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A Hybrid HMM/ANN Based Approach for Online Signature Verification

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Abstract: **This paper presents a new approach based on HMM/ANN hybrid for online signature verification. A group of ANNs are used as local probability estimators for an HMM. The Viterbi algorithm is employed to work out the global posterior probability of a model. 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

I. INTRODUCTION

Biometrics authentication, including voice and fingerprint identification, face recognition, retina scan, and signature verification, is a very active research area these years, stirred by the need for positive identification of personal in law enforcement, information security operations, and commercial transactions. Among these methods, signature verification is particularly important because it is one of the oldest means of identity validation and has been accepted widely while other methods unavoidably have the stigma of being associated with criminal investigation.

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, in which case 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, Neural Network [2,3], the Euclidean Distance Classifiers, 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. Among these limitations, its poor discriminative power [9] 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 a group of ANNs 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 acoustic models; ii) Discrimination: ANNs can easily accommodate discriminant training; and iii) Context sensitive, etc.[10].

For most of the works related to the HMM/ANN hybrid, the probability estimator is an ANN and each output is corresponding to a state of the HMM [9, 10]. Since the HMM is usually left-right topology regardless its application on the automatic speech recognition (ASR) or signature verification, it is greatly possible that the ANN would include many redundant connections. Instead of applying a single ANN, we use a group of ANNs, each of which is corresponding to a state and has only two outputs. Owing to this modification, the number of the ANNs' parameters decreases greatly. At the same time, the recognition of states becomes much simpler for each ANN.

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

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Section 3. Section 4 gives the experimental results and Section 5 concludes this paper with some conclusive remarks.

II. SIGNATURE DATA AND PREPROCESSING

A. Signature Data

Signatures used in this paper were all acquired from our laboratory, which belong to 22 students. Every student was asked to provide 20 genuine signatures and 20 forgeries of another one's, so there are totally 880 signatures, where the 20 genuine signatures were collected at three different times. Before the forgeries were captured, the imitators can watch the genuine signatures (including dynamics) and make some practices. Signatures were acquired using a WACOM FAVO430B pen tablet. This tablet can provide 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) Altitude angle t of the pen with respect to the tablet.

B. Preprocessing

There are many methods for preprocessing; most of them have been discussed in [12]. In this paper, each signature is normalized on the position and scale firstly, then it is re-sampled to N equidistant point along the signature curve, where N equals the point number before re-sampling.

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 $x(t)$.

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

K is a constant that equals *16* in this paper.

C. Feature Extraction

As most of the related works based on HMM, this paper computes the tangent angles on each point along the signature trajectory by using the following equation:

$$\theta(t) = \arctan\left(\frac{\Delta y}{\Delta x}\right) \quad (3)$$

And the angle sequences are regarded as observations for HMM.

III. HMM/ANN HYBRID BASED SIGNATURE VERIFICATION

A. 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 $P(X|W_i)$ for the observed sequence X. Whereas the goal of the Discriminant HMM is to find a model W_i that maximizes a posterior probability $P(W_i|X)$ for a given sequence X. The Viterbi formulation of the posterior probability can be written as

$$P(W_i \mid X) = \max_{l_1 \ldots l_T} P(q_{l_1}^1, \ldots, q_{l_T}^T, W_i \mid X) \quad (4)$$

where $q_{l_t}^t \in S$ with $l_t \in [1,K]$, $t \in [1,T]$ represents states sequence. The right-hand side of (4) can be factorized into

$$P(q_{l_1}^1, \ldots, q_{l_T}^T, W_i \mid X) = P(q_{l_1}^1, \ldots, q_{l_T}^T \mid X) P(W_i \mid q_{l_1}^1, \ldots, q_{l_T}^T, X) \quad (5)$$

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

$$P(W_i \mid q_{l_1}^1, \ldots, q_{l_T}^T, X) = P(W_i \mid q_{l_1}^1, \ldots, q_{l_T}^T) \quad (6)$$

For ASR, the first factor of (5) 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 (6) is usually simplified by regarding it as a constant, e.g., 1. This simplification means that the second step is nearly ignored at all. So this paper assumes several models for each signer, and the states of the model are defined for each model with setting the probability of (6) as 1. The states are defined for each model, but not for each subject, since there are not enough referent signatures (no more than 10 for each signer usually). Consequently there are not enough training data for (6) if the states are defined within the training data.

