An On-line Handwritten Text Search Method based on Directional Feature Matching

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Abstract—In this paper, we describe a method of retrieving on-line handwritten text based on directional feature matching. Although text search into the character recognition candidate lattice has been elaborated, the character recognition based approach does not support languages which are not assumed. The proposed method is liberated from this constraint. It first hypothetically segments on-line handwritten text into character pattern blocks and prepares the object text patterns by combining the character pattern blocks. On the other hand, it employs handwritten text as a query pattern or prepares a query pattern by combining character ink patterns from query character codes. Then, it extracts directional features from the object text patterns and the query pattern, and the dimensionalities of those features are further reduced by Fisher linear discriminate analysis (FDA). Finally, the similarity is measured between the object text patterns and the query pattern by block-shift matching. This paper discusses the retrieval performance in comparison with our previous character recognition based method.

Keywords- text search; on-line handwritten text; digital ink; directional feature matching

I.   INTRODUCTION

Recently, a wide variety of handwriting input interfaces are available. High-specification portable devices are equipped with pen of finger input functions. On-line handwritten patterns in the form of digital ink (a time-sequence of pen-tip coordinates), sampled on these devices will be accumulated. However, without a search method, the accumulated handwritten digital ink data would not be utilized effectively.

Text search methods for handwritten documents employing character recognition technology have been developed for many years and character recognition technology has been elaborated for the search purpose. In offline recognition, Marukama et al. proposed a search method, which reduced search loss from incorrect recognition results by using two or more character recognition candidates and a confusion matrix [1]. Ota et al. further extended the above idea by producing search terms considering mis-segmentation as well as mis-recognition with the confidence from them and from bi-gram [2]. Imagawa et al. investigated reliability of recognition results using a neural network and they showed that both the recall rate and the precision rate were improved by their method [3].

In on-line recognition, Oda et al. proposed a search method for retrieving a Japanese keyword in digital ink by employing handwritten character recognizer [4]. They prepared a candidate lattice from digital ink and searched a keyword from the lattice, which was much richer representation than just a sequence of top candidates. Cheng et al. improved the above method by re-sorting the results and removing all the results which were included partially in the top candidate [5]. However, those methods support only languages for which character recognition is provided.

For degraded documents, character recognition may not include correct answers even in the candidate lattice. In offline document images, Manmatha et al. proposed a search method by indexing handwriting based on matching the images of the words using Euclidean Distance Mapping and SLH Algorithm [6]. Lu et al. proposed a search method using a word image annotation technique which captured the document content by converting each word image into a word shape code [7].

For on-line handwritten text, Senda et al. also proposed a search method by pattern matching without character recognition [8].

This paper presents a method for on-line handwritten text search, which is liberated from the language constraint. First handwritten digital ink is hypothetically segmented into character pattern blocks and the object text patterns are generated by combining the character pattern blocks. On the other hand, a query pattern is presented from a tablet as handwritten text pattern or it is generated by combining character ink patterns according to query character codes presented from a keyboard. Then, the directional features are extracted from the object text patterns and a query pattern, and the dimensionalities of those features are further reduced by Fisher linear discriminate analysis (FDA). Finally, the results of dimensionality reduction are employed to calculate the degree of similarity between the object patterns and the query pattern by block-shift matching. This paper discusses the retrieval performance in comparison with a character recognition based method by Cheng et al. [5].

The structure of this paper is organized as follows: the method of text search is described in section II, the process of directional features extraction and dimensionality reduction are presented in section III, the results of experiments and evaluations are shown in section IV, and the conclusion and suggestion for future work are given in section V.

II. Text Search Method

We propose a text search method for locating a keyword in on-line handwritten text patterns produced in free format without imposing any constraint of writing boxes, grids or baselines. The keyword may be presented from a keyboard as character codes or from a tablet while the target of the search is on-line handwritten text patterns, i.e., digital ink rather than a sequence of character codes.

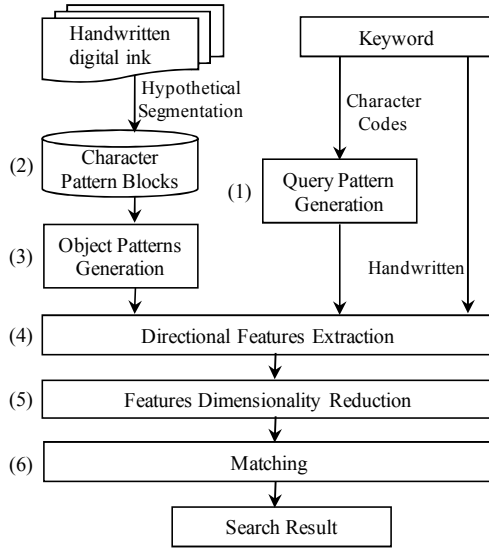The proposed method is composed of the following processes (Figure 1).

