Recognition of Unconstrained Legal Amounts Handwritten on Chinese Bank Checks

Hanshen Tang [1], Emmanuel Augustin [2], Ching Y. Suen [1], Olivier Baret [2], Mohamed Cheriet [3]
1 Centre for Pattern Recognition and Machine Intelligence, Concordia University,
1455 de Maisonneuve Blvd. West, Montréal, Québec H3G 1M8, Canada
{hstang, suen}@cs.concordia.ca
2 Artificial Intelligence and Image Analysis (A2iA), 40 bis, rue Fabert, 75007 Paris, France
{ea, ob}@a2ia.com
3 Laboratoire d'Imagerie, de Vision et d'Intelligence Artificielle, École de Technologie Supérieure,
1100 rue Notre-dame Ouest, Montréal, Québec H3C 1K3, Canada
Mohamed.Cheriet@etsmtl.ca

Abstract

This paper presents a novel research investigation on legal amount recognition of unconstrained cursive handwritten Chinese character in the environment of A2iA CheckReader™ – a commercial bank check recognition system. The following problems and their solutions are described: character set of Chinese legal amounts, preprocessing (slant detection and correction), segmentation, feature extraction, grammar, automatic annotation of Chinese characters before and during training, and neural network/hidden Markov model training and recognition. The system is trained with 47.8 thousand real bank checks, and validated with 12 thousand real bank checks. The recognition rate at the character level is 93.5%, and the recognition rate at the legal amount level is 60%. This is the first successful commercial product in this domain.

1. Introduction

A lot of research for Chinese character recognition has been done [1] [2]. Several available commercial products have good recognition rates on printed Chinese. A lot of research on automatic bank check processing has been done [3] [4]. A2iA CheckReader™ is one of the most successful commercial products that can process bank checks handwritten in several Latin languages [5].

However, the recognition of unconstrained hand-written cursive Chinese in legal amounts remains a difficult problem.

Noises on the cheques make accurate segmentation, accurate recognition very difficult. The relatively large size of character set, different characters, similarity in shape, and the ambiguity of the grammar make the annotation of character, training and recognition very difficult. A wide variety of fonts and sizes, handwritten styles, and very cursively written scripts also bring a lot of problems. Because of all the above, the recognition performance of unconstrained handwritten cursive Chinese is still not very satisfactory.

Figure 1 shows two real bank check images, which can illustrate some of the difficulties.

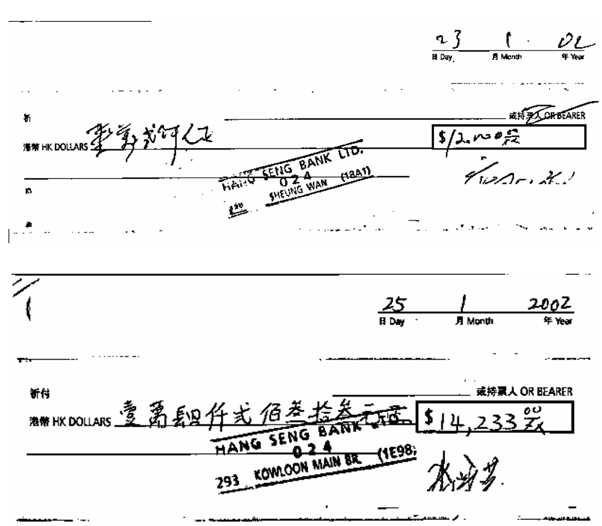

Figure 1. Binary images of two Chinese bank checks. The upper one is very cursive, and the lower one is very noisy.

2. System Overview

We developed the system in the environment of A2iA CheckReader™ system. The technical details about A2iA CheckReader™ can be found in "Industrial bank check

Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04)
1051-4651/04 $ 20.00 IEEE

processing: the A2iA CheckReader™" [5]. Figure 2 shows the whole Chinese bank check recognition system.

