden and output layers) computing the post probability of the input field which is constituted by several units, each unit representing an observed value o_t. Thus, if $2p+1$ is the width of the contextual window, there are $2p+1$ units in the input layer. Let the number of output units equal that of the states, N, and each of the units correspond to a state. During training, the output of the network is set according to the state associated with the center or “current” input in a particular left and right context. Moreover, the minimum squared error (MSE) criteria and the back-propagation algorithm is adopted for training the TDNN. Thus the outputs of the TDNN can be interpreted as estimates of the local posteriori probability of the states conditioned on a window of observations $p(q_l \mid O_{t-p}^{t+p})$ [11].

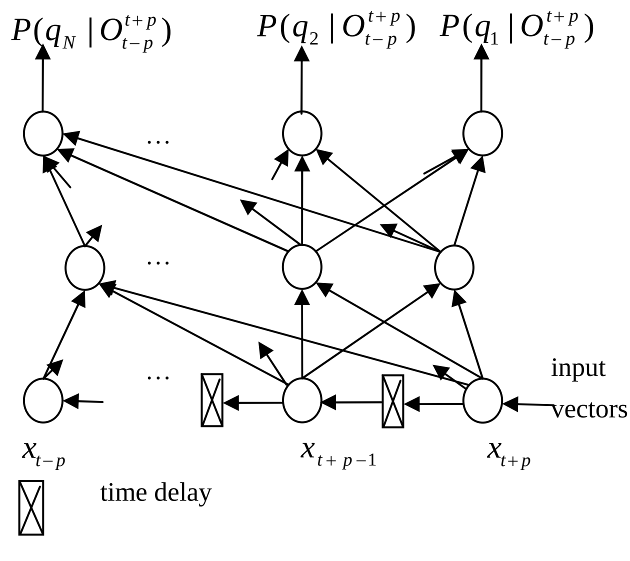

Figure 3. TDNN scheme for probability estimator

It should be noticed that the previous state has not been take into account in computing the local probability, since including the previous decision will result in a trouble of unbalanced training data for the networks. It is clear at a glance that the numbers of self transitions are much more than that of transitions from one state to another.

For simplification, it can be assumed that the posterior probability of states depend on the current state only, then the outputs of TDNN can be substituted into Eq.(14) directly.

$$P(q_l \mid O_1^t) = \max_k [P(q_k \mid O_1^{t-1}) \cdot p(q_{l_t}^t \mid o_t)] \quad (15)$$

These equations hold valid when the context of observations are taken into account. Then the Viterbi algorithm to find the best state sequence can be efficiently implemented by a dynamic programming procedure.

3.4 Initialization and Training of the Hybrid Model

In experiments, HMM and ANN are trained separately, and the training process of ANN is embedded in that of the HMM. The whole training procedure of the hybrid system is composed of iterations with the two steps:

- Recognition (segmentation): Each training signature is recognized by the hybrid HMM/ANN for the corresponding signer using the current parameters.
- Parameter reestimate: The HMM and ANN are trained according to the above segmentation, where the output of the ANN is assumed to 1 for the correct state, and 0 otherwise.

This iteration stops when the difference between the global posterior probability of the current iteration and that of the previous reaches a given threshold, e.g., 10^{-6}.

Up to now, all of the discussion about HMM scheme in the above sections have not taken the state duration into account. While the bounded state duration is included, it can be found that some identical computations will have to be performed repeatedly if the conventional algorithm is adopted in implementing the Viterbi algorithm to recognize the states sequence (or to segment signatures). A strategy to circumvent such a problem is to treat the state duration index d as the third independent variable, and to perform the dynamic programming searching on a three-dimensional (t,i,d) space [15]. Therefore, let

$$\phi_t(j,d) = \log(p(q_j, d_{q_j} = d \mid O^t)) \quad (16)$$

represents the maximum cumulated posterior probability in logarithm scale of progressing to state q_i along the best state path and producing observations o_1 through o_{t-d}, and then entering state q_j and producing the observations o_{t-d+1} through o_t at this state, i.e.,