Figure 1.   Handwritten text search process.

(1) Query pattern generation:

A search query is input form a keyboard as character codes, and its on-line handwritten pattern is generated from a character standard pattern database (TUAT Nakagawa Lab. HANDS-TEHON) which include 7,722 character patterns (Kanji: 7116, Kana: 169, Roman character: 52, Number and Symbol: 385).

(2) Segmentation of handwritten text into character pattern blocks:

The proposed method is devised to hypothetically segment on-line handwritten text into character pattern blocks by examining distance between adjacent strokes. Here, we employ the method for character segmentation for Japanese text. Although we seek the method to be language independent, the Japanese character segmentation method may provide a considerably stable segmentation of character pattern blocks. In any case, however, we must verify that the method provides satisfactory segmentation into character pattern blocks even for other languages than Japanese.

For the search purpose as the same as the recognition purpose, we prefer over-segmentation, i.e., two characters must be segmented but a single character might be segmented. A character pattern block bounded by two adjacent segmentation points is assumed as a character pattern and it might be a character or a part of a character.

(3) Object text patterns generation:

The object text patterns are generated by combining the character pattern blocks and shifting positions of the character pattern blocks according to segmentation points. The widths for object text patterns can be limited by a segmentation threshold which is obtained by analyzing the width of the query pattern with the result of reduced number of object text patterns and improved processing speed.

(4) Extraction of directional features from object patterns and a query pattern:

After a query pattern and object patterns are generated, the proposed method extracts a multi-dimensional feature vector for all of those patterns. A method of extraction is described in the section III [9].

(5) Reduction of features dimensionality:

The features are further compressed to lower dimensionality by FDA [10].

(6) Matching between object patterns and a query pattern:

The proposed method employs the results of dimensionality reduction to calculate Euclidean distances between object patterns and a query pattern while changing the start position of object patterns by block shift (Figure 2). The search results will be produced if their Euclidean distances are less than a search threshold.

We can calculate the optimal search threshold by employing a number of training sets. We assume that the optimal search threshold may vary depending on the length of a search keyword. That is because the probability of search loss is high when a search query is long. On the other hand, the probability of search noise is high when a search query is short.
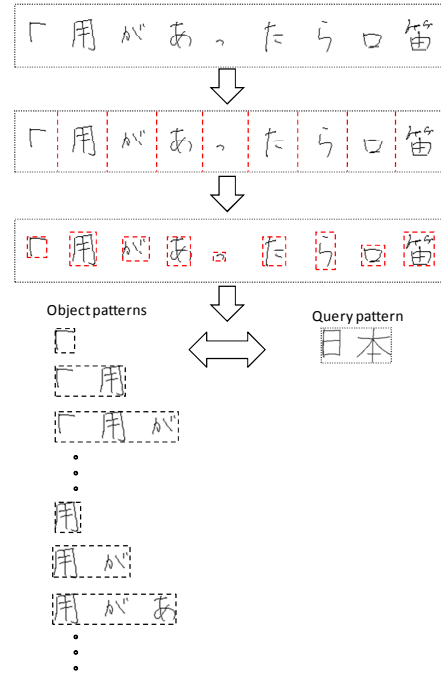

Figure 2.   Pattern matching.

III. DIRECTIONAL FEATURES EXTRACTION

As shown in Figure 3, the proposed method first scales the pattern to a 64x64 grid by non-linear normalization [11]. Then, it decomposes the normalized pattern into 4 contour sub-patterns representing directional feature of the 4 main orientations. Finally, it extracts a (NxN)-dimensional feature vector for each contour pattern from the convolution with a blurring mask (Gaussian filter). Therefore, it can obtain a (NxNx4)-dimensional feature vector. In this paper, we set N=8 to get a 256-dimensional feature vector and then reduce it to a 100-dimensional feature vector by FDA.
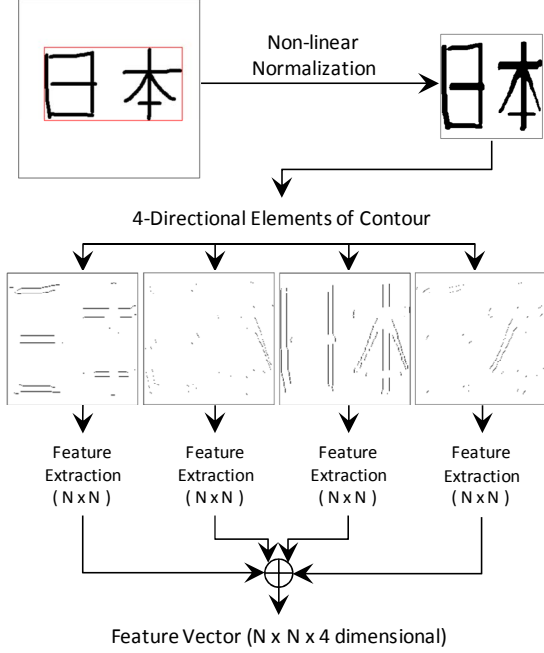

