Handwritten Chinese Character Recognition Using Nonlinear Active Shape Models and Viterbi Algorithm

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Abstract

Since many thousands of Chinese characters are made from a small set of fundamental structural shapes – radicals, the problem of recognizing large number of Chinese characters can be converted to extracting small number of radicals and then finding their optimal combination. In this paper, radical extraction is carried out by nonlinear active shape models, in which kernel principal component analysis is employed to capture the nonlinear variation. Treating Chinese characters as discrete-time Markov process, we also propose an approach for character composition with the Viterbi algorithm. Our initial experiments are conducted on 200 radicals covering 2154 character categories. The correct recognition rate

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is 93.5% on these 430,800 loosely-constrained characters. A comparison with existing radical approaches shows that our method achieves superior performance.

Keywords: Handwritten Chinese character recognition, active shape model, kernel principal component analysis, Viterbi algorithm

1 Introduction

Chinese characters follow a hierarchical representation. A graph of the Chinese writing system stands not for a unit of pronunciation but for a morpheme, a minimal meaningful unit of the Chinese language (Sampson 1985). These simple graphs are known as *radicals* (Chang 1973, Suen and Huang 1984), can compose many different Chinese characters. Radical approaches decompose Chinese characters into a small set of categories, so the complex character recognition problem is converted to a simpler problem of radical extraction and optimization of combination with the radical sequences. In Figure 1, if the redundant information is ignored, the four complex Chinese characters can be classified by recognising the following simple radicals "⊟", "土", "巾", and "𠂇", which is far easier than recognizing the whole characters.

Handwritten Chinese character recognition is one of the most difficult pattern recognition problems because it concerns complex structure, serious interconnection among the components, numerous pattern variations, and a large number of characters. Existing radical extraction methods of handwritten Chinese characters can be divided in two ways, i.e., from a character skeleton or on the basis of strokes. Skeleton-based methods, such as Chung and Ip (2001) and Fukushima et al. (1991), treat a radical as a subimage of the character skeleton image. These methods aim to discover the relationship among the hierarchically represented graphs and capture their variations. Stroke-based methods, such as Wang and Fan (2001) and Liao and Huang (1990), de-

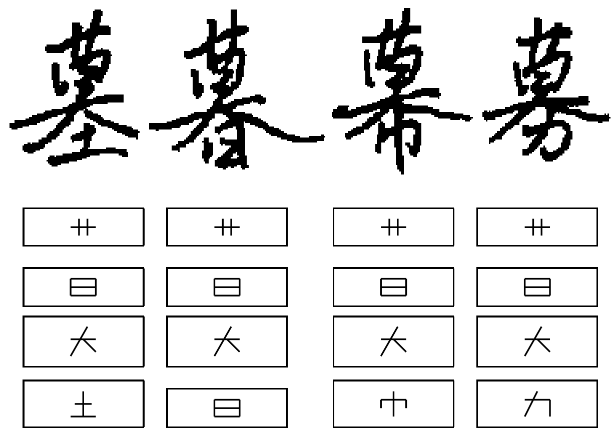


Figure 1: Examples of complex handwritten Chinese characters decomposed into their radicals.

compose a radical further into its primitive structural parts, i.e., straight-line strokes, and then recognize the whole character by structural analysis. The advantage of the latter approach is that it requires far less computation than skeleton-based methods, but it suffers from a problem of ambiguity when strokes intersect. At the point of intersection, it is problematic which of the radiating lines should be associated together so that some strokes may be spurious.

Chung and Ip (2001) applied snake fitting (Kass et al. 1988) to Chinese radical extraction with energy functional minimization. The external energy in their work consists of two different functionals, i.e., displacement and intersection functionals. The displacement functional is employed to avoid the snake deviating too much from the original template. The intersection functional is devised to avoid the intersection of character strokes and the template, by developing a mechanism which has three levels consisting of a window of size 7 pixels around a pixel on the snake. The closer to the snake, the higher the intersection energy value which results. In the work of Chung and Ip (2001), experiments were conducted on 100 character categories written by 10 people, and the initial results were promising. However, snakes are forced on to the image by smoothness and some salient features. In their work, they did not give further discussion how to deal with false salient features because of broken strokes and thinning algorithms.

