Handwritten Nushu Character Recognition Based on Hidden Markov Model

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Abstract—**This paper proposes a statistical-structural character learning algorithm based on hidden Markov model for handwritten Nushu character recognition. The stroke relationships of a Nushu character reflect its structure, which can be statistically represented by the hidden markov model. Based on the prior knowledge of character structures, we design an adaptive statistical-structural character learning algorithm that accounts for the most important stroke relationships, which aims to improve the recognition rate by adapting selecting correct character to the current handwritten character condition. We penalize the structurally mismatched stroke relationships using the prior clique potentials and derive the likelihood clique potentials from Gaussian mixture models. Theoretic analysis proves the convergence of the proposed algorithm. The experimental results show that the proposed method successfully detected and reflected the stroke relationships that seemed intuitively important. And the overall recognition rate is 93.7 percent, which confirms the effectiveness of the proposed methods.**

Index Terms—**character recognition, statistical-structural learning algorithm, Nushu character, hidden Markov models**

I. Introduction

Nushu (female scripts) was derived from square Chinese characters, and were variations of the later [1]. Nushu was popular in the valley of the Xiaoshui River in Jiangyong County of Hunan Province, and is still used by some senile women nowadays. Researches show that Nushu had more than 1,000 characters, among which 80% were created based on Chinese characters, and only 20% were coinages with unknown origin. Its characters took the shape of rhombus, and were higher on the right part and lower on the left part. They are slender and beautiful, look like Jiaguwen (scripts on tortoise shells and animal bones) at first glance, and retain much familiar trace of Chinese characters [2]. Nushu is composed of very strange characters, which feature strange shapes, a strange way of marking, strange social functions and history. Different from Chinese ideographic characters, Nushu characters are ideographic characters that have a single syllable and indicate their sound. Nushu was the tool of cultural communication for local countryside women, especially middle- and old-aged women. It played its unique social function, and was basically used to create women's works and record women's songs. Nushu works normally were written on delicately made manuscripts, fans, handkerchiefs and pieces of paper. Nushu has academic value from the perspectives of philology, linguistics, sociology, ethnography, and history, etc. Therefore, it is reputed as a wonderful discovery and a wonder in the history of Chinese characters by scholars home and abroad.

A. Related Work

Since more than 80% Nushu characters were created based on Chinese characters, the original Nushu material was handwritten. Therefore, the research scheme of handwritten Nushu character recognition can adopt the scheme of Chinese characters recognition, which is the most common way to. The Chinese character structure is hierarchical: many straight-line strokes constitute independent radicals, which in turn constitute characters [3, 4]. The statistical recognizer extracts the information of the character image into a feature vector by a feature extraction process. The feature vector does not represent the pen-trajectories directly. Generally, the recognizer represents and analyzes the character image by one of the two kinds of method, the statistical method and the structural method [5, 6]. However, it represents the property of the character image, reflecting the character structure indirectly. With such a representation, the statistical recognizer models and analyzes the character using various kinds of statistical methodologies. Wu et al. [7] projected a two–dimensional (2-D) character image along x and y directions. The key features for coarse classification are the Fourier coefficients of the projected profiles. Tseng et al. [8] selected contour direction and crossing count to be the features of their coarse classification method. Chang and Wang [9], inspired by Dr. W. Yun-Wu, used the peripheral shape coding technique to preclassify handwritten Chinese characters. They used ten categories of stroke patterns to code the four corners of a character. However, such systems focused only on the relationship between near or connected stroke pairs. As the result, they were difficult to represent the relationship between the strokes far from each other. Moreover, they were not effective to represent the relationship between more than two strokes because the interstroke feature is difficult to define for more than

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two strokes. Also, they had a problem in combining the stroke matching scores with the matching scores of the stroke relationships. They computed the overall matching score by simply accumulating or multiplying all stroke matching scores and matching scores of the stroke relationships. As the result, the information about the stroke relationship was duplicated because the matching scores of individual strokes also reflect some information about the stroke relationships.