$$\phi_t(j,d) = \max_i \{\delta_{t-d}(i) + \sum_{\tau=0}^{d-1} \log(p(q_j \mid o_{t-d}))\} \quad (17)$$

all of the elements of $\phi_t(j,d)$ are initialized to $-\infty$, except that

$$\phi_{l_j}(j,l_j) = \sum_{t=1}^{l_j} \log(p(q_j \mid o_t)) \quad (18)$$

where l_j is the low boundary of duration for state q_j. And

$$\delta_t(j) = \max_d \{\phi_t(j,d)\} \quad (19)$$

Finally, the global posterior probability score can be obtained according to the equation:

$$\delta_T = \max_j \{\max_d \{\phi_T(j,d)\}\} \quad (20)$$

The best state sequence can be retrieved from the matrix which records the dynamic programming path:

$$\varphi_j(t) = [\arg\max_i \{\delta_{t-d}(i) + \sum_{\tau=0}^{d-1} \log(p(q_j \mid o_{t-d}))\}, \arg\max_d \{\phi_t(j,d)\}] \quad (21)$$

where each element of the matrix records the best path including the previous state and the duration of the previous state.

The initialization of the hybrid HMM/ANN is accomplished by the following operations. At first, all of the reference signatures are segmented by the special points [13], then the signature which includes the maximum number of segments is selected to initialized the hybrid HMM/ANN model. The segments are labeled according to the direction of each segment as displayed in Figure 1 and Figure 2. Then, the number of the states is set to equal the number of labels, for example, the state number for the subject displayed in Figure 2 is set as 4. At last, the TDNN is trained according to the labeled signature.

4 Signature Verification Based on the Hybrid HMM /ANN and Local Comparison

4.1 HMM/ANN Based verification

Training of the hybrid HMM/ANN model is accomplished by using the maximum a posterior probability (MAP) criterion and applying the Viterbi algorithm. Based on the trained model λ_i, the global posterior probability $P(\lambda_i \mid O_j)$ for the training signatures can be worked out, and the mean and the variance of which can be computed upon the referent signatures.

$$\mu_{map} = \sum_j P(\lambda_i \mid O_j) \Big/ N \qquad (22)$$

$$\sigma_{map} = \left(\Sigma_j (P(\lambda_i \mid O_j) - \mu_{map})^2 \Big/ N \right)^{0.5} \qquad (23)$$

where O_j represents the observed sequence of the jth signature, and the N equals the total number of training signatures.

During verification, each signature claimed for belonging to a signer would be recognized by the corresponding model, thus the global MAP and the segmentation of the signature can be worked out by the Viterbi algorithm. Assuming that the distribution of the genuine MAP is Gaussian distributions, the score of similarity between the signature and the model can be defined as

$$S_{map} = (\log P(\lambda_i \mid O) - \mu_{map}) \Big/ \sigma_{map} \qquad (24)$$

If S_{map} is less than a threshold, we can reject it directly. Otherwise, it should be verified further by the local comparison.

4.2 Local Comparison Based Verification

Local time functions (such as $v(t)$, $x(t)$, $y(t)$ and $p(t)$) of a test signature and a template are compared, addition to the HMM/ANN based verification. In this paper, all the referent signatures are saved and one of which is selected as template. Further more, the local functions are compared between the aligned segments which worked by the HMM/ANN model.

While a signature is recognized by the HMM/ANN model, not only a MAP is obtained, a segmentation of the signature which is characterized by the label sequence of states is worked out also. However, as variation of handwriting, it is impossible that the segments of different signatures are identical. And the HMM employed are not left-right topology, segments are not aligned instinctively. Thus a DP approach is employed to match the segments and local comparison is performed consequently [14].

The distances of the local time functions are produced by the local comparison procedure, e.g., for the velocity sequence, the distance can be computed by:

$$D_v = \sum_t v_{ref}(t) - v'_{test}(t) \Big/ T \qquad (25)$$

where v_{ref} represents the line speed of the template, v'_{test} represents the speed of the test signature after time warping and T equals the total length of the v_{ref}. In this paper, the $v(t)$, $x(t)$, $y(t)$ and

$p(t)$ are used for local comparison, so the measure of similarity of the comparison can be defined as

$$S_{local} = -\sum_{u \in [v,x,y,p]} D_u - \mu_{D_u} / \sigma_{D_u} \quad (26)$$

where the μ and the σ are computed from the training data as in Section 4.1.