Figure 3. Directional feature extraction process.

IV. EXPERIMENT AND EVALUATION

A. Criterions for Search

We evaluate the overall performance of our search method in term of the F-measure. The F-measure is defined by the formula (1). Where R is recall rate, P is precision rate and they are expressed by the formula (2), (3) respectively.

$$F = \frac{2}{\frac{1}{R} + \frac{1}{P}} \qquad (1)$$

$$R = \frac{\text{Number of correct search}}{\text{Number of search keywords in the target data}} \qquad (2)$$

$$P = \frac{\text{Number of correct search}}{\text{Number of searched patterns}} \qquad (3)$$

The recall rate represents tolerance to search losses, while the precision rate represents tolerance to search noise.

B. Database

In [5] Cheng et al. employed the database "TUAT Nakagawa Lab. HANDS-Nakayosi_t-98-09" (in brief, Nakayosi) [12], the database "TUAT Nakagawa Lab. HANDS-Kondate bf-2001-11" (in brief, Kondate), and the database "TUAT Nakagawa Lab. HANDS-Kuchibue_d-97-06" (in brief, Kuchibue) [13] in the experiments for evaluating their search method. Nakayosi is a set of on-line handwritten text patterns written by 163 participants with each composed of 10,403 character patterns written by a single participant. Kondate is a set of on-line handwritten text and line-drawing patterns written by 100 participants with each composed of more than 2,000 character patterns written by a single participant (all of the character patterns in meaningful context). Kuchibue is a set of on-line handwritten text patterns written by 120 participants with each composed of 11,962 character patterns written by a single participant (10,152 character patterns in meaningful context, 1,810 character patterns without context).

Cheng et al. employed all of the Nakayosi to train their character classifier and geometric scoring functions, and used all of the Kondate to train their SVM classifier for the candidate segmentation point probability. They also employed 60 sets of Kuchibue to train their weighting parameters.

In our experiments, however, we employed only 60 sets of Kuchibue as training sets to calculate the search threshold which brings the highest F-measure.

C. Evaluation

Cheng et al. tested their search method with the rest 60 sets of Kuchibue and all of the Kondate. They employed 1,000 kinds of search keywords for every length of 2, 3, 4 characters to test on Kuchibue, and other 200 kinds of search keywords for every length of 2, 3, 4 characters to test on Kondate. Their results are shown in TABLE I and TABLE III. Under the same conditions, we tested our search method and the results are given in TABLE II and TABLE IV.

From TABLE II and TABLE IV, we can see that the proposed method has achieved the F-measure over 0.66 when a 256-dimensional feature vector is reduced to 100-dimensions, that it to say, the optimal F-measure is obtained when a higher dimensional feature vector with a constant sampling interval is compressed to a lower dimensionality before matching process.

TABLE I.   CHENG ET AL.'S SEARCH PERFORMANCE TO KUCHIBUE [5]

Length of query	Recall (%)	Precision (%)	F-measure
2	92.0	88.2	0.900
3	93.6	94.1	0.937
4	94.4	96.3	0.952

TABLE II.   OUR SEARCH PERFORMANCE TO KUCHIBUE

Length of query	Original 256-dimensional feature			Dimensionality reduction 100-dimensional feature		
	R (%)	P (%)	F	R (%)	P (%)	F
2	59.0	54.4	0.566	61.6	56.3	0.588
3	61.2	62.4	0.617	63.4	64.2	0.637
4	62.0	63.1	0.625	63.9	64.5	0.641

TABLE III.   CHENG ET AL.'S SEARCH PERFORMANCE TO KONDATE [5]

Length of query	Recall (%)	Precision (%)	F-measure
2	77.4	74.2	0.756
3	87.1	86.3	0.867
4	88.7	89.8	0.891