Structure approach has high tolerance to non-structure distortions, such as noise and writing style variations. Since Chinese characters are composed of strokes formed by line segments, most approaches use the geometrical and topological features of strokes as the recognition basis. In order to represent finer information, Liu et al. and Zhang and Xia categorized the strokes into several types, such as horizontal, vertical, slash, back-slash, dot, tick, and hook [10], [11]. The character model was composed of a set of model strokes, each of which belongs to one of the predefined types. By assigning different attributes to each of the stroke types, they represented the properties of the stroke more accurately. However, the performance of such systems heavily depends on the developer's knowledge because the character models were not systematically trained but manually designed. Kim and Kim represented the stroke by the distributions of its position, slope, and length [12]. Such a statistical modeling is more systematic than the previous methods. Although the character structure was manually specified as was in the previous methods, the position and the shape of each stroke were statistically modeled. Their distributions were estimated from training samples. The statistical stroke modeling is desirable to tolerate writing variation and more robust than the heuristic-based method. Character recognition proceeds by finding the best structural match between the input strokes and the stroke models. Compared with the statistical method, the structural method extracts feature points and line segments from character images and represents their spatial relationships by a relational graph, in which the node denotes the feature point or line segment, and the edge between two nodes denotes their relationships (for example, constraint graph model [10], attributed relational graph [11], and hierarchical random graph [12]). Despite the excellent descriptive ability for fine details of character structures, there are two major problems yet to be solved. The first is the stroke extraction problem—because the strokes are often ambiguous and degraded how to extract the stable ones for modeling their spatial relationships. This problem becomes much more difficult if the thinning preprocessing techniques cause junction-distortions in character skeletons [13]. The second problem lies in that the structural method usually depends heavily on developer's heuristic knowledge [14, 15], leading to neither the rigorous matching algorithm nor the automatic leaning scheme from training samples.

B. Motivation

Chinese character, as well as Nushu character recognition is admitted as a very difficult problem in character recognition due to (1) very large character set, (2) high complexity of Chinese characters and (3) many similar character patterns. Since both statistical scheme and structural scheme have their merit and demerit. Therefore, a hybrid statistical-structural method is necessary for modeling character structures and recognizes characters. Our approach can be considered to be a convergence between these two threads of research. However, it improves the performance on both sides in term of overall recognition rate.

In this paper, we concentrate on the handwritten Nushu character recognition problem where few research works have done. A statistical-structural character learning algorithm based on hidden Markov model is proposed to recognize the handwritten Nushu characters. The stroke relationships of a Nushu character reflect its structure, which can be statistically represented by the hidden markov model. Based on the prior knowledge of character structures, we design an adaptive statistical-structural character learning algorithm that accounts for the most important stroke relationships, which aims to improve the recognition rate by adapting selecting correct character to the current handwritten Nushu character condition. We penalize the structurally mismatched stroke relationships using the prior clique potentials and derive the likelihood clique potentials from Gaussian mixture models.

The rest paper is organized as follows. In section II, the proposed Nushu characters recognition scheme is proposed in detail. Detailed experimental results are shown in section III. Finally, the conclusion and future work are given in section IV.

II. Proposed Algorithm

A. Statistical-Structural Character Modeling

In the proposed modeling method, a character is represented by a set of model strokes. The structure of the model strokes is manually designed. As shown in Fig. 1, the model stroke is composed of a poly-line connecting K feature points. In Handwritten process, a model stroke is instantiated into various shapes of input strokes and, therefore, the feature points are instantiated into various pixels of the input strokes. In order to model such a variation, the feature point is represented by a distribution of the pixels. Because each pixel is identified by its position and direction, the feature point is represented by their distribution. Additionally, the direction at the feature point was also modeled to reflect more information.

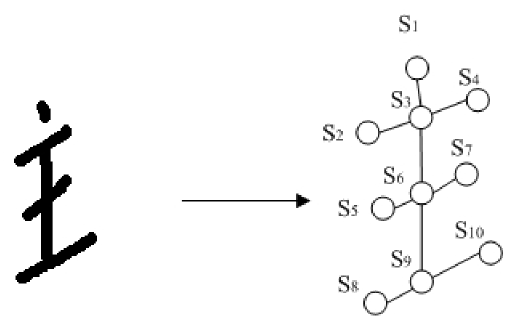

Figure 1. Statistical stroke model of Nushu character.

Denote the set of links of Nushu character Q, and let $|Q|$ denote the cardinality of the set Q. We define the stroke crosspoint as T_{event}. We refer to N consecutive crosspoints as n -graph. The special case of single crosspoints is referred to as unigraph. Two consecutive crosspoints are referred to as digraph in the literatures, and trigraph means three consecutive crosspoints, etc. Given a sequence of consecutive crosspoints $S=\{s_1,s_2,\cdots,s_m\}$, where m is the number of crosspoint sequence, we have n -graph with the size of $m-n+1$. We define the duration of n -graph $GD=\{d_1,d_2,\cdots,d_k \mid k\in N, k\in[1,m-n+1]\}$ as follows:

