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An approach to integration of off-line and on-line recognition of handwriting

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Abstract

On-line recognition algorithms free from writing constraints and high-quality thinning algorithms are important subjects in research on handwriting recognition and are also essential for the integration of off-line and on-line recognition of handwriting. We present an approach to the integration of off-line and on-line recognition of unconstrained handwritten characters by adapting an on-line recognition algorithm to off-line recognition, based on high-quality thinning algorithms. In the experiments, high recognition rate has been attained with a small number of class descriptions (typically one class for one character).

Keywords: Character recognition; Handwriting recognition; Structural description

1. Introduction

Recently, handwriting recognition has become more and more important and has received much attention in research, development, and marketing. Off-line character recognition (optical character recognition, *OCR*) has been applied to various areas such as automatic postal address readers, office automations, and automatic data entry from paper documents to computers. On-line character recognition has attracted much attention recently as a means of human-computer interface more friendly and flexible than traditional key board input. In research and development, OCR has a longer history and extensive researches have been conducted (Mori et al., 1992). On the other hand, the intensive research and development on on-line character recognition have just started (Tappert et al., 1990) and there is much room for improvement in recognition accuracy and relaxation of writing constraints.

Although both off-line handwritten character recognition and on-line character recognition address the problem of recognition of human handwriting, there has been, unfortunately, only a little interaction between the two areas and they have been studied separately. However, the interactions between the two areas will promote the research and development, and will benefit one another. Researchers on on-line recognition could utilize some experiences in research on off-line recognition in order to improve the recognition accuracy, relax the writing constraints, and develop sophisticated recognition methods. There have been a number of researches accumulated in off-line handwritten character recognition and some methods have attained high recognition accuracy. On the other hand, from experiences in research on on-line recognition, researchers on off-line recognition could ob-

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tain some insights into stroke-based feature extraction and shape description. Furthermore, in on-line recognition, we do not need to consider noise and shape distortions caused by the imaging defects proper to off-line recognition, and therefore, we can concentrate on the aspects of shape analysis.

In this paper, we discuss the integration of off-line and on-line methods for handwriting recognition. In particular, we address the adaptation, to off-line recognition, of the on-line recognition algorithm that requires a small number of class descriptions and tolerates arbitrary numbers, orders, and directions of strokes along with stroke connection and breaking.

This paper is organized as follows: In Section 2, we discuss the advantage and significance of the integration of off-line and on-line recognition algorithms. In Section 3, we describe the adaptation of an on-line recognition algorithm free from writing constraints (Nishida, 1995a) to off-line recognition of unconstrained handwritten characters. In Section 4, we present performance statistics of the method presented in Section 3, using the public-domain database. Section 5 is the conclusion.

2. Integration of off-line and on-line recognition algorithms

Many on-line character recognition algorithms employ stroke-based features, and therefore, some constraints on the stroke number, order, and directions are required in order to extract stable features. In current technology, high recognition accuracy is attained at the expense of flexibility and user-friendliness. An essential problem of on-line handwritten character recognition is how to relax such writing constraints. The relaxation of writing constraints leads to recognition algorithms independent of temporal information and the number of stroke, and therefore, on-line recognition becomes closer to off-line recognition. The development of on-line character recognition algorithms free from writing constraints (stroke order, number, and directions) is an important theme in the fields of pattern recognition and human-computer interface.

An alternative approach to on-line recognition free from writing constraints is to apply some off-line recognition algorithms by transforming on-line data to a form of off-line data in the following ways: (1) convert on-line data to bitmap data; (2) regard stroke data as results of thinning by eliminating temporal information. Hamanaka et al. (1993) apply a method for off-line handwritten character recognition to bitmap data obtained from on-line data and have reported that high recognition accuracy has been attained for on-line recognition of unconstrained handwritten characters. Since many algorithms for off-line handwritten character recognition have attained high recognition accuracy, such an approach is a possibility for constructing on-line recognition methods free from writing constraints.