TABLE IV.   OUR SEARCH PERFORMANCE TO KONDATE

Length of query	Original 256-dimensional feature			Dimensionality reduction 100-dimensional feature		
	R (%)	P (%)	F	R (%)	P (%)	F
2	59.8	57.7	0.587	61.4	58.7	0.600
3	63.7	63.2	0.634	65.2	64.8	0.649
4	64.3	65.1	0.646	66.1	66.3	0.661

D. Consideration

Compared with Cheng et al.'s results, the performance of our method is lower. Several reasons can be considered. First, Cheng et al. employed a larger set of training patterns. Second, it is a language dependent system. Third, it exploits the recent elaboration on character recognition and the candidate lattice includes search keywords with high probability. In order to verify the reasons, we must enlarge the training set.

On the other hand, our method is language independent so that it may be applied to other languages. Verification of this nature must be made using ink patterns of other languages.

Since our method is different from Cheng et al.'s method, combinations of the two methods is another interesting topic.

V.   CONCLUSION

This paper proposed a retrieval method for handwritten digital ink based on directional feature matching without recognizing characters. The proposed method has shown encouraging results, having achieved the F-measure over 0.66 for testing sets. For future work, we investigate the effects of extracting more features based on the range of patterns, and work on experiments employing other handwritten language database.

REFERENCES

[1] K. Marukawa, H. Fujisawa, Y.Shima: "Evaluation of Information Retrieval Methods with Output of Character Recognition Based on Characteristic of Recognition Error (Japanese)," Trans IEICE, vol. J79-D-II, no.5, pp.785-794 (1996.05).

[2] M. Ota, A. Takasu, J. Adachi: "Full-text search Methods for OCR-recognized Japanese Text with Misrecognized Characters (Japanese)," Trans. IPSJ, vol.39, no.3, pp.625-635 (1998.03).

[3] T. Imagawa, Y. Matsukawa, K. Kondo, T. Mekata: "A document image retrieval technique using each character recognition reliability (Japanese)," TECHNICAL REPORT OF IEICE PRMU99-72, pp.63-68 (1999).

[4] H. Oda, A. Kitadai, M. Onuma and M. Nakagawa: "A search method for on-line handwritten text employing writing-box-free handwriting recognition", Proc. 9th International Workshop on Frontiers in Handwriting Recognition (IWFHR), Tokyo, Japan, pp. 545-550 (2004.10).

[5] C. Cheng , B. Zhu , Xiaorong Chen , Masaki Nakagawa: Improvements in Keyword Search Japanese Characters Within Handwritten Digital Ink , Proc. 10th International Conference on Document Analysis and Recognition (ICDAR), pp.863-866, Spain (2009.07).

[6] R. Manmatha, C. Han and E. Riseman: "Word Spotting: A New Approch to Indexing Handwriting", Proc. the IEEE Computer Vision and Pattern Recognition Conference, San Francisco, CA (1996.06).

[7] S. Lu, L. Linlin, C. L. Tan: "Document Image Retrieval through Word Shape Coding", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 30, No. 11, pp. 1913-1918 (2008.11).

[8] S. Senda, Y. Matsukawa, M. Hamanaka, K. Yamada, "MemoPad: Software with functions of Box-free Japanese Character Recognition and Handwritten Query Search (Japanese)," TECHNICAL REPORT OF IEICE, PRMU99-75 pp.85-90 (1999.09).

[9] C.-L. Liu, Y.-J. Liu, R.-W. Dai, Preprocessing and statistical/structural feature extraction for handwritten numeral recognition, in progress of handwritting Recognition, A.C. Downton and S. Impedovo(Eds.), World Scientific, pp.161-168 (1997).

[10] W. Yang and J. Wang: Feature Extraction Using Fuzzy Inverse FDA, Neurocomputing, pp.3384-3390 (2009).

[11] J. Tsukumo, H. Tanaka: "Classification of handprinted Chinese characters using non-linear normalization and correlation methods", Proc. 9th ICPR, Roma, Italy, 168-171 (1988).

[12] M. Nakagawa, T. Higashiyama, Y. Yamanaka, S. Sawada, L. Higashigawa, and K. Akiyama: "On-line handwritten character pattern database sampled in a sequence of sentences without any writing instructions,"Proc. 4th ICDAR, vol.1, pp.376-381 (1997.08).

[13] M. Nakagawa and K. Matsumoto, "Collection of on-line handwritten Japanese character pattern databases and their analysis", IJDAR, vol.7, no.1, pp.69-81 (2004.03).