$$d_k = T_{event}^{s_{n+k-1}} - T_{event}^{s_k}. \tag{1}$$

The durations of n -graph are used as sequence features for further analysis in our proposed model. We make a natural assumption that the n -graph, with duration y, $P(y|q)$, forms a Gaussian distribution, such that:

$$P(y|q)=\frac{1}{\sqrt{2\pi}\sigma_q}e^{-\frac{(y-\mu_q)^2}{2\sigma_q^2}}, \tag{2}$$

where μ_q is the mean value of the duration y for n -graph , and σ_q is the standard deviation. Since behavioral characteristics of the individuals could be influenced by many reasons, the statistical analysis method used by previous work can be viewed as the same probability was given to the valid attempts of digraph latencies and durations within the standard deviations of the mean durations. By using Gaussian modeling, we can give higher probability to the n -graph durations of test samples that is more close to the n -graph mean durations of reference samples, and lower probability to the n -graph duration that is far from the mean of the n -graph for the reason that the individuals could be temporarily out of regular typing behavior, and we can take the irregular typing behavior without discarding the possibility that the set of n -graph durations provided by the corresponding individuals.

With the limitation that we are unable to collect all the typing crosspoints of the individual and calculate the exact parameters of the means and variances for each distinct combination of n -graph durations. We have to deduce $\{(\widehat{\mu_q},\widehat{\sigma_q})\}$ of n -graph durations, give a crosspoint sequence S, by the method of maximum likelihood estimation of the parameters. Fortunately, the maximum likelihood estimation of the parameters for Gaussian distribution can compute the sample mean and sample variance as follows.

$$\widehat{\mu_q}=\frac{\sum_{i=1}^{k} d_i(q)}{k}, \tag{3}$$

$$\widehat{\sigma_q}^2=\frac{\sum_{i=1}^{k}\left[d_i(q)-\widehat{\mu_q}\right]^2}{k-1}, \tag{4}$$

where is the number of n -graph q appeared in S.

In order to mine Nushu structural character, the proposed HMM models sequential data, such as the sequence of the crosspoints of Nushu characters and handwritten character information that we take into consideration. The HMM we use to model the structural character information of crosspoint and structural character sequence. HMMs are a modeling technique derived from Markov models, which are stochastic processes whose output is a sequence of states corresponding to some physical event. HMMs have the observation as a probabilistic function of the states, i.e. the resulting model is a doubly embedded stochastic process with an underlyings to chastic that is not observable (it is hidden), but can only be observed through another set of stochastic processes that produce these queue of observations.

Considering that it is a statistical graphical model, where each circle is a random variable. Unshaded circles q_t represent are unknown (hidden) state variables we wish to infer, and shaded circles y_t are observed state variables, where t is a specific point in time. A is a state transition matrix holding the probabilities of transitioning from q_t^i to q_{t+1}^j, where q^i means the i -th state. So we have:

$$P(q_{t+1}^j=1 \mid q_t^i=1)=A_{ij}. \tag{5}$$

η is a state emission matrix holding the output probability $P(y_t \mid q_t^i=1)$ of i -th state. π_i is the initial state probability of i -th state. A compact notation $\lambda=(A,\eta,\pi)$ is used to indicate the complete parameter set of the model.

In our setting, given a crosspoint sequence S, n -graph G, $[n+1]$-graph G', such that:

$$S=\{s_1,s_2,\cdots,s_m\}, m\in N. \tag{6}$$

$$G=\{g_1,g_2,\cdots,g_{m-n+1}\} \tag{7}$$

$$G'=\{g_1^{'},g_2^{'},\cdots,g_{m-n}^{'}\} \tag{8}$$

The state transition matrix A is the probability of the frequency that the [$n+1$]-graph appeared in the as follows:

$$A_{g_t,g_{t+1}} = |g_t^{'}|/(m-n). \tag{9}$$

The state emission matrix η here is defined as the Gaussian distribution probability of the n -graph $G=\{g_1,g_2,\cdots,g_{m-n+1}\}$ with duration $GD=\{d_1(g_1),d_2(g_2),\cdots,d_{m-n+1}(g_{m-n+1})\}$ as follow:

$$\eta_g(d(g'))=\begin{cases} P(d(g')\,|\,g)=\dfrac{1}{\sqrt{2\pi}\sigma_g}e^{-\frac{(d(g')-\mu_g)^2}{2\sigma_g^2}}, g=g' \\ 0, otherwise \end{cases} \tag{10}$$

There are three basic problems to solve with the HMM $\lambda=(A,\eta,\pi)$:

1). Given a model parameters $\lambda=(A,\eta,\pi)$ and observation output sequence $O=O_1O_2\cdots O_t$, compute the probability $P(O\,|\,\lambda)$ of the observation output sequence.