Fukushima et al. (1991) proposed a skeleton-based radical approach to handwritten Japanese Chinese character recognition with the neocognitron (Fukushima 1982), which is capable of recognizing distorted patterns as well as tolerating positional shift. When a composite stimulus consisting of two patterns or more is presented, the neocognitron focuses its attention selectively on one of them, and recognizes it. Until now, it is difficult to bring neocognitron-based methods to practical use, because too much domain expert knowledge is required to design its training patterns. Although genetic algorithms were incorporated with the neocognitron to search for optimal parameters in previous work (Shi et al. 1999), it is unsuitable for the case of Chinese character recognition, in which there are a great number of training patterns involved.

Wang and Fan (2001) proposed a radical based optical character recognition (OCR) system for recognising handwritten Chinese characters. Their recursive hierarchical radical extraction consists of three layers. Layer 1 is character pattern detection which classifies a given character into a shape pattern, such as left-right, up-down, etc.. Layer 2 is straight cut-line detection which detects gaps among radicals. A stroke clustering technique is devised in layer 3 to decompose Chinese characters that are left-right or up-down patterns into radicals. Their hierarchical radical-matching scheme also consists of three matching phases. The first phase is radical matching which is based on a modified relaxation method to match each radical with templates in the radical database. The second phase is matching with the knowledge database. The third phase is the matching of the whole character. Using their methodology, the complexity of off-line handwritten Chinese character recognition, the templates and the size of the radical database are all greatly reduced.

Liao and Huang (1990) described their work on radical extraction which is not confused by spurious strokes due to stroke interconnection and the inherent defects of thinning algorithms. Their method consists of three parallel matching algorithms. The first algorithm can extract radicals from a Chinese character on the basis of stroke segmentation. Then based on this algorithm, two additional algorithms are applied to avoid spurious strokes. The second algorithm considers the fork-points and end-points in the thinning image character, and matches radicals by all the possible unions of the line segments. The third algorithm uses a small number of points to represent a stroke, and it can extract radicals even when inflection points have not been found by the stroke segmentation techniques. However, this method is quite time consuming. In addition, one further practical issue is that a decision must be made as to which algorithm to select.

Cootes et al. (1995) proposed active shape models to capture the shape variation and exploit the linear formulation of point distribution models (PDMs) in an iterative search procedure, capable of locating the modeled structures in noisy, cluttered images – even if they are partially occluded. Active shape models have similarities to snakes, in which a contour is fitted to the image evidence by minimizing an energy function. However, a snake only has generic prior knowledge, such as smoothness. A much greater amount of prior information can be recovered from training sets and encoded within an active shape model. In our previous work, active shape models were applied to radical modeling (Shi et al. 2001a), which can be regarded as a special case of skeleton-based approaches. However, the original active shape models are only suitable for representing linear variations within the point distribution models. As a matter of fact, nonlinear shape variations are common in handwriting, such as different writing styles from person to person, and different image distortion from time to time.

In radical extraction, each class has a corresponding recognition score with respect to a given input character. The next step is to combine these radical sequences to produce a ranking of character candidates. In our research, the Viterbi algorithm (Viterbi 1967, Forney 1973) is applied to carry out character composition with radicals. The Viterbi algorithm is a dynamic programming technique used to derive an optimal path with linear time complexity on the length of input sequence. In its most general form, the VA may be viewed as a solution to the problem of maximum *a posteriori* probability (MAP) estimation of the state sequence of a finite-state discrete-time Markov process observed in memoryless noise. In recent researches, Tseng and Lee (1999) used Viterbi algorithm for recognition-based handwritten Chinese character recognition, and Jung and Kim (2000) applied it to on-line recognition of cursive Korean characters using graph representation.

The remainder of this paper is organized as follows. In Sections 2, nonlinear active shape modeling is described, in which kernel PCA is employed to capture the nonlinear handwriting variations, and dynamic tunneling algorithm is incorporated with gradient descent to search for the optimal shape parameters. In Section 3, the Viterbi algorithm is used to find the optimal radical combination for character composition. Experiments and their results are given in Section 4, followed by conclusions in Section 5.