Recently, thinning of line pictures has received much attention (Suen and Wang, 1993), and a number of algorithms have been developed (Lam et al., 1992). Furthermore, some criteria and methodologies for the objective evaluation of thinning algorithms have been presented by Jaisimha et al. (1994). Thinning is essential for extraction of structural, stroke-based features in off-line handwritten character recognition, because an effective, high-level, abstract representation of line pictures can be obtained from character images through thinning. However, throughout literatures on thinning, few systematic discussions can be found from the viewpoint of representation of handwritten characters. Nishida et al. (1992) considered the role of thinning in handwritten character recognition and emphasized the importance of the recovery of the strokes and the instrument trajectory. In particular, strokes sometimes intersect each other, and therefore, the analysis and description of *singular regions* such as junctions are keys to the stroke recovery. Based on this discussion, Suzuki and Mori (1993) proposed a high-quality thinning algorithm along with application to handwritten character recognition. Doermann and Rosenfeld (1992) extended the analysis by Nishida et al. (1992) to grey-scale intensity images and attempted to extract temporal information from static images. On-line character recognition is based on the stroke-based features, and therefore, on-line recognition algorithms free from writing constraints can be applied to thin-line representations of off-line handwritten characters.

On-line character recognition algorithms free from writing constraints and high-quality thinning algorithms recovering the strokes and the instrument trajectory are important subjects in research on handwriting recognition. Furthermore, as discussed in this section, these two subjects are essential for the integration of off-line and on-line recognition algorithms for unconstrained handwritten characters.

3. Algorithm

In this section, based on the discussions in Section 2, we present an off-line recognition algorithm for unconstrained handwritten characters by adapting an on-line recognition algorithm free from writing constraints to off-line recognition. In the first part of this section, we describe the conversion of off-line data to a form that can be processed by some on-line recognition algorithms. In the second part, we mention an outline of the on-line recognition algorithm free from writing constraints proposed by Nishida (1995a). This algorithm requires a small number of prototypes (typically one class for one character) and it has the following properties from the viewpoint of on-line character recognition: (a) Stroke order, direction, and number are free; (b) Stroke connection and breaking are allowed. Therefore, this algorithm can recognize off-line handwritten characters by converting line pictures to some particular form.

3.1. Conversion of off-line data to on-line data

The input to on-line recognition algorithms is time-sequential data of coordinates on the two-dimensional plane. Therefore, for adapting an on-line recognition algorithm to off-line recognition, we need to obtain thin-lines representing strokes (instrument trajectory) from a character image and convert the thin-lines to a point sequence that can be processed by on-line recognition algorithms. For this purpose, three types of processing are required for the thin-lines obtained by such high-quality thinning algorithms as proposed by Suzuki and Mori (1993).

(1) Around each singular point such as a branch point or a crossing, strokes (instrument trajectory) are recovered by grouping pairs of branches based on some good-continuity criteria. This processing is called the *singular point decomposition* in (Nishida and Mori, 1992).

(2) If there is a loop after the singular point decomposition, the loop needs to be broken at a certain point.

(3) By the singular point decomposition and breaking loops, the thin-lines are converted to a set of curves topologically equivalent to line segments. By connecting end points of curves so that there comes out no loop, the thin-lines are converted to sequential data of coordinates on a two-dimensional plane.

Each step is described in detail in the rest of this subsection.

3.1.1. Singular point decomposition

The vertex v whose order (the number of branches incident to the vertex) is equal to or more than three is called a *singular point*. Let n be the order of the singular point v $(n \geqslant 3)$. For branches b_i $(i = 1, \ldots, n)$ incident to v, we introduce a smoothness function $S(i, j)$ $(1 \leqslant i < j \leqslant n)$. The simplest form of $S(i,j)$ is as follows: On each b_i $(i = 1, \ldots, n)$, we select one point $w(i)$ close to v. Let (x_0, y_0) be the coordinates of v and (x_i, y_i) be the coordinates of $w(i)$. $S(i, j)$ is defined as

$$S(i,j) = \frac{\boldsymbol{q}_i \cdot \boldsymbol{q}_j}{|\boldsymbol{q}_i| \cdot |\boldsymbol{q}_j|}, \tag{1}$$