2) Given a model parameters $\lambda=(A,\eta,\pi)$ and observation output sequence $O=O_1O_2\cdots O_t$, find the most probable state sequence $Q=Q_1Q_2\cdots Q_t$ which could have generated the observation output sequence.

3) Given an observation output sequence $O=O_1O_2\cdots O_t$, generate a HMM $\lambda=(A,\eta,\pi)$ to maximize the $P(O\,|\,\lambda)$.

We make the assumption that each individual has his/her own HMM with $\lambda=(A,\eta,\pi)$ for characters crosspoint and character structural characteristics. The problem to solve is that, given a crosspoint sequence and its character structural characteristics information, we have to choose one from the number of HMMs which has the highest probability to generate the crosspoint sequence S . Consequently, first we have to calculate the probability of crosspoint sequence S for each HMM. This is similar to the first basic problem to solve with HMM as described above, and we will show how to solve the problem with Forward algorithm.

The state probabilities α 's of each state can be computed by first calculating α for all states at $t=1$:

$$\alpha_1(g_1)=\pi(g_1)\cdot\eta_{g_1}(d_1). \tag{11}$$

Then for each time step $t=2,\cdots,k$, the state probability α is calculated recursively for each state:

$$\alpha_{t+1}(g_{t+1})=\alpha_t(g_t)\cdot A_{g_t,g_{t+1}}\cdot\eta_{g_{t+1}}(d_{t+1}). \tag{12}$$

Finally, the probability of crosspoint sequence S given a HMM $\lambda=(A,\eta,\pi)$ is as follows:

$$P(S,G,GD\,|\,\lambda)=\alpha_k(g_k)=\alpha_{k-1}(g_{k-1})\cdot A_{g_{k-1},g_k}\cdot\eta_{g_k}(d_k). \tag{13}$$

The emission probabilities take less computation to obtain since we use the Gaussian distribution to model observed states. Additionally the observed states are only connected to the corresponding unknown states because we know the exact combination of n -graph the individual typed. So the summation of all partial probability of the state at time is ignored and only one probability is calculated.

In original version of the Forward algorithm, the computation involved in the calculation of $\alpha_t(j)$, $t\in[1,T], j\in[1,N]$, where T is the number of observations in the sequence and is the number of states in the model, requires $O(N^2T)$ calculations. In our modified version of the Forward algorithm, we can see that it only requires $O(NT)$ calculations.

B. Structural Learning

In the character building and extraction module, first we have to build the reference character for each Nushu character. It requires the user to provide the reference samples or handwritten profile. The more quantity of reference samples or histories provided, the more exact parameters can be extracted. After collecting sufficient number of reference samples, we use the maximum likelihood estimation for Gaussian modeling to calculate the parameters of each n -graph duration. We also have to compute the transition probability matrix and initial probability vector with respect to HMM. Then the parameters calculated for HMM are treated as the base element of the reference profile for each user. The feature building and extraction module extracts two observation sequences based on a sliding-window approach. One observation sequence is extracted in the horizontal direction, representing column observations, and the other one is extracted in the vertical direction, representing row observations. Each discrete observation represents a multidimensional feature vector, which is mapped by means of vector quantization (VQ).

The multidimensional feature vector combines both foreground and background information. The foreground features represents local information about the writing, observed from background–foreground transitions. The other two features represent a global point of view about the writing in the frame from which they are extracted. The background features are based on a configuration chain code, representing concavity information.

The learning algorithm includes three steps: setting up Nushu prototypes, initializing Nushu parameters, and the HMM parameter estimation. First, we set up Nushu prototypes for each category of characters using the observation from a well-segmented standard character, where the number of sites I of standard characters equals the number of labels J of the Nushu for each category.