2 Radical Extraction with Nonlinear Active Shape Modeling

Active shape modeling extracts the eigenvectors, $\mathbf{U}$, of the training examples by principal component analysis (PCA), and then any examples $\mathbf{\Gamma}$ in the training set can be approximated by adjusting shape parameters, $\mathbf{b}$, corresponding to the principal modes:

$$\mathbf{\Gamma} = \mathbf{\Psi} + \mathbf{U}\mathbf{b}. \tag{1}$$

where $\mathbf{\Psi}$ is the mean vector of the training examples.

To generalize the active shape models to nonlinear case, Sozou et al. (1995a) introduced polynomial regression. The basis for the polynomial regression model is to further reduce the residuals once a linear mode has been extracted, by fitting a polynomial along the direction of the principal components. However, the polynomial regression model requires that the second eigenvector be modeled as a function of the first, otherwise implausible shapes may be generated. To solve this problem, they also applied a multi-layer perceptron (MLP) (Sozou et al. 1995b). This method is actually to find the nonlinear functionals among the shape parameters, $\mathbf{b}$, in equation (1). The disadvantages of MLP method are overfitting and the sensitivity to number of neurons.

This section will develop nonlinear active shape models with kernel PCA and apply them to radical extraction. In training, the handwriting variation is captured by nonlinear kernel PCA, and in recognition, each radical model will be fitted to the target character by adjusting the shape parameters.

2.1 Training Phase

The training phase includes landmark point labeling and kernel PCA. The first step is image thinning to get character skeletons. Then, landmark points are labeled manually to represent a radical, and kernel PCA is applied to obtain the main shape parameters which capture the radical variations.

The PCA is a technique for extracting structure from possibly high-dimensional data sets. It is readily performed by solving an eigenvalue problem, or by using iterative algorithms which estimate principal components (Jolliffe 1986). The PCA is useful when the original pattern space can be accurately described by a subspace spanned by the first several principal eigenvectors. It is often the case that the data lies in a subspace, and if this is linear then a small number of principal components is sufficient to account for most of the variation in the data.

Kernel PCA (Schölkopf, Smola, and Müller 1998) provides a way to extend linear PCA to nonlinear subspaces of the data. Here, linear PCA is performed in some high-dimensional feature space F, which is related to the input space by a nonlinear map $\Phi : \mathcal{R}^N \rightarrow F$. The number of nonlinear components obtained by kernel PCA can be greater than the original input dimension. The dimension size of feature space is specified by the number of training examples. However, the method will confer no advantage if the data lies in a linear subspace. The main challenge with this method is how to choose an appropriate nonlinear transformation.

Given a set of examples for a particular character $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_M\}$, which are represented by N landmark points, i.e., $\mathbf{e}_k = (x_{k0}, y_{k0}, \ldots, x_{k(N-1)}, y_{k(N-1)})^T$. The mean vector of the set is defined by $\mathbf{\Psi} = \frac{1}{M}\sum_{k=1}^{M} \mathbf{e}_k$.

In the feature space, the covariance matrix takes the form

$$\mathbf{C} = \frac{1}{M}\sum_{j=1}^{M} \mathbf{\Phi}(e_j)\mathbf{\Phi}(e_j)^T. \tag{2}$$

The kth eigenvector $\mathbf{V}^k$ and its eigenvalue λ_k of the covariance matrix $\mathbf{C}$ are solutions to: $\lambda_k \mathbf{V}^k = \mathbf{C}\mathbf{V}^k$. Since all solutions $\mathbf{V}$ with $\lambda \neq 0$ lie in the span of $\mathbf{\Phi}(e_1), ..., \mathbf{\Phi}(e_M)$, there exist coefficients $\alpha_i^k (i = 1, ..., M)$ such that

$$\mathbf{V}^k = \sum_{i=1}^{M} \alpha_i^k \Phi(e_i). \tag{3}$$

We then solve the following eigenvalue problem (see Schölkopf et al. (1998) for details):

$$M\boldsymbol{\lambda}\boldsymbol{\alpha} = \mathbf{K}\boldsymbol{\alpha} \tag{4}$$

where both $\mathbf{K}$ and $\boldsymbol{\alpha}$ are $M \times M$ matrices, and $K_{ij} = \Phi(e_i)^T\Phi(e_j)$.