At last, the same strategy as that in Section 4.1 is adopted to reject the test signature as a forgery or accept it as a genuine one according to the similarity.

4.3 Decision Fusion

The HMM/ANN based verification and the local comparison based verification are combined by sum the similarity score of them.

$$S_{total} = S_{map} + S_{local} \quad (27)$$

And the signature is rejected as a forgery if S_{total} is greater than a threshold, otherwise it is accepted as a genuine one.

5 Experimental Results

The MCYT-100 signature data used in this paper includes 100 signers, where there are 25 genuine signatures and 25 forgeries for each signer. For each signer, 10 genuine signatures are randomly selected as training samples and with the remained as test samples.

For online signature verification, two important indicators are usually employed to evaluate the performance of a verification system: false accept rate (FAR) and false reject rate (FRR). The first represents the error rate of accepting forgeries as genuine signatures, and the later represents the error rate of rejecting genuine signatures.

The FAR and the FRR can be represented as a function of the decision threshold. The trade-off-curve of the FAR and the FRR for the proposed approach is shown in Figure 4.

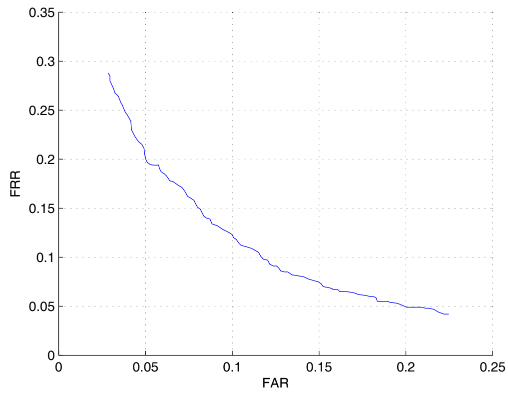

Figure 4: The trade-off curve for the FAR/ARR

From the Figure 4, it can be found that the EER (where FAR equals FRR) of the approach presented in this paper is about 0.12. Due to lacking of training samples, the statistical parameters for the similarity scores are not accurate so that a unified threshold is adopted for every subject. Nevertheless using a unified threshold is not a good choice It can be validated by such a deed that the EER of the HMM/ANN based approach would decreased as low as 0.04 if a personalized threshold is adopted.

6 Conclusions

This paper proposed a heuristic approach for online signature verification based on HMM/ANN hybrid model where an ANN is employed to recognize the states underlying the observations. To the best of our knowledge, it is the first time for this model to be applied to online signature verification. The most important advantage of employing the ANN as probability estimators is that the contextual information is taken into account. Further more, a distinct characteristic for the presented approach compared with the others methods based on the HMM is that an ergodic model with bounded states duration is adopted, so this model can describe the handwriting process more accurately. At last, experimental results validate the presented method is promising and competing.

The possible improvement on this work mainly lies in two aspects: 1) The combination of this approach with other methods such as comparison of the global features; 2) Fusion of the decision. There are several verifiers combined in this paper, and the decision making based on the combined verification is straightforward which need more investigation for improvement. And these will be our future works.

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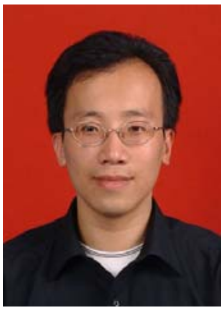
Zhong-Hua Quan received the Bachelor and Master degree of military in HeFei Artillery Academy of the PLA, in 1994 and 2003, respectively. From Sept. 2003 on, in pursuit for Doctor degree in Pattern Recognition & Intelligent System in USTC.



Kun-Hong Liu received the B.S. and M.S. degree in the School of Physics OptoElectronics Technology of Fujian Normal University in June 1999 and June 2004, respectively. From Sept. 2005 on, in pursuit for Doctor's degree in Pattern Recognition & Intelligent System in University of Science & Technology of China, Hefei