The proposed adaptive learning algorithm maintains a control probability vector to select an accurate character among a set of characters at time. A good policy to update the probability vector is a pursuit algorithm that always rewards the action with the current minimum penalty estimate and that stochastic learning control performs well in speed of convergence. In this system, the probability vector is the rate selection probability vector $p(n)=[p_1(n),...,p_K(n)]$, where n is the index of the sequence of structural characters. The error of the nth handwritten character during is expressed by $\gamma(n)$. The set of characters available are $\{R_i : i=1,2,......,K\}$. At beginning the $p(n)$ are assigned equal values:

$$p(0)=[1/K,...,1/K]. \tag{14}$$

In order to maximize the likelihood, the recognition algorithm is required to find the index of the best character. Such an approach requires the knowledge of handwritten state during each recognition. The stochastic learning algorithm presented in this paper randomly selects a character. The character selection probability vector is altered by an iterative updating process, which maximizes the probability of maximizing the character recognition rate. Then, the character recognition proceeds with the fixed $p(n)$ until every character is selected at least M number of times after which $p(n)$ is augmented at each n. Following each recognition period, an update of $S(n)'$ and $p(n)$ are carried out considering the last M recognition signals of each recognition period. Then we can get:

$$S(n)'=\frac{R_i}{M}\sum_{j=L_i(n)-M+1}^{L_i(n)} I_i(j) \tag{15}$$

where $I_i(j)$ is an indicator function:

$$I_i(j)=\begin{cases}1, & if\ \ Recognization\ \ is\ \ correct\\ 0, & else\end{cases} \tag{16}$$

$L_i(n)$ is the number of recognition periods for which the character structural R_i is selected during the nth recognition period.

The structural learning algorithm can be summarized as follows:

Step 1. If it is the first recognition period, initialize the probability vector as in equation (14). Else selects a character structural R_i ($i\in[1,K]$) according to probability distribution $p_i(n)$.

Step 2. Update $I_i(j)$ and $L_i(n)$. Then update $S(n)'$ according to (15).

Step 3. If for all $L_i(n)\ge M$ for all i go to next step, else go to step 1.

Step 4. Detect the index m' of the estimated best character structure and update according to the following equations:

$$p_i(n+1)=\begin{cases}p_i(n)-\Delta p, & i\ne m'\\ 1-\sum\limits_{j=1,\,j\ne m'}^{K} p_i(n+1), & i=m'\end{cases} \tag{17}$$

where Δp is a tunable penalty probability parameter.

The structural learning algorithm finds the index m' of the estimated best character $R_{m'}(n)$ maximizing the likelihood $S_{m'}(n)$ at time n:

$$m'=\arg\max_i\{R_i\sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k)\} \tag{18}$$

For the probability of making the right decision, let the best recognition rate at time n, $R_m(n)$ be unique. Let $\phi_m(n)$ be the probability that the estimated best recognition rate is the actual best rate. Then we can get:

$$\phi_m(n)=\Pr\{\sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k)<\frac{R_m(n)}{R_i}\sum_{k=L_m(n)-M+1}^{L_m(n)} I_m(k)\forall i\ne m(n)\} \tag{19}$$

The above probability is readily obtained by using binomial probability distribution.

Since $M\ge\sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k)\ge 0$ for all $i\in[1,K]$, when $\sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k)>\sum_{k=L_m(n)-M+1}^{L_m(n)} I_m(k)$, $\frac{R_m(n)}{R_i}\sum_{k=L_m(n)-M+1}^{L_m(n)} I_m(k)$ may exceed M. Let's take into account the fact that $\sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k)<\frac{R_m(n)}{R_i}\sum_{k=L_m(n)-M+1}^{L_m(n)} I_m(k)$ in such cases.

Let ε_i be the largest nonnegative integer less than $\alpha(R_m(n)/R_i)$, where α is a nonnegative integer. Define the indicator function $O(\cdot)$ which value is 1 when condition within parentheses is satisfied, else is 0. Define the parameter θ_i for $i\in[1,K]$:

$$\theta_i=\varepsilon_i\cdot O(\varepsilon_i\le M)+M\cdot O(\varepsilon_i>M) \tag{20}$$

Then we have:

$$\phi_m(n)=\sum_{\alpha=1}^{M}[\Pr\{\sum_{k=L_m(n)-M+1}^{L_m(n)} I_m(k)=\alpha\}\prod_{i=1,i\ne m}^{K}\sum_{\beta=0}^{\theta_i}\Pr\{\sum_{k=L_i(n)-M+1}^{L_i(n)} I_i(k)=\alpha\}] \tag{21}$$

Considering that:

$$\theta_i=M\ ,\ \varepsilon_i\ge M \tag{22}$$

We can get:

$$\phi_m(n)=\sum_{\alpha=1}^{M}\binom{M}{\alpha}Q_m^{\alpha}(1-Q_m)^{M-\alpha}\cdot\prod_{i\ne m}\sum_{\beta=0}^{\theta_i}\binom{M}{\beta}Q_i^{\beta}(1-Q_i)^{M-\beta} \tag{23}$$

where Q_i is the probability of successful recognition of a Nushu character using the structural R_i .