For each non-zero λ_k, the eigenvector expansion coefficients $\boldsymbol{\alpha}^k$ are normalized by requiring that $\lambda_k {\boldsymbol{\alpha}^k}^T \boldsymbol{\alpha}^k = 1 \quad \forall k, \lambda_k \neq 0$, which leads to the corresponding vectors $\mathbf{V}$

in F be normalized, i.e., ${\mathbf{V}^k}^T\mathbf{V}^k = 1$. The projections of a data $\mathbf{e}$ onto the eigenvectors $\mathbf{V}^k$ in F can be defined as:

$$\beta_k(\mathbf{e}) = {\mathbf{V}^k}^T\mathbf{\Phi}(\mathbf{e}) = \sum_{i=1}^{M'} \alpha_i^k \mathbf{\Phi}(\mathbf{e}_i)^T\mathbf{\Phi}(\mathbf{e}) = \sum_{i=1}^{M'} \alpha_i^k K(\mathbf{e}_i, \mathbf{e}). \tag{5}$$

where, M' is the number of principal components. Any example in the training set can be approximated using the mean vector and a weighted sum of these deviations obtained from the first M' modes.

Our purpose is to build up models for each handwriting class, which requires approximate representations of the data in input space rather than in feature space. To this end, by introducing shape parameters, we can also generate active shape models on the basis of kernel PCA with the following two steps.

First, generate active shape models in feature space with the mean vectors $\mathbf{\Psi}$. We define an operator $P_{M',b}$ by

$$P_{M',b}\mathbf{\Phi}(\mathbf{\Psi}) = \sum_{k=1}^{M'} \beta_k(\mathbf{\Psi}) b_k \mathbf{V}^k. \tag{6}$$

Second, we find the active model $\mathbf{\Gamma}$ which is a *pre-image* in the feature space (Schölkopf et al. 1998) such that

$$\begin{aligned} \rho(\mathbf{\Gamma}) &= \|P_{M',b}\mathbf{\Phi}(\mathbf{\Psi}) - \mathbf{\Phi}(\mathbf{\Gamma})\|^2 \qquad (7) \\ &= \mathbf{K}(\mathbf{\Gamma}, \mathbf{\Gamma}) - 2\sum_{k=1}^{M'} b_k \beta_k(\mathbf{\Psi}) \sum_{i=1}^{M} \alpha_i^k \mathbf{K}(\mathbf{e}_i, \mathbf{\Gamma}) + \mathbf{K}(\mathbf{\Psi}, \mathbf{\Psi}). \end{aligned}$$

is minimized.

2.2 Recognition Phase

Radical models can be generated by adjusting the shape parameters in equation (7). The recognition phase consists of performing a chamfer distance transform (Barrow et al. 1977, Borgefors (1988)) on the target image and shape parameter searching via gradient descent with dynamic tunneling algorithm. Optimal shape parameters will be obtained by minimizing the mean-square distance between the model and the input character in the input space. Figure 2 shows this procedure.

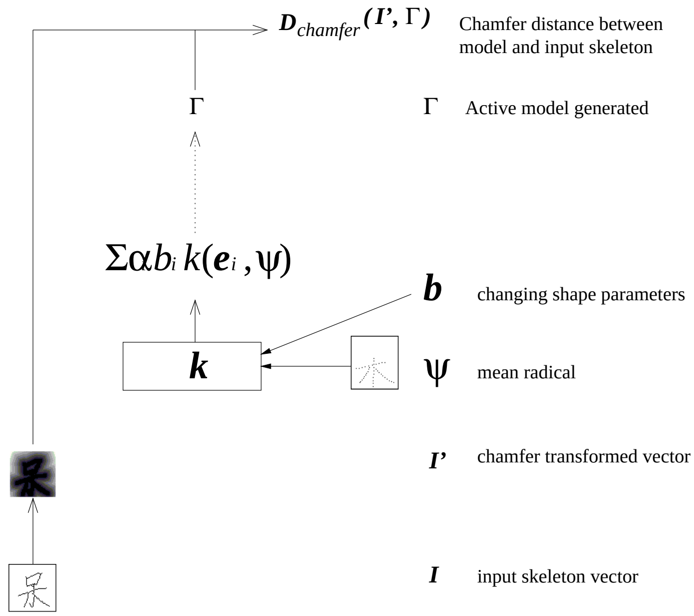


Figure 2: Illustration of radical extraction with nonlinear active shape models.