where

$$\boldsymbol{q}_k = (x_k - x_0, y_k - y_0), \quad k = 1, 2, \ldots, n.$$

Next, find the sequence

$$S(i_1, j_1) \leqslant S(i_2, j_2) \leqslant \cdots \leqslant S(i_m, j_m) \tag{2}$$

such that

$$S(i_1, j_1) = \min\{S(i,j) \mid i, j \in I, i < j\},$$

$$S(i_k, j_k) = \min\{S(i,j) \mid i, j \in I - \bigcup_{l=1}^{k-1} \{i_l, j_l\}, i < j\}$$

for $k = 2, 3, \ldots, m$, where $I = \{1, 2, \ldots, n\}$ and $m = \lfloor n/2 \rfloor$ ($\lfloor r \rfloor$ is the greatest integer that is equal to or smaller than r).

We now introduce n new vertices $v(i)$ $(i = 1, \ldots, n)$ which have the same coordinates as v. Though the vertices $v(i)$ $(i = 1, 2, \ldots, n)$ have the same coordinates as v, they are regarded as different from each other. Next, for n vertices $w(i)$ adjacent

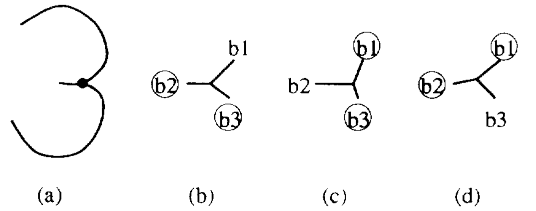

Fig. 1. Structural instability around branch points. (a) is a thin-line picture with a branch point and (b) is the configuration around the branch point. The local configuration is changed as shown in (c), (d) by small perturbations. The pairs of branches that minimize $S(\cdot,\cdot)$ are denoted by circles.

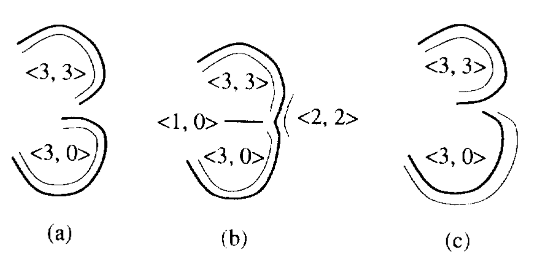

Fig. 2. $S(i,j)$ for three possible configurations. $S(2,3) = S(1,2) = 6$ and $S(1,3) = 9$. Either (a) or (c) is selected as the decomposition of the branch point.

to v, add edges $(v(i), w(i))$ $(i = 1, \ldots, n)$ and remove the vertex v. After applying this operation, the thin-line picture is decomposed into connected components each of which is a simple arc. Then, connect a pair of edges $(v(i_k), w(i_k))$ and $(v(j_k), w(j_k))$ by regarding the two vertices $v(i_k)$ and $v(j_k)$ $(k = 1, 2, \ldots, m)$ as identical.

A series of the above operations is called the *singular point decomposition*. It decomposes the vertex v into $\lceil n/2 \rceil$ ($\lceil r \rceil$ is the smallest integer that is equal to or greater than r) vertices, and generates $\lceil n/2 \rceil$ pairs of branches incident to v. By this operation, the thin-line picture is decomposed into components topologically equivalent to line segments or loops. In this paper, we refer, as a *stroke*, to a connected component obtained by the singular point decomposition.

However, the above definition of $S(i,j)$ is based on the local features around the singular point, and it sometimes causes some structural instability as shown in Fig. 1. Small perturbation around the singular point may change the local configuration, and therefore, decision should be made based on structurally stable criteria in terms of global features around the singular point. To cope with such a case sometimes observed for branch points (order 3), we use the following definition for $S(i,j)$ when $n = 3$ and $S(i_1, j_1) \approx S(i_1, k)$ $(j_1 \neq k)$ or $S(i_1, j_1) \approx S(k, j_1)$ $(i_1 \neq k)$: Suppose that there are M primitive sequences with PS-labels (Nishida and Mori, 1992; Nishida, 1993, 1995b, 1995c) $\langle r_k, d_k \rangle$ $(k = 1, \ldots, M)$ on the thin-line picture after we connect the two branches b_i and b_j. Then, $S(i,j)$ is defined as $\sum_{k=1}^{M} r_k$, i.e., sum of rotation numbers in quantized directions. For instance, as shown in Fig. 2, $S(2,3) = S(1,2) = 6$ and $S(1,3) = 9$ when the thin-line pictures are analyzed in four directions (Nishida and Mori, 1992). Therefore, either $(2,3)$ or $(1,2)$ is selected as (i_1, j_1).