Since the main objective in the work was to speed up the learning process, the proposed structural learning algorithm works by dividing an off-line training database into smaller blocks. Each iteration of the algorithm processes a different block of data. Thus, given an initial HMM, and the block data drawn from the training set, this algorithm works according to the algorithm.

HMMs are able to perform recognition tasks in pattern recognition systems. The most popular approach for such tasks consists of creating a set of HMMs so that each class is represented by an independent HMM. The classification of an unknown observation sequence $S=\{s_1,s_2,\cdots,s_m\}$, into a class, can be carried out by computing which HMM outputs the highest likelihood related to O. In detail, consider a class problem in which each class is represented by a single HMM. The likelihood can be easily computed by the forward–backward procedure.

C. Adjusting and Recogntion

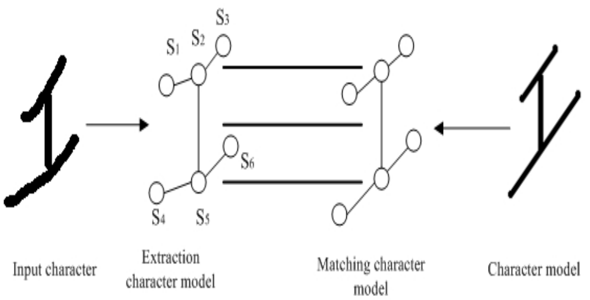

Figure 2. Nushu character adjusting and recognition.

In the adjusting module, given a crosspoint sequence S with claimed identity ID , we wish to examine the possibility that S generated by ID . First we transform the crosspoint sequence S to n -graph combinations G and calculate the character structural information of n -graph duration as usual. At this moment, we have $S=\{s_1,s_2,\cdots,s_m\}$, $G=\{g_1,g_2,\cdots,g_{m-n+1}\}$ and $GD=\{d_1,d_2,\cdots,d_{m-n+1}\}$. Now we produce a vector V , such that:

$$V=\{\mu_{g_1}-\varepsilon\sigma_{g_1},\mu_{g_2}-\varepsilon\sigma_{g_2},\cdots,\mu_{g_{m-n+1}}-\varepsilon\sigma_{g_{m-n+1}}\}, \quad (24)$$

where ε is the weighting factor, μ_{g_k} is ID 's duration mean of n -graph g_k , and σ_{g_k} is ID 's duration standard deviation of n -graph . V is the n -graph duration vector to evaluate the threshold value of the probability produced by the proposed modified forward algorithm. With the inputs GD , V , and λ_{ID} , we can apply the proposed forward algorithm mentioned above to obtain two probability value $P(S,G,GD\mid\lambda_{ID})$ and $P(S,G,V\mid\lambda_{ID})$. $P(S,G,GD\mid\lambda_{ID})$ can be viewed as the possibility if all the n -graphs durations in G are deviating ε times of duration σ from duration μ . $P(S,G,V\mid\lambda_{ID})$ is the threshold value of probability used to decide that the acceptance of the crosspoint sequence S is confirmed if following expression is true.

$$P(S,G,GD\mid\lambda_{ID})\geq P(S,G,V\mid\lambda_{ID}). \quad (25)$$

The weighting factor ε can be specified with respect to different level of security strength. In the Identification procedure, given a crosspoint sequence $S=\{s_1,s_2,\cdots,s_m\}$ from the individual and a set of HMMs $\lambda's=\{\lambda_1,\lambda_1,\cdots,\lambda_l\}$, where l is the number of HMM. The problem is to choose the best one from λ 's which most probably generated S or there is no such one existed. In the beginning, the crosspoint sequence is transformed to n -graph combinations $G=\{g_1,g_2,\cdots,g_{m-n+1}\}$ and the timing information of n -graph duration $GD=\{d_1,d_2,\cdots,d_{m-n+1}\}$ is calculated. $P(S,G,GD\mid\lambda_{ID})$ for each HMM in λ 's is produced by the proposed forward algorithm. We select user U with the maximum probability over others', such as:

$$P(S,G,GD\mid\lambda_U)=\max(P(S,G,GD\mid\lambda_j)),\ j\in[1,l]. \quad (26)$$

After that, we produce a vector for user U , such that V

$$V^U=\{\mu^U_{g_1}-\varepsilon\sigma^U_{g_1},\mu^U_{g_2}-\varepsilon\sigma^U_{g_2},\cdots,\mu^U_{g_{m-n+1}}-\varepsilon\sigma^U_{g_{m-n+1}}\}, \quad (27)$$

where ε is the weighting factor, $\mu^U_{g_1}$ is U 's duration mean of n -graph g_k , and $\sigma^U_{g_k}$ is U 's duration standard deviation of n -graph . Again we apply the proposed forward algorithm mentioned above to obtain two probability value $P(S,G,GD^U\mid\lambda_U)$ and $P(S,G,V^U\mid\lambda_U)$. If the expression $P(S,G,GD^U\mid\lambda_U)\geq P(S,G,V^U\mid\lambda_U)$, the crosspoint sequence generated by user U is confirmed. Otherwise, we consider the crosspoint sequence is not generated by any user in the user profile database.