In our previous work, the chamfer distance transform was introduced to enhance the basin of attraction (Shi et al. 2001a). The most significant property of this transform is its ability to handle noisy and distorted data, as the edge points of one image are transformed by a set of parametric transformations, which describe how the images can be geometrically distorted in relation to one another.

The criterion to search for the optimal shape parameters is to minimize the chamfer distance between each model and a target image. Shi et al. (2001b) used a dynamic tunneling algorithm (DTA, Yao 1989) to overcome problems with local minima when employing gradient descent method. The DTA procedure can jump to another basin of attraction where the new, initial search point is even lower in energy. In the nonlinear case in this paper, the shape parameters are operating in the feature space. However, the parameter vectors are not orthogonal in the input space, and there is no direct gradient descent information. Hence, the DTA in the nonlinear case is playing a role of multi-point sampling.

3 Character Composition with the Viterbi Algorithm

The output of radical extraction level is a set of radicals ranked by their chamfer distance to the given character. This section describes the character composition based on these radical sequences. Treating Chinese characters as discrete-time Markov processes, the optimal radical combination is equivalent to the best path in the graph made up by all radical classes.

3.1 Markov Process of the Character Composition

Markov methods invoke the assumption that the language is a Markov source and uses transition probabilities. The process is Markov in the sense that the probability $P(x_{k+1}|x_0, x_1, ...x_k)$ of being in state x_{k+1} at time $k+1$, given all states up to time k, depends only on the state x_k at time k: $P(x_{k+1}|x_0, x_1, ...x_k) = P(x_{k+1}|x_k)$. The transition probabilities $P(x_{k+1}|x_k)$ may be time varying. Figure 3 illustrates the Markov process of Chinese composition. Each position in the figure indicates a possible state in composing a character, and the double-lined circle signifies a terminal position where the character composition is completed. In terms of Figure 3, any character consists of less than four radicals.

We can assume that the probability of occurrence of each radical depends on the ν previous radicals ($1 \leq \nu \leq 4$ in our current research), and estimate these probabilities

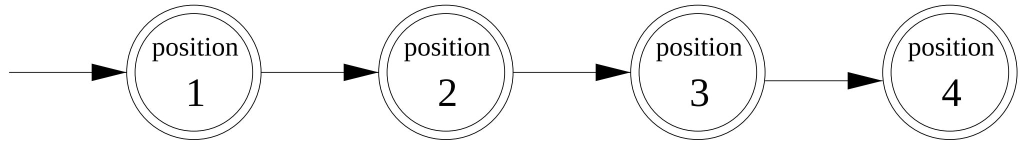


Figure 3: Markov process of the Chinese character composition with peripheral radicals.

from the frequencies of $(\nu+1)$-radical combinations. While such models do not fully describe the generation of Chinese characters, they account for a large part of the statistical dependencies in the language and are easily handled. With such a model, Chinese characters are viewed as the outputs of an m^{ν}-state Markov process, where m is the number of distinguishable radicals ($m = 200$ in our current research).

3.2 Searching Algorithm

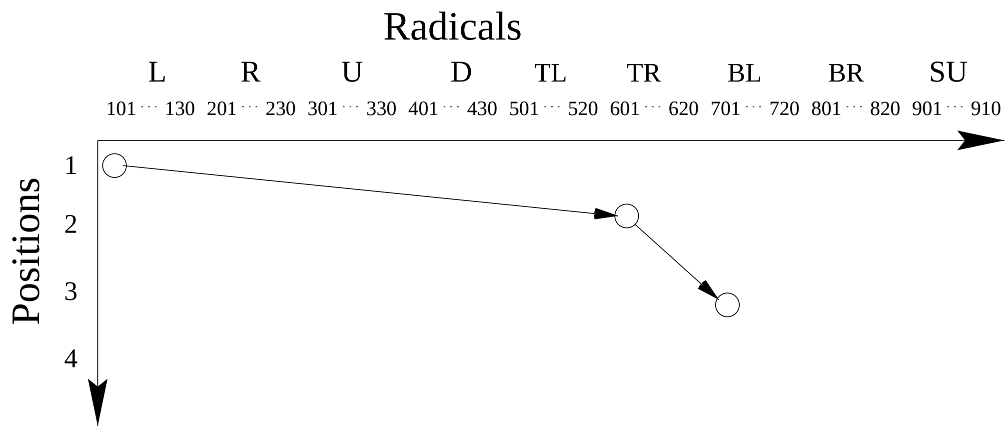
In this research, Chinese character recognition is associated with a graph where the nodes contain radical recognition scores. A one-to-one correspondence exists whereby every path through the graph branches corresponds to a particular legal segmentation of the input character into radicals, and conversely, every possible legal segmentation of the input character corresponds to a particular path through the graph.