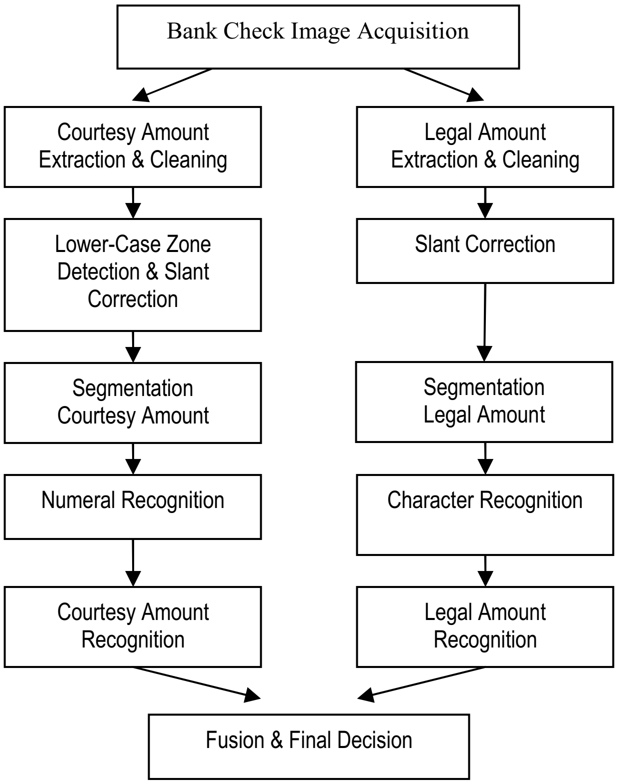

Figure 2. Overview of the Chinese check recognition system

This paper focuses on the right-hand side of the system - legal amount recognition. Some parts on both sides of the system are similar, such as amount extraction, and recognition with neural network/hidden Markov model. These will not be presented in detail in this paper, unless necessary, as more details can be found in [5].

3. Character Set and Grammar

After the analysis of the database of 60 thousand handwritten Chinese bank checks, we found that the character set consists of 49 characters that can be categorized into 19 meaning classes. Table 1 shows all of them, including many different characters that belong to the same meaning class. There are not enough samples to train each distinct character as a distinct class in the neural network, while it is syntactically impossible to differentiate characters belonging to the same meaning class. Thus, we had to train each meaning class as a whole in the neural network. However, some of the characters in the same meaning class are very different in shape. This led to troubles in the training of the neural network, such as convergence.

Table 1. Character set of Chinese legal amount

Digit or Amount	0	1	2	3	4	5	6
Simplified Chinese	0 零	一	二 两	三	四	五	六
Traditional Chinese	零	壹	貳 兩	叁	肆	伍	陆 陸
Commonly Accepted Synonym	另		貮 贰 弍 弐	弎	镸四		

Digit or Amount	7	8	9	10	100	1k	10k
Simplified Chinese	七	八	九	十	百	千	万
Traditional Chinese	柒	捌	玖	拾	佰	仟	萬
Commonly Accepted Synonym			玌				

Digit or Amount	100,000k	Dollar	10 Cents	1 Cent	Only
Simplified Chinese	亿	元	毛 角 毫	分 仙	正 整
Traditional Chinese	億	圆			

Analyses of the database of Chinese bank checks showed that many possible presentations in legal amount (sequences of characters) may be valid for the same numerical amount. We implemented the Chinese legal amount grammar tools based on automata.

The grammar tools have two usages. One is to check whether a certain legal amount is valid, if so, output its numerical value. This is used in the Monte Carlo process for training, and the recognition with the neural network/hidden Markov model. The other usage is to generate possible legal amount candidates from a given numerical value. This is used in the automatic annotation (this will be presented in Section (7)) and the training of the neural network/hidden Markov model. The grammar tools are not built to be stochastic. However, frequently used presentations are generally placed on the top of the candidate list of possible legal amounts generated by the grammar tools. One big remaining problem is that there may be more than tens of possible presentations in legal amount or even more for a given numerical amount. This made the training of the neural network/hidden Markov model difficult to converge. Thus we developed the method of automatic annotation.

4. Slant Correction

Unconstrained handwritten Chinese usually has two types of slant: horizontal slant, and vertical slant. On the other hand, in general, Latin ones only have vertical slant. This is illustrated in Figure 3. Thus the slant detection/correction for Chinese is different from the slant detection/correction for Latin languages.

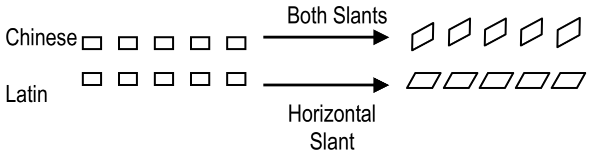

Figure 3. Slant (Horizontal and Vertical) in Chinese and Latin

5. Segmentation.

In many legal amounts found in the Chinese bank check database, two consecutive unconstrained hand-written Chinese characters are touching with each other in more than one position, rather than connected by a ligature. T. Yamaguchi, et al introduced an approach for the segmentation of touching Japanese characters [6].