III. EXPERIMENTAL RESULTS

We evaluated the proposed algorithm on the Nushu database, which has 1783 classes with 200 samples for each class. Fig. 3 shows some typical samples in the Nushu database.

Figure 3. Samples in Nushu database.

We used a Matlab implementation on a PC with 2.4 GHz CPU and 1GB of memory. The average time on preprocessing is 0.002 seconds, and the stroke extraction (0.03 seconds) and the learning algorithm (0.01 seconds) consume a total of 0.04 seconds in the connected neighborhood system per character image. Although the structural match with one character model is efficient, requiring less than a second in our implementation, practically, we have to repeat the structural match with all categories of character models, such as 783 categories in Nushu database, to recognize one input character image.

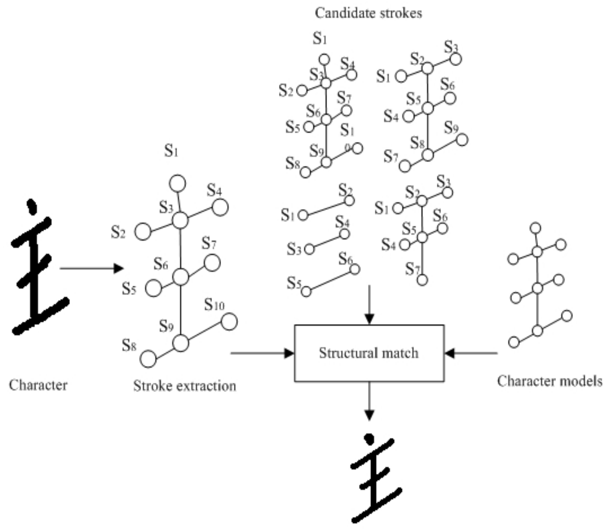

Figure 4. The stroke extraction and structural matching result of the proposed algorithm.

When the number of categories increases, the total time cost to recognize one character image increases. Currently, there are two commonly adopted strategies to expedite the recognition process. The first simultaneously uses several computers to perform the structural match with all the character models in parallel. The second is the hierarchical classification system that uses a fast algorithm to select a few candidate character models and then performs the structural match between the input strokes and these models to determine the best one.

Fig. 4 shows the proposed stroke extraction and the structural matching results. The first column shows the input character. The second column shows the slant and moment normalization of the character skeleton. The third column shows the proposed character models, where the labels are numbered and the adjusting and recognition functions are performed. The structural learning algorithm assigns the best labels to the extracted candidate strokes.

We compared our method with the SCSM [3] and the attributed relational graph MBSEM [10]. The recognition rate of different scheme is shown in Fig. 5. The SCSM used the first 1000 odd number of samples of each category for training, and the first 2000 samples of even number of samples for test on Nushu database. By handling degraded region, the baseline recognition rate was 90.45 percent. For MBSEM, the recognition rate varies with the training samples increasing. The reason is

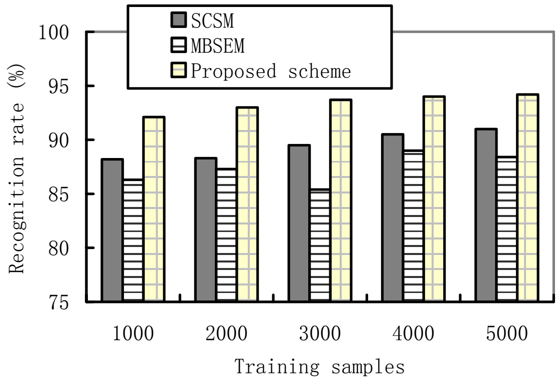

Figure 5. Recognition rate of different scheme.

that MBSEM can not recognize the handwritten Nushu characters, although training sample increases. For the proposed scheme, the recognition rate increases with the training samples increasing, which proves the proposed character structural learning algorithm can increase the recognition rate. It is clear that the recognition rate of the proposed scheme is 3.7% and 4.9% higher than those of SCSM and MBSEM respectively. The reason is that the proposed scheme not only takes the character structures but statistical-structural character into considerations, and the adaptive character structure learning algorithm guarantee the recognition rate. The HMM-based statistical-structural character modeling also truly depicts the Nushu character structure.