Let $L, R, U, D, TL, TR, BL, BR$ and SU denote left, right, up, down, top-left, top-right, bottom-left, bottom-right and surrounding radicals, respectively. In the lexicon, each character consists of 9 codes, 1xx, 2xx, ..., 9xx, representing the 9 types of radicals. Figure 4(a) shows an example in the lexicon. Figure 4(b) shows its graph representation, in which the vertical line indicates the position of a character model, and the horizontal line indicates the radicals.

In this graph representation, the Viterbi algorithm provides a convenient method for rapidly determining the best-scoring path (corresponding to an interpretation for a character).

唉 101 — — — — 601 701 — —

(a)



(b)

Figure 4: Chinese characters composed by radicals. (a) A Chinese character in the lexicon consists of 9 codes, representing the radicals $L, R, U, D, TL, TR, BL, BR$ and SU, respectively. (b) Its graph representation.

The radicals are extracted from 9 different peripheral positions. The outputs of the radical extraction are then considered as symbol probabilities. Given a character, all the nodes in the same column j have the same symbol probability given by:

$$f(j) = \frac{\text{chamfer distance of radical } j}{\text{sum of chamfer distance of all radicals in same position as } j} \tag{8}$$

The transition probability is:

$$P(x(i,j)|x(a,b)) = \frac{\text{number of transitions from } x(a,b) \text{ to } x(i,j)}{\text{number of transitions from } x(a,b)} \tag{9}$$

Table 1 shows an example of non-zero transition probabilities of radical number 10, i.e. 亻, coded 110 in the lexicon. Here, the number of transitions from $x(1, 10)$ is equal to the number of characters with first code being 10; the number of transitions from

$x(1,10)$ to $x(2,j)$ is equal to the number of characters which first and second codes are 10 and j, respectively.

Table 1: Non-zero transition probabilities of $P(x(1,10)|x(2,-))$.

Serial Number	62	66	67	68	78	134	135	148	149
Radical	攵	勿	白	白	专	日	大	目	几
Transition Prob.	0.053	0.031	0.111	0.025	0.048	0.105	0.005	0.012	0.143

The initial state probability is:

$$\pi(x(1,j)) = \frac{\text{number of characters begining with radical } j}{\text{total number of characters}} \tag{10}$$

The *survivor* is defined the shortest path corresponding to a node. Let define the following symbols:

$x(i,j)$ refers to the node of ith row,jth column;

$\widehat{x}(x(i,j))$ refers to the survivor path ending in $x(i,j)$;

$L(x(i,j))$ refers to the survivor path value;

K refers to the end time, or the total rows in the graph, $K = 4$ in our research;

M refers to the total number of states, or the total column in the graph.

A formal statement of the algorithm is given as follows:

STEP 1 **Initialization**. $L(x(i,j)) = 0, \quad \forall i, j \neq 0; \quad j = 1.$

STEP 2 $L(x(1,j)) = \pi(x(1,j) * f(j); \quad \widehat{x}(x(1,j)) = x(1,j).$

STEP 3 $i = 2.$

STEP 4 Calculate:

$$L(x(i,j)) = \max_{1 \leq m \leq M} [L(x(i-1,j)) * P(x(i,m)|\widehat{x}(x(i-1,j))] * f(j));$$
$$\widehat{x}(x(i,j)) = x(i,m), \quad s.t. \quad \max_{1 \leq m \leq M} [L(x(i-1,j)) * P(x(i,m)|\widehat{x}(x(i-1,j))];$$

STEP 5 i++; Repeat Step 3 while $i \leq K$.

STEP 6 j++; Go to Step 2 while $j \leq M$.