The other factor of (5) is immediately related to the local probability, which can be factorized into:

$$P(q_{l_1}^1, \ldots, q_{l_T}^T \mid X) = p(q_{l_1}^1 \mid X) p(q_{l_2}^2 \mid q_{l_1}^1, X) \ldots p(q_{l_T}^T \mid q_{l_1}^1, \ldots, q_{l_{T-1}}^{T-1}, X) \quad (7)$$

Now each factor of (7) can be simplified by relaxing the conditional constraint; especially, in the following the factors of (7) 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

$$p(q_{l_t}^t \mid q_{l_1}^1, \ldots, q_{l_{t-1}}^{t-1}, X) = p(q_{l_t}^t \mid q_{l_{t-1}}^{t-1}, X_{t-p}^{t+p}) \quad (8)$$

The following dynamic programming recurrence holds:

$$P(q_l \mid X_1^n) = \max_k [P(q_k \mid X_1^n) p(q_l \mid x_n, q_k)] \quad (9)$$

Where k runs over all possible states before states q_l, and $P(q_l \mid X_1^n)$ denotes the cumulated best path probability of reaching state q_l with emitting the partial sequence X_1^t.

B. ANN 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]. ANNs are employed to estimate local probability of (8), which can be illustrated in Figure 1.

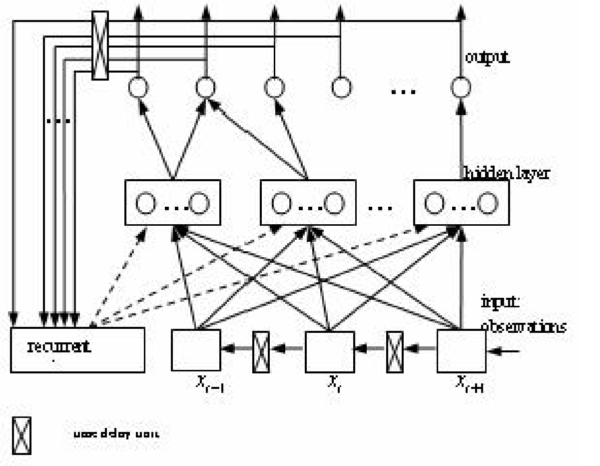

Figure 1: The scheme of ANN used as probability estimator

In this model, the hidden layers are divided into N groups, where N equals the number of the HMM states. For each group of hidden units, there are only two output units connected with them. And each time there is only one hidden unit group activated by the recurrent signal, which represents the previous state. So this model is equivalent to a group of ANNs, and in the group, each ANN includes only two output units and the corresponding inputs are only the observation vectors.

C. *Initialization and Training*

In experiments, HMM and ANN are trained alternately, 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:

i) Recognition (training of the HMM): Each training signature is recognized by the HMMs for the corresponding signer according to the current input parameters with the ANNs as local probability estimators.

ii) Parameter re-estimate (training of the ANN): ANNs are trained according to the above segmentation, then the output of the correct state is assumed to 1, 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.

The initialization of the hybrid HMM/ANN is accomplished according to a signature segmented by an external method such as "segmenting signatures by the special points" [13].

As mentioned in Sec. 3.1, there are more than one models for each signer, so more than one training signatures (usually say 3) are selected for the initialization of the hybrid. And for the same reason, the recognition process at the first step of iterations includes two levels, i.e., the model level and the state level. Each signature is recognized by the models alternatively, and then the model and the corresponding segmentation with the highest global posterior probability are chosen. Within the iterations, the models which have not been selected in the current iteration will be canceled. Therefore the number of models can be determined heuristically.