We implemented a segmentation approach, Multiple Ranked Segmentation Options, based on: a. stroke connectivity. b. histogram. c. stroke cutting count (counting of cutting number across the strokes). d. character width estimation and character height/width analysis. e. noise isolation. The output of the segmentation is a candidate list of possible segmentation options with probability. Figure 4 displays one of the samples.

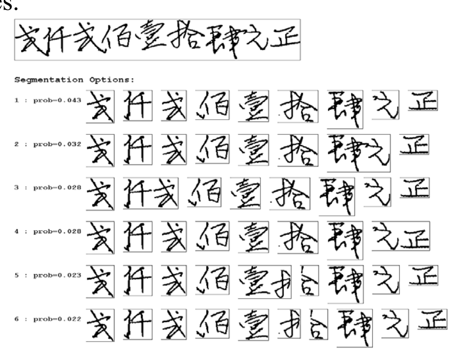

Figure 4. A candidate list of segmentation options.

6. Feature Extraction

A feature extraction tool has been implemented to handle the size variety without normalization. The input image is not required to be normalized in size, but the output features are standardized according to the size. The aspect ratio of the character retains, which is useful in differentiating characters, over-segmentation, and under-segmentation. Some common useful features for Chinese character recognition such as aspect ratio, symmetry, peripheral features, and direction contribution of strokes, [7] etc, are extracted.

7. Automatic Annotation Tool and Training

The recognizer of the original A2iA CheckReader™ is based on neural network/hidden Markov model. However, because of the ambiguity of the grammar, and because certain meaning class has a variety of character shapes (as mentioned in the Section (3)), the training of the system did not perform well for Chinese legal amount recognition.

To feed and train the neural network, we need annotated samples of the classes. We introduced the strategy of spiral recognition. The idea is illustrated in Figure 5. With the annotation tool, we can get more samples for each class. With the recognition results and the grammar rules, we can annotate more classes.

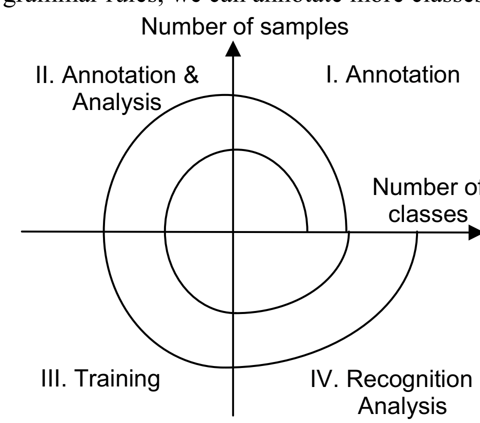

Figure 5. Spiral recognition

In the first iteration of training the system, we developed a tool to get such samples from neat bank checks with the aid of the segmentation and the grammar tools. We considered only samples in those cases that the segmentation options are of very high (close 1.0) probabilities and there are not too many candidates for given numerical amounts.

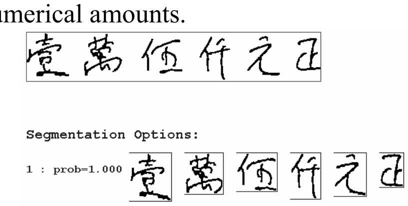

Figure 6. This bank check image is neat and the segmentation probability is 1.0, thus all the six segments can be automatically annotated. They are “one”, “ten thousand”, “five”, “thousand”, “dollar”, and “only”, respectively.

Figure 6 illustrates the tool. The analysis of the result of the tool showed that the key classes (such as classes for “ten”, “hundred”, “dollar”, and “only”) can be identified fairly well (error rate less than 4%). The overall annotation error rate is 6%.

Proceedings of the 17th International Conference on Pattern Recognition (ICPR’04)
1051-4651/04 $ 20.00 IEEE

In the second and following iterations of training of the system, we developed a tool to get annotated class samples with the aid of the segmentation, the grammar tools, and the recognizer trained in previous iterations. While the system iterated, the annotation error rate decreased, and the recognition rate increased.