IV. Conclusion and Future Work

A statistical-structural character learning algorithm based on hidden Markov model is proposed to recognize the handwritten Nushu characters. The approach is a convergence between statistical and structural threads of research. However, it improves the performance on both sides in term of overall recognition rate greatly. The stroke relationships of a Nushu character reflect its structure, which can be statistically represented by the hidden markov model. Based on the prior knowledge of character structures, an adaptive statistical-structural character learning algorithm accounts for the most important stroke relationships, which aims to improve the recognition rate by adapting selecting correct character to the current handwritten Nushu character condition. The experimental results and the comparisons with other methods show that the proposed method successfully detected and reflected the stroke relationships that seemed intuitively important. And the overall recognition rate is 93.7 percent, which is obviously higher than those of other schemes.

As a future research challenge, we will investigate how to decrease the use of the external knowledge for the proposed algorithm. For example, the use of a k-fold cross-validation would be useful to determine the number of iterations to train each block of data, Furthermore, topology learning could be employed to determine the best HMM topology.

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REFERENCES

[1] Z.-B. GONG, "New Findings about Female Scripts," *Journal of South-Central University for Nationalities*, Vol. 23, No. 4, pp. 93-97, 2003.

[2] Z.-B. GONG, "Nushu in Jiangyong Is absolutely Not Ancient Characters during pre-Qin Day," *Journal of South-Central University for Nationalities*, Vol. 21, No. 6, pp. 130-133, 2001.

[3] I.-J. Kim, J.-H. Kim, "Statistical character structure modeling and its application to handwritten Chinese character recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 25, Is. 11, pp. 1422-1436, 2003.

[4] R. M. Suresh, S. Arumugam, "Fuzzy technique based recognition of handwritten characters," Image and Vision Computing, v 25, n 2, pp. 230-239, 2007.

[5] R. Zhang, X. Ding, H. L. Liu, 'Discriminative training based quadratic classifier for handwritten character recognition," *International Journal of Pattern Recognition and Artificial Intelligence*, v 21, n 6, pp. 1035-1046, 2007.

[6] M. F. Zafar, O. Dzulkifli, "Writer independent online handwritten character recognition using a simple approach," *Information Technology Journal*, v 5, n 3, pp. 476-484, 2006.

[7] W. W. Lin, "Recognition of handwritten Chinese characters by feature matching," in Proc. 1991 Int. Conf. Computer Processing of Chinese and Oriental Languages, 1991, pp. 154–157.

[8] Y. L. Wu, T. M. Wu, and B. S. Jeng, "Optical Chinese character recognition using a projection profile and the Fourier transformation," J. Telecommun. Lab. Technique, vol. 20, pp. 137–145, 1990.

[9] H. D. Chang and J. F. Wang, "Preclassification for handwritten Chinese character recognition by a peripheral shape coding method," Pattern Recognition., vol. 26, pp. 711–719, 1993.

[10] C.L. Liu, I.J. Kim, and J.H. Kim, "Model-Based Stroke Extraction and Matching by Heuristic Search for Handwritten Chinese Character Recognition," Proc. Sixth Int'l Workshop Frontiers in Handwritten Recognition, pp. 547-556, 1998.

[11] X. Zhang and Y. Xia, "The Automatic Recognition of Handprinted Chinese Characters—A Method of Extracting an Order Sequence of Strokes," Pattern Recognition Letters, vol. 1, no. 4, pp. 259-265, 1983.

[12] H.Y. Kim and J.H. Kim, "Hierarchical Random Graph Representation of Handwritten Characters and Its Application to Hangul Recognition," Pattern Recognition, vol. 34, no. 2, pp. 187-201, 2001.

[13] I.-J. Kim and J.-H. Kim, "Statistical Character Structure Modeling and Its Application to Handwritten Chinese Character Recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 25, no. 11, pp. 1422-1436, Nov. 2003.

[14] M. Aksela, J. Laaksonen, "Adaptive combination of adaptive classifiers for handwritten character recognition," *Pattern Recognition Letters*, v 28, n 1, pp. 136-143, 2007.

[15] P. M. Patil, T. R. Sontakke, "Rotation, scale and translation invariant handwritten Devanagari numeral character recognition using general fuzzy neural network," *Pattern Recognition*, v 40, n 7, pp. 2110-2117, 2007.

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