3.1.2. Breaking loops

We need to break a loop somewhere in order to convert the thin-line pictures to a point sequence that can be processed by on-line recognition algorithms. In general, the breaking points can be arbitrarily selected. Since the loop is usually drawn from the top (for instance, "0") and a corner in the upper part is likely to be the starting point (for instance, "D"), we break the loop at the point where the following heuristic function is maximized: $y_p + \alpha H \cos \theta_p$, where y_p is the y-coordinate of the point p, θ_p is the angle of two line segments around the point p, H is the height of the character image, and α is a parameter.

3.1.3. Connecting end points

The last step is to connect end points by virtual edges. A virtual edge corresponds to pen-up in on-line handwriting, and it is treated differently from normal strokes corresponding to pen-down. Based on distance, end points are connected so that a connection does not create a loop. Suppose that there are N_e end points P_i $(i = 1, \ldots, N_e)$ and $d(P_i, P_j)$ $(i, j = 1, \ldots, N_e)$ is the distance between P_i and P_j. The following is the algorithm for connecting end points by virtual edges corresponding to pen-up of on-line data.

Let I be $\{1, \ldots, N_e\}$.
while $\sharp I > 2$ {
  $d_0 = \infty$
  for each $(i,j) \in I \times I$ $(i < j)$ {
    if $d(P_i, P_j) < d_0$, and the connection of P_i and P_j does not create a loop
      $d_0 = d(P_i, P_j)$
      $(e_0, e_1) = (i, j)$

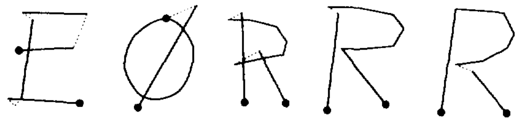

Fig. 3. Conversion of thin-line pictures to sequential data. Dotted lines denote virtual edges corresponding to pen-up in on-line data.

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        endif
    end
    connect P_{e0} and P_{e1} by a virtual edge.
    Let I be I − {e0, e1}.
end
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Fig. 3 illustrates the results of the three steps for converting thin-line pictures to sequential data that can be processed by on-line recognition algorithms.

3.2. Recognition algorithm

We mention an outline of the on-line recognition algorithm free from writing constraints proposed by Nishida (1995a). The algorithm is based on the structural analysis of thin-line pictures and the class description is essential in structural approaches. We describe a shape class with a set of curve components called *primitive sequences* proposed by Nishida and Mori (1992) and Nishida (1993, 1995b, 1995c). Topological, global structure of the shape is changed by stroke breaking or connection. In particular, a stroke connection may create an extra curve longer than a regular stroke, and therefore, some knowledge is needed to explain the extra parts caused by stroke connection.

A class is described as (N, π, C, S, m), where N is a number of primitive sequences, π is a mapping from $\{1, \ldots, N\}$ to the family of subsets of the PS-label set, where $\pi(k)$ is a set of eligible labels of the primitive sequence k, C is a set of possible connections of strokes or primitive sequences, S is statistics (means and standard deviations) for parameters (size, position, etc.) of primitive sequences, and m is a mapping from $\{1, \ldots, N\}$ to $\{0, 1\}$, where the primitive sequence k is mandatory *iff* $m(k) = 1$.

For instance, based on the eight-direction features (Nishida, 1993, 1995b), a class of "R" is described as $(3, \pi, C, S, m)$, where $\pi(1) = \{13, 14, 15\}$, $\pi(2) = \{20, 30, 37, 40, 46, 47, 55, 56, 57, 64, 65, 66, 75, 76\}$, $\pi(3) = \{15, 16, 17\}$ ($\langle rot, idr \rangle$ is denoted by an integer $10 \times rot + idr$), $C = \{(1,$ "upper end point"; $2,$ "h-point"$), (1,$ "lower end point"; $2,$ "h-point"$), (2,$ "t-point"; $3,$ "upper end point"$)\}$, and $m(1) = m(2) = m(3) = 1$. (S is omitted here.) In Fig. 4, the three primitive sequences are illustrated as solid lines and the three stroke connections are illustrated as dotted lines.