After the training, the character recognition results – a ranked candidate list of character hypotheses - from the neural network can be passed to the amount recognizer with the grammar tool. A candidate list of recognized amounts is outputted.

8. Experimental Results and Analyses

After 8 iterations of training on the database of 47.8 thousand of real bank checks, and validation with 12 thousand of real bank checks, the average annotation error rate reduces to 3%. The recognition rate in annotated samples is 90.66% for the top candidate. The real recognition at character level is estimated by

$$\text{Real Recognition Rate} = \frac{\text{Annotation Recognition Rate}}{1 - \text{Annotation Error Rate}}.$$

Thus the estimated real recognition rate is 93.5% for the top candidate, while the amount level recognition rate is 60% for the top candidate, and 76% for the top 4 candidates. Analyses of the errors shows: 40% of the errors are due to excessive noises on the bank checks; 15% are due to excessive cursive handwritten scripts; 10% are due to inseparable handwritten scripts; 12% are due to rare occurrences of some characters (too few samples to train the recognizer); 19% are due to excessive similarity among some characters; and 4% are due to excessive long strokes in some handwritten scripts.

The original A2iA CheckReader™ has an average read rate at the document level (combining the courtesy amount and the legal amount recognition) between 65% and 85% with a misread rate of 1% for checks in Latin languages. With the Chinese legal amount recognizer, the improvement on a mixed flow of checks is around 5% increase in the read rate (where 30% of the checks were written in Chinese, and the rest were written in English).

9. Conclusions

A legal amount recognition system of unconstrained cursive handwritten Chinese characters is presented. The system has a good recognition rate while the misread rate is low, on a large database of bank checks. This system is the first successful commercial product in the domain.

The recognition performance may be further improved by employing radical recognition and structural and hierarchical approaches [8] [9]. The automatic annotation strategy is promising, which enables the system to train on more samples for each class, as well as on more classes if a proper grammar and vocabulary are given.

Acknowledgements. The authors would like to express their thanks to Professor G. Stamon for his help for the initiation and the proceeding of the collaboration project.

References

[1] J. W. Tai, "A syntactic-semantic approach for describing Chinese characters," *Computer Processing of Chinese and Oriental Languages, Vol. 1, No.3*, Chinese Language Computer Society, San Francisco, CA, USA, May 1984, pp. 186-194

[2] H. Chen, L. Gareth, Y. Wu, and R. Zitserman, "Segmentation and recognition of continuous handwriting Chinese text," *Advances in Oriental Document Analysis and Recognition Techniques,* World Scientific, Singapore, 1998, pp. 223-232

[3] K. Liu, C. Y. Suen, and C. Nadal, "Automatic extraction of items from check images for payment recognition," *Proc. 13th ICPR, Vol. 3,* Vienna, Austria, 1996, pp. 798-802

[4] C. Y. Suen, L. Lam, D. Guillevic, N. W. Strathy, M. Cheriet, J. N. Said, and R. Fan, "Bank check processing system," *Int. Journal of Imaging Systems and Technology, Vol. 7,* Wiley, New York, N.Y., USA, 1996, pp. 392 –403

[5] N. Gorski, V. Anisimov, E, Augustin, O. Baret, and S. Maximov, "Industrial bank check processing: the A2iA CheckReader™," *Int. Journal on Document Analysis and Recognition (2001) 3*, Springer, Berlin, Germany, 2001, pp. 196-206

[6] T. Yamaguchi, T. Yoshikawa, T. Shinogi, S. Tsuruoka, and M. Teramoto, "A segmentation method for touching Japanese handwritten characters based on connection condition of lines," *Proc. of ICDAR 2001*, Seattle, WA, USA, 2001, pp. 837 – 841

[7] C. H. Leung, and L. Sze, "Feature selection in the recognition of handwritten Chinese characters," *Eng. Appl. of Artificial Intelligence 10 (5)*, 1997, pp. 495-502

[8] D. Shi, S. R. Gunn, and R. I. Damper, "Active Radical Modeling for Handwritten Chinese Characters," Proc. of ICDAR 2001, Seattle, WA, USA, 2001, pp. 236 – 240

[9] A. B. Wang and K. C. Fan, "Optical recognition of handwritten Chinese characters by hierarchical radical matching method," Pattern Recognition, 3491, Pergamon Press, Oxford, New York, USA, 2001, pp. 15-35