A New Approach of Integrating Multiple Contexts for Chinese Handwritten Text Recognition

G Sirisha Kumari[#1], V Srikanth[*2]

[#1]M.Tech Scholar
Department of CSE ,

[*2] Associate Professor
Department of CSE
Pydah College Of Engineering,
Visakhapatnam ,AP,India.

Abstract

A Chinese handwriting database named **CASIA-HWDB** is presented to facilitate the offline Chinese handwritten text recognition. Both the writers and the texts for hand copying are carefully sampled with a systematic scheme. This paper presents an effective approach for the offline recognition of unconstrained handwritten Chinese texts. Under the general integrated segmentation-and-recognition framework with character over segmentation, we investigate three important issues: candidate path evaluation, path search, and parameter estimation. For path evaluation, we combine multiple contexts (character recognition scores, geometric and linguistic contexts) from the Bayesian decision view, and convert the classifier outputs to posterior probabilities via confidence transformation. In path search, we use a refined beam search algorithm to improve the search efficiency and, meanwhile, use a candidate character augmentation strategy to improve the recognition accuracy. The combining weights of the path evaluation function are optimized by supervised learning using a Maximum Character Accuracy criterion. We evaluated the recognition performance on a Chinese handwriting database **hanzidict JAR**, which contains nearly four million character samples of 7,356 classes and 5,091 pages of unconstrained handwritten texts. The experimental results show that confidence transformation and combining multiple contexts improve the text line recognition performance significantly. On a test set of 1,015 handwritten pages, the proposed approach achieved character level accurate rate of 90.75 percent and correct rate of 91.39 percent, which are superior by far to the best results reported in the literature

Keywords:

Handwritten Chinese text recognition, confidence transformation, geometric models, language models, refined beam search, candidate character augmentation, maximum character accuracy training

1. Introduction

Handwritten Chinese text recognition (HCTR) is a challenging problem due to the large character set, the diversity of writing styles, the character segmentation difficulty, and the unconstrained language domain. Fig. 1 shows an example of a Chinese handwritten page. The large set of Chinese characters (tens of thousands of classes) brings difficulties to efficient and effective recognition. The divergence of writing styles among different writers and in different geographic areas aggravates the confusion between different classes. Handwritten text recognition is particularly difficult because the characters cannot be reliably segmented prior to character recognition. The difficulties of character segmentation originate from the variability of character size and position, character touching and overlapping. A text line of Chinese handwriting must be recognized as a whole because it cannot be trivially segmented into words (there is no more extra space between words than between characters). Last, handwritten text recognition is more difficult than bank check recognition and mail address reading because the lexical constraint is very weak: Under grammatical and semantic constraints, the number of sentence classes is infinite.

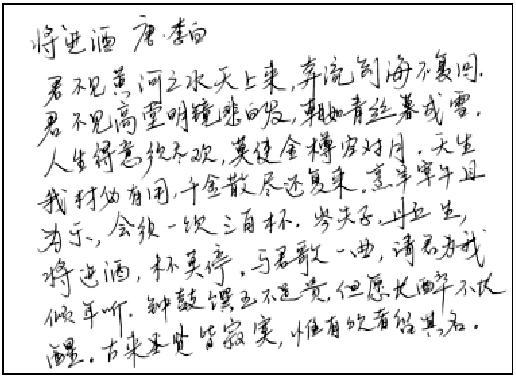

Fig. 1. A page of handwritten Chinese text.

HANDWRITTEN Chinese character recognition has long been considered a challenging problem. It has attracted much attention since the 1970s and has achieved tremendous advances [1], [2]. Both isolated character recognition and character string recognition have been studied intensively but are not solved yet. In isolated Chinese character recognition, most methods were evaluated on data sets of constrained writing styles though very high accuracies (say, over 99 percent on Japanese Kanji characters and over 98 percent on Chinese characters) have been reported [1]. The accuracy on unconstrained handwritten samples, however, is much lower [3]. In Chinese character string recognition, most works aimed at the recognition of text lines or phrases in rather constrained application domains, such as legal amount recognition in bank checks [4] and address phrase recognition for postal mails [5], [6], [7], [8], where the number of character classes is very small or there are very strong lexical constraints. Works on Chinese handwriting recognition of general texts have been reported only in recent years, and the reported accuracies are quite low. For example, Su et al. reported character-level correct rate (CR) of 39.37 percent on a Chinese handwriting data set HIT-MW with 853 pages containing 186,444 characters [9]. Two later works on the same data set, using character classifiers and statistical language models (SLM) based on over segmentation, reported a character-level correct rate of 78.44 [10] and 73.97 percent [11], respectively. On the other hand, many works on online Japanese/Chinese handwritten text recognition have reported higher accuracies [12], [13], [14], [15]. Online handwriting recognition has the advantage over offline recognition in that the sequences of strokes are available for better segmenting and discriminating characters. Due to the large number of character classes and the infinite sentence classes of Chinese texts, HCTR can only be solved by segmentation-based approaches using character models [16], preferably by explicit segmentation, also called over segmentation, which can take advantage of the character shape and overlapping and touching characteristics to better separate the characters at their boundaries. The result of over segmentation is a sequence of primitive segments, each corresponding to a character or a part of a character, such that candidate characters can be generated by concatenating consecutive segments [5].

The candidate character sequences can be represented in a network called a candidate lattice [17], and each candidate segmentation path in the lattice can be split into many segmentation-recognition paths by assigning character classes to the candidate characters. The result of character segmentation and recognition is obtained by evaluating the paths in the lattice and searching for the optimal path. The existing methods either integrated incomplete contexts [9], [10], [18] or combined the contexts heuristically without optimizing the combining weights [12], [13], [19], [20]. Zhou et al. optimize the combining weights using the conditional random field (CRF)model [14], which is hard to incorporate into language models of higher order than the bi-gram. Zhu et al. optimize the combining weights using the genetic algorithm(GA) [15], which is computationally expensive and is sensitive to some artificial parameters. The previous works have addressed handwritten text (character string) recognition from different viewpoints and have contributed various techniques. However, none has investigated these techniques comprehensively and integrated them in a high-performance system for Chinese/Japanese handwritten text recognition.

In this study, we investigate three key issues of integrated segmentation-and-recognition for HCTR: candidate path evaluation, path search, and parameter estimation. By elaborating the techniques for these issues, we achieved significant improvements on unconstrained handwritten Chinese texts. In path evaluation, we integrate character recognition scores, geometric context, and linguistic context from the Bayesian decision view, and convert the classifier outputs to posterior probabilities via confidence transformation (CT). In path search, a refined beam search algorithm is used to improve the search efficiency and, meanwhile, a candidate character augmentation (CCA) strategy is applied to benefit the recognition accuracy. To balance the multiple contexts in path evaluation function, we optimize the combining weights on a data set of training text lines using a Maximum Character Accuracy (MCA) criterion. We evaluated the recognition performance on a large database CASIA-HWDB [21] of unconstrained Chinese handwritten characters and texts, and demonstrated superior performance by the proposed methods.

2. Backgroud Work

In the context of handwritten text (character string) recognition, many works have contributed to the related issues of over segmentation, character classification, confidence transformation, language model, geometric model, path evaluation and search, and parameter estimation. For over segmentation, connected component analysis has been widely adopted, but the splitting of connected (touching) characters has been a concern [5], [22], [23]. After generating candidate character patterns by combining consecutive primitive segments, each candidate pattern is classified using a classifier to assign similarity/dissimilarity scores to some character classes. Character classification involves character normalization, feature extraction, and classifier design. The state-of-the-art methods have been reviewed in [24], [25]. For classification of Chinese characters with large number of classes, the most popularly used classifiers are the modified quadratic discriminate function (MQDF) [26] and the nearest prototype classifier (NPC) [27]. The MQDF provides higher accuracy than the NPC but suffers from high expenses of storage and computation.

For the Handwritten recognition, transforming the similarity/dissimilarity measures output by classifiers to probabilistic confidence measures can benefit from fusing multiple classifiers or fusing multiple patterns, as has been demonstrated in previous works (e.g., [28], [29]). In character string recognition, Jiang et al. [18] transformed classifier outputs to confidence values under the soft-max framework. Li et al. [30] used the logistic regression model for confidence transformation. Our recent work [31] compared various confidence transformation methods in HCTR and found a better solution. Language models are widely used in speech recognition, machine translation, handwriting recognition, and so on [31]. The most popular language model is the n-gram, which characterizes the statistical dependency between characters or words. Character-level n-gram models have been popularly used in character string recognition (e.g., [12], [13], [14], [15], [18], [19], [20]. Word-level and hybrid language models were used in post processing for correcting recognition errors after character segmentation [30], but have been rarely used in integrated segmentation-and recognition [10].

The path evaluation function is hoped to be insensitive to the path length (number of characters on the path). The summation of classifier output similarity/dissimilarity scores or product of class probabilities is not appropriate since this is biased to short paths. Normalizing the summation or product by the path length overcomes the bias problem [31], but this normalized form does not enable optimal path search by dynamic programming (DP). Beam search can be used instead, but does not guarantee optimality [31]. Another way to overcome the path length bias is to add a compensative constant in the summated path evaluation function [20], but the constant needs to be estimated empirically. Wuthrich et al. called this constant a word insertion penalty, and Quiniou et al. also used this constant to control the deletion and insertion of words. Another effective way is to weight the character classification score with the number of primitive segments forming the character pattern [10], [15], motivated by the variable duration HMM of Chen et al. [31]. This not only makes the number of summated terms in the path evaluation function equal the number of primitive segments (and thus independent of the path length), but also preserves the summation form and enables optimal path search by DP.

In character string recognition, the pruning or augmentation of character classes affects the search efficiency and accuracy. Ideally, a candidate character pattern is assigned as few classes as possible by the classifier, including the true class. For Chinese handwriting, it often entails a large number (e.g., several hundred) of candidate classes to guarantee a high probability of including the true class, however. This complicates the search space on one hand and, on the other hand, may deteriorate the recognition accuracy because there are too many wrong classes competing with the true class. Therefore, some works have attempted to reduce the candidate classes output by the classifier by confidence evaluation and some other works attempted to supplement candidate classes for reducing the probability of missing the true class, according to the linguistic context or the classification confusion matrix . These techniques, however, have not been evaluated in integrated segmentation-and-recognition.

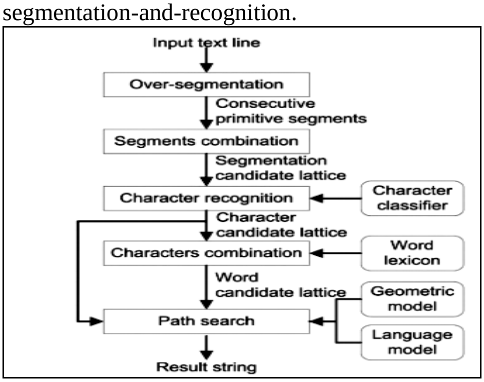

Fig. 2. System diagram of handwritten Chinese text line recognition.

3. System Overview

This study focuses on the recognition of text lines, which are assumed to have been segmented externally. For the convenience of academic research and benchmarking, the text lines in our database have been segmented and annotated at character level Fig. 2 shows the block diagram of our system for text line recognition. First, the input text line image is over segmented into a sequence of primitive segments (Fig. 3a) using the connected component-based method [5].

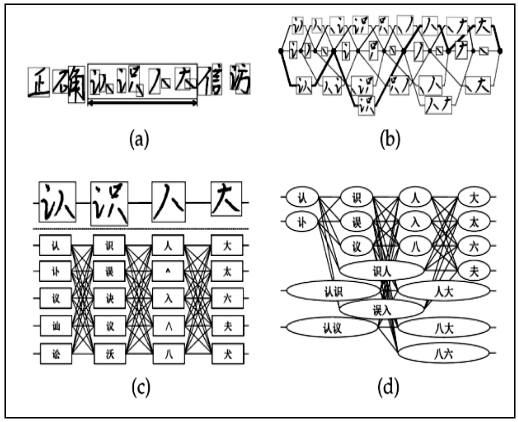

Fig. 3. (a) Over segmentation to a sequence of primitive segments (each is bounded by a small box), (b) segmentation candidate lattice of the arrowed part of (a), (c) character candidate lattice of the thick path in (b), (d) word candidate lattice of (c).

Consecutive primitive segments are combined to generate candidate character patterns, forming a segmentation candidate lattice (Fig. 3b). After that, each candidate pattern is classified to assign a number of candidate character classes, and all the candidate patterns in a candidate segmentation path generate a character candidate lattice (Fig. 3c). If a word level language model is used, each sequence of candidate characters is matched with a word lexicon to segment into candidate words, forming a word candidate lattice (Fig. 3d). All of these character (or word) candidate lattices are merged to construct the segmentation-recognition lattice of text line image. Each path in this lattice is constructed by a character sequence paired with a candidate pattern sequence, and this path is called a candidate segmentation recognition path. Finally, the task of string recognition is to find the optimal path in this segmentation-recognition lattice. Considering that the text lines are segmented from text pages, we utilize the linguistic dependency between consecutive lines to improve the recognition accuracy by concatenating multiple top-rank recognition results of the previous line to the current line for recognition.

4. Proposed Techniques

We formulate the problem of handwritten Chinese text recognition from Bayesian decision view. According to Bayesian decision under the 0/1 loss, maximizing a posterior probability of character sequence (string class) C =<c1 ... cm> given a text line image X is the optimal criterion for recognition. This posterior probability is formulated by

$$P(C|X)=\sum_s P(C,s|X)=\sum_s P(s|X)P(C|s,X) = \sum_s P(s|X)P(C|X^s), \qquad (1)$$

Where s is the segmentation path index, P(s|X) denotes the posterior probability of the sth segmentation path given the text line image, and P(C|X) Þ represents the posterior probability of string class given the sth segmentation path. P(s|X) is formulated by

$$P(s|X)=\prod_{i=1}^{m} p(z_i^p=1|g_i^{ui})\,p(z_i^g=1|g_i^{bi}), \qquad (2)$$

where m is the number of segmented candidate patterns (i.e., character number) of the segmentation path, z^p_i =1means that the ith candidate pattern is a valid character, and z^g_i=1 means that the gap between the (i- 1)th and ith candidate patterns is a valid between-character gap, the terms g_i^{ui} and g^{bi}_i are the class-independent geometric features extracted from the ith candidate pattern and from the pair of the (i- 1)th and ith candidate patterns, respectively. The two probabilistic terms in (2) correspond
to the unary and binary class-independent geometric model respectively. To avoid summing over a huge number of segmentation paths in (1), the optimal string class can be decided approximately by

$$C^* = \arg\max_{s,C} P(s|X)P(C|X^s). \qquad (3)$$

This is to search for the optimal segmentation and string class simultaneously in the lattice.

4.1Segmentation

The accuracy of segmenting Chinese character, especially connected Chinese characters, is essential for the performance of a Chinese character recognition system. Because the key for Chinese recognition is individual character recognition, usually, the main effort is focused on segmenting pages into lines, then into characters. And the word segmentation is mostly ignored if semantic information (word lexicon) is not available. A general segmentation process of handwriting Chinese is shown in figure 4.

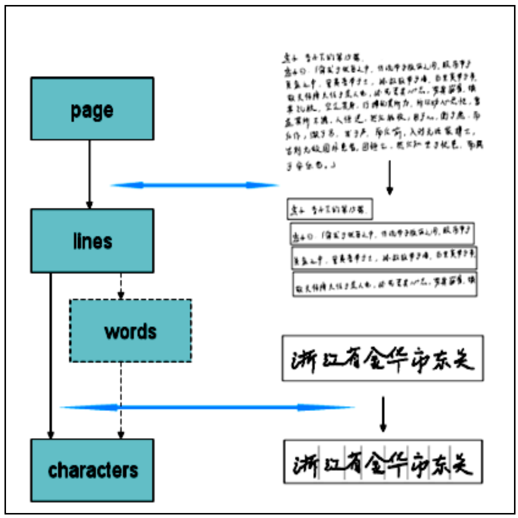

Fig.4. Process of Chinese segmentation

4.2 Path Search

On defining a score for each path in the segmentation-recognition lattice, the next issue is how to efficiently find the path of maximum score. In addition, to alleviate the loss that the candidate classes assigned by character classifier do not contain the true class, we propose an augmentation technique to supplement candidate classes in the lattice.

Search Algorithm

If the segmentation-recognition path is evaluated by the accumulated score (WIP, WSN, and WCW), it satisfies the principle of optimality, and the optimal path with maximum score can be found by dynamic programming. Nevertheless, when binary or higher order contexts are used, the complexity of DP search is high. For the NPL function, which does not satisfy the principle of optimality, DP search does not guarantee finding the optimal path, and the beam search strategy can better find an approximately optimal solution. In beam search, it is critical to retain the correct partial path in fewer survived paths. A simple strategy of beam search is to retain the multiple top-rank partial paths ending at each primitive segment [16]. This simple strategy, though it works efficiently, is too rough, particularly when high-order context models are used refined beam search algorithm was presented in our previous work (called pruned DP there) [10], which is suitable for using high-order context models.

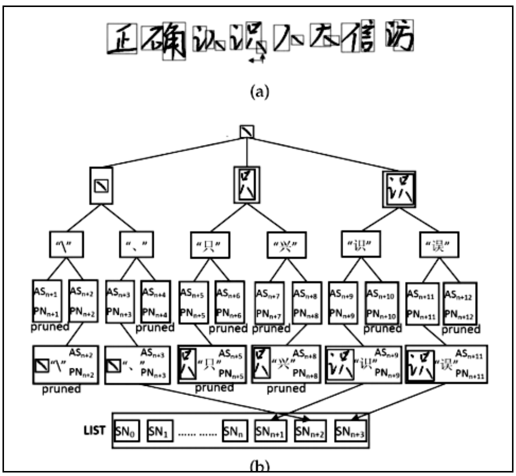

Fig. 5. An illustrative example of refined beam search (K = 3, CN = 2,BW = 3) at a primitive segment. (a) A sequence of consecutive primitive segments (the upward arrow points to current primitive segment and the leftward arrow points to the direction of segments combination to generate candidate patterns), (b) search space expansion at the pointed primitive segment of (a) (the pruned nodes are labeled).

After over segmentation, the text line image is represented as a sequence of primitive segments. A candidate pattern composed of k consecutive segments and ending at the ith segment is denoted by (I, k). A node in the search space is represented as a quadruple SN=fCP, CC, AS, PNg, where SN denotes a search node, CP is a candidate pattern, CC is a candidate character of CP, and AS is the accumulated score from the root node (calculated by (11)-(14), where m is the length of the current partial path), and PN is a pointer to the parent node of SN. All nodes are stored in a list named LIST to backtrack the final path. The refined beam search process is described in detail as follows, and Fig. 5 gives an illustrative example.

5. Hanzidict Jar File

A Chinese character dictionary app using (crude) handwriting recognition. This is a version of an older lookup app using the newer lookup component. Jar file should be directly runnable as both an Applet and as a stand-alone app. Main class is hanzidict/HanziDict. This Chinese language database jar file is downloaded from Dictionary CEDICT(CHINESE ENGLISH DICTIONARY).

http://www.mandarintools.com/cedict.html

6. Conclusion

This paper presented an approach for handwritten Chinese text recognition under the character over segmentation and candidate path search framework. We evaluate the paths from the Bayesian decision view by combining multiple contexts, including the character classification scores, geometric and linguistic contexts. In experiments on the unconstrained Chinese handwriting database CASIA-HWDB, the proposed approach achieved the character-level accurate rate of 90.75 percent and correct rate of 91.39 percent. The objective of over segmentation is to improve the tradeoff between the number of splitting points (affecting the complexity of search space) and the accuracy of separating characters at their boundaries. The objective of character classification is to improve the classification accuracy and the tradeoff between the number of candidate classes and the probability of including the true class. For path evaluation, both the geometric model and the language model deserve elaboration. Particularly, our experimental results show that mismatch of language model and text domain leads to inferior recognition performance. Therefore, the domain adaptation of language model will be an important research direction. In addition, the real semantic context and long-distance context will also be considered in the future.

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8. About the Authors

G Sirisha Kumari is currently pursuing her M.Tech (CSE) in Computer Science & Engineering Department, Pydah College of Engineering, Visakhapatnam. Her area of interests includes Image Processing.

V Srikanth is currently working as an Associate Professor in Computer Science & Engineering Department, Pydah College of Engineering, Visakhapatnam. His research interests include Data Mining & Warehousing, Networks Security and Image Processing.