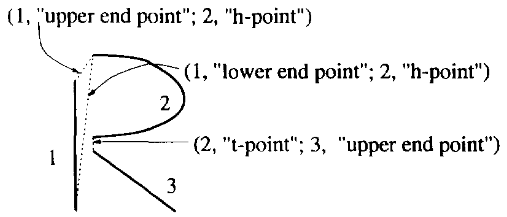

Fig. 4. A class description for "R."

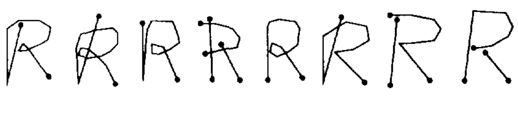

Fig. 5. Instances of the character "R" recognized by the shape matching algorithm with a single class of "R".

Based on of this class description, Nishida (1995a, 1996) proposed a shape matching algorithm that can tolerate topological deformation such as stroke connection and breaking as well as a variety of stroke orders, numbers, and directions. The matching is formalized as a problem of finding a mapping from the local features called *primitives* in the input to the global features called *primitive sequences* and stroke connections in the class. All the shapes in Fig. 5 can be recognized by the shape matching algorithm with the single class of "R". Refer to (Nishida, 1995a, 1996) for the details of the recognition algorithm.

4. Experiments

We present performance statistics of off-line handwritten digit recognition using the public-domain database ETL-1. The test was conducted on 7000 samples of unconstrained handwritten digits in the database ETL-1, and the training was based on the other 7000 samples in ETL-1. The class descriptions for digits were created from the training data using the model construction algorithm by Nishida and Mori (1993) and Nishida (1995d). In the decision making, geometrical transforms and statistical dis-

Table 1
Confusion matrix in recognition of handwritten digits

I\O	0	1	2	3	4	5	6	7	8	9	Rejection
0	99.9						0.1				
1		92.6	2.2					3.2			2.0
2	0.7		98.5								0.8
3				99.8							0.2
4	0.2				98.6		0.1	0.1		0.6	0.3
5						99.3					0.7
6	0.1				0.1		99.6		0.1		
7			0.3					99.1		0.2	0.4
8	0.1								99.6		0.3
9	0.3				0.2	0.1		0.3		99.1	

tance were also considered in addition to structural descriptions (Nishida, 1996). The experiment was carried out under the simple, hard condition without incorporating second-level classifiers or additional heuristic rules into the decision making process. The result for the test data is as follows: 98.6% were correctly recognized, 0.5% were rejected, and 0.9% were substituted. The details are shown in Table 1 as a confusion matrix.

In general, a large number of prototypes are required in handwritten character recognition systems based on structural approaches. We used only twelve class descriptions for ten digits (1.2 classes/character) in this experiment, and this result demonstrates the expressive power of the structural descriptions and the effectiveness of the recognition algorithm proposed in this paper.

5. Conclusion

On-line recognition algorithms free from writing constraints and high-quality thinning algorithms are important subjects in research on handwriting recognition and are also essential for the integration of off-line and on-line recognition of handwriting. We have presented the adaptation of an on-line recognition algorithm to off-line recognition of unconstrained handwritten characters. In general, a large number of prototypes are required for off-line recognition of unconstrained handwritten characters, but high recognition rate has been attained with a small number of class descriptions (typically one class for one character) in the experiments.

We need to integrate multiple algorithms in total systems for off-line recognition of unconstrained handwritten characters. In particular, recognition methods based on structural approaches, in general, are sensitive to noisy data. Suzuki et al. (1994) have shown that the integration of structural approaches and pattern matching approaches compensates for the weakness of one another, and attains high recognition performance. The proposed method can be used in the part of such systems as a reliable structure-based classifier.

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