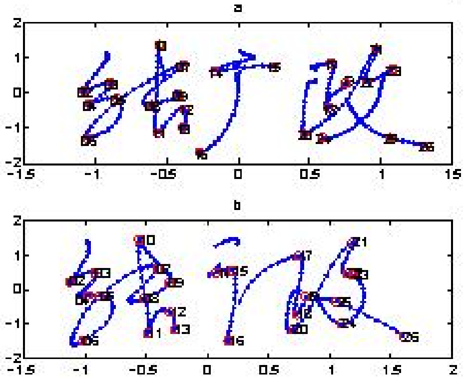

Figure 2: An example for the initialization of the HMM/ANN hybrid

The two samples in Figure 2 are all genuine signatures from a signer. The sample in a) is segmented by its special points (including the start and end of strokes, extrama) and the HMM/ANN is initialized according to this sample. The sample in b) is another and it is segmented by the trained HMM/ANN model. It can be seen that although the shape of the two samples are much different from each other, the segmentation by the trained HMM/ANN is consistent with that of initialization.

D. *Signature Verification*

When a signature claimed for belonging to a signer is submitted to the system, it is recognized with the corresponding models. That is, the model with the highest score of a posterior probability is selected. If the highest score is greater than a threshold, the input signature is regarded as a genuine signature; otherwise it is rejected as a forgery. The threshold is set as $\xi = \mu - w\delta$, where μ is the mean of the score of the training signatures, δ is the standard deviation, and w is a weight coefficient.

IV. EXPERIMENTAL RESULTS

The signature data used in this paper includes 22 signers, where there are 20 genuine signatures and 20 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 coefficient w. The trade-off-curve of the FAR and the FRR for the proposed approach is shown in Figure 3.

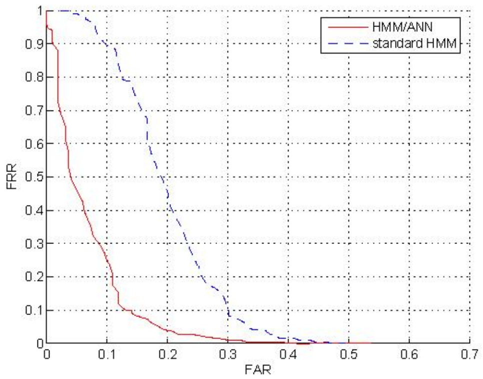

Figure 3: The trade-off curve for the FAR/ARR

For comparison, a standard HMM based verification is implemented in this paper, where the probability is predicted by a Gaussian model, the state number is determined according to the number of special points heuristically [14], and the models are trained by Viterbi algorithm also. The dashed curve in Figure 3 represents the trade-off curve of the standard HMM based approach, and the solid line represents the curve of the proposed method. It can be found that the performance of the HMM/ANN based approach is much better than that of the standard HMM based, where the equal error rate (EER) of the standard HMM based approach is about 0.22 and that of our approach is about 0.12. It should be noticed that these results are worked out on a uniform weight coefficient *w* for all signers, and if a personalized coefficient is employed then the EER of the HMM/ANN based approach can be further decreased as low as 0.02.

V. Conclusions

This paper proposed a heuristic approach for online signature verification based on HMM/ANN hybrid model. And to the best of our knowledge, it is the first time for this model to be applied to online signature verification. Different from the other works also based on HMM/ANN, a group of ANNs are employed as probability estimators for an HMM so as to achieve an efficient prediction system. With this hybrid model, some promising experimental results are achieved.

The possible improvement on this work mainly lies in two aspects: 1)The combination of this approach with other methods; 2) The employment of others time sequences such as coordinates, pressure, which can also be used as informative features along with the angle sequence. And these will be our future work directions.

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