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A WEIGHTED COMPETITIVE LEARNING EXTRACTING SKELETON STRUCTURE FROM CHARACTER PATTERNS WITH NON-UNIFORM WIDTH

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ABSTRACT

In the handwritten character recognition, it is very important to extract essential structure of character patterns. Requirements for skeletonization can be summarized as follows: (a) Insensitive to irregular edge lines. (b) Non-structure patterns are not extracted. (c) Insensitive to non-uniform line width. (d) Line information is held. In this paper, a weighted competitive learning method is proposed in order to achieve the above requirements. Regarding (a) and (b), unnecessary pattern information is removed by representing some region of the pattern using a single representative point (RP). In order to optimize the RPs, the competitive learning is employed. For the requirement (c), the region, covered by a RP, is adjusted according to the line width. The condition (d) is satisfied by connecting the RPs along the line and also through the border of the regions. Simulation results, obatined using so many kinds of distorted patterns, including digits, alphabet and Japanese Kanji, demonstrate the proposed method can extract essential skeleton structure despite of several distortions.

I INTRODUCTION

Neural networks (NN) have been successfully applied to character recognition [1]-[4]. Handwritten character recognition has been also tried using NNs. However, performance of recognition are easily affected by distortion, such as non-uniform line width and blurred lines. Therefore, in some cases, it is very important to extract essential structural pattern, that is a skeletonized pattern. Conventional skeletonizing methods are mostly based on shaving bold lines. Therefore, they are sensitive to the above distortion. Extracting unnecessary structures and missing important parts easily occur [1],[3].

In this paper, a weighted competitive learning method is proposed for extracting structural pattern, which is insensitive to the above distortions. The idea behind the proposed is quite different from existing methods. Simulation using so many distorted characters, including digits, alphabet and Japanese Kanji, have been carried out. Some of them will be shown in this paper.

II BASIC STRATEGY OF NEW SKELETONIZATION METHOD

Assuming handwritten character recognition, requirements for skeletoniza -tion can be summarized as follows: (a) Insensitive to irregular edge lines. (b) Non-structure patterns are not extracted. (c) Insensitive to non-uniform line width. (d) Line information is held.

The proposed method has been developed so as to achieve the above requirements. Regarding (a) and (b), unnecessary pattern information is removed by representing some region of the pattern by a single representative point. This is a sort of 'vector quantization', that is data compression. For convenience, a representative point is abbreviated as 'RP' in the following. In order to optimize the RPs, the competitive learning is employed.

For the requirement (c), the range, covered by a RP, is adaptively changed according to the line width of the corresponding part. Therefore, this method is called 'weighted competitive learning' in this paper. The condition (d) is satisfied by connecting the RPs along the line and also through the border of the regions covered by them.

III WEIGHTED COMPETITIVE LEARNING

3.1 Generation and Movement of Reference Points

A pixel of the pattern is abbreviated as 'point' in this paper. At the initial state, there is no RP. In the learning process, RPs are generated and moved toward the optimum position. The process is described in the following.

(1) One point of the pattern is randomly selected.

(2) Look for the RP, whose region includes this point. If a RP is found, then this RP is slightly shifted toward the above point. The shifting distance is determined according to the distance between the RP and the point, which is measured along the pattern. If there is no such a RP, then a new RP is generated on the same position as the point.

(3) Repeat the above steps for all points on the pattern.

(4) When the RPs locate close to each other after shifting, they are combined, resulting a single RP.

The process including Steps(1) through (4) is counted as one iteration. The above steps are repeated until RPs converge to the stable state. How to evaluate convergence will be described later. After the RPs reach the optimum positions, their movement become very small.

The number of RPs and their location are automatically optimized through the weighted competitive learning.

3.2 Adjusting Region Covered by Representative Point

In order to extract the precise structural pattern from the distorted pattern with non-uniform line width, it is very important how to control the region covered by a single RP. If the region is narrow, then a zigzag line will be extracted. On the other hand, when the region is wide, fine structure cannot be extracted.

In the proposed method, the region is adjusted according to the line width of each part of the pattern. Length of the lines crossing the RP are measured. They include the horizontal and vertical lines, and slopes with ± 45 degrees. Length of these lines are expressed l_1, l_2, l_3 and l_4, respectively. The minimum distance is taken as the line width around this RP. By introducing some parameter, the maximum diameter of the region is determined by

$$d_{max} = \alpha \cdot \min_i \{l_i\} \qquad (1)$$

The points of the pattern, included in the circle, whose diameter is d_{max}, form the region covered by the above RP. In a fine pattern, some time d_{max} takes just 1. In this case, however, the region determined by d_{max} is very narrow, and is not useful. Therefore, the lower boundary for d_{max} is set.

α is determined based on complexity of the pattern and line widths. At the present, α is determined by experience.

Overlapped Regions:

When the point is included in several regions, the structural distances d_{si}, which is measured along the pattern, between the selected point and the RPs are measured. Ratios d_{si}/d_{max} are calculated. The RP, having the minimum ratio d_{si}/d_{max} is selected. Figure 1 shows an example of the RPs and their region.