STEP 7 **Termination and backtracking for best path**. Best path is

$$\widehat{x}(x(1,v)), \widehat{x}(x(2,v)), ..., \widehat{x}(x(K,v))$$
$$s.t. \quad L(x(K,v))] = \max_{1 \leq j \leq M} L(x(K,j))]$$

When investigating the best path using the VA, some uncomposable character interpretations can occur. These search paths are pruned, whereby any path that corresponds to an improper character interpretation can be removed from the graph. These will be considered in the implementation.

4 Experiments and Results

In our experiments, the complete database was collected by Harbin Institute of Technology and Hong Kong Polytechnic University, and comprises a collection of 751,000 loosely-constrained handwritten Chinese characters, consisting of 3755 categories written by 200 different writers (Shi et al. 2001a, 2001b). We are now in a position to compare some representative works on radical extraction with our proposed nonlinear active shape modeling method.

Method 1: Nonlinear active shape modeling with Viterbi algorithm. The experiments are conducted on 200 radicals covering 2154 loosely-constrained Chinese character categories written by 200 different writers (i.e., 430,800 characters).

Method 2: Stroke-based approach (Wang and Fan 2001). Their experiments for radical extraction were conducted on just 1856 test characters.

Method 3: Snake-fitting approach (Chung and Ip 2001). Their character image database consists of 100 character categories written by 10 people (i.e., 1000 test examples only). They considered and reported results on six most common radical combination schemes, namely, vertical, left-down, surrounding, horizontal, up-left, and cover, respectively. The recognition performance was given in their work Ip et al. (1995).

From Table 2, we can see that the method of our nonlinear active shape models is easily the best among the existing radical approaches. It deals with the largest number of radicals on a test set which is significantly larger than what other works have used, and still achieves the best correct matching rate.

The lower correct rate of the method 4 resulted from a problem of ambiguity when strokes intersect. At the point of intersection, it is problematic as to which of the radiating lines should be grouped together so that some strokes may be spurious. As snakes are forced on to the image by smoothness and some salient features, the method 4 is suffering from false salient features due to broken strokes and thinning algorithms.

The advantage of our method is the capabilities to handle the individual writer variation with only a small number of shape parameters. Our models can also avoid stroke extraction, as mentioned above, which is difficult in handwriting recognition as there will be considerable interconnection among the strokes as well as many broken strokes. The Viterbi algorithm helps finding the maximum *a posteriori* probability (MAP) estimation of the radical combination.

Table 2: Performance comparison of different radical approaches to Chinese character recognition.

	Test set size (characters)	Number of radicals trained	% radicals correct	% characters correct
Method 1 (AHM, Viterbi)	2154*200	200	96.5	93.5
Method 2 (stroke-based)	1856	32	92.5	98.2 (training set) 80.9 (testing set)
Method 3 (snake fitting)	1000	20	89.0 (Vertical) 78.5(Horizontal) 81.0 (Left-Down) 68.0 (Up-Left) 95.0 (Surrounding) 75.0 (Cover)	79.1

5 Conclusions

In this paper, a novel radical approach to handwritten Chinese characters recognition is proposed, in which radicals are extracted by nonlinear active shape models, and then character composition is carried out based on the Viterbi algorithm. In training, nonlinear active shape models capture the handwriting variations by kernel PCA. In matching, the dynamic tunneling algorithm is incorporated with gradient descent to search for the optimal shape parameters by minimizing the chamfer distance between radical models and the input skeleton. Treating any Chinese character as a discrete-time Markov process, it can be represented by a graph, in which the vertical lines indicate the position of a character model, and the horizontal lines indicate the radicals. Hence, the solution to character composition is obtained by finding the best path with the Viterbi algorithm. The symbol probabilities can be calculated from the chamfer distance at the radical extraction level, whereas the transition probabilities and initial state probabilities can be calculated from the lexicon. Experiments are conducted on 200 radicals covering 2154 loosely-constrained characters from 200 writers, and the recognition rate obtained is 93.5% characters correct. We also compare our method to some representative radical approaches. The conclusion is that our method gives superior performance, which benefits from the avoidance of (straight line) stroke extraction, as well as the ability to capture the nonlinear handwriting variations by only a small number of shape parameters.

A benchmarking database of Chinese characters is required, on which different authors can report results. Until now, no such established database has existed. To correct this situation, we are making the database used here freely available to other researchers on CD-ROMs from the corresponding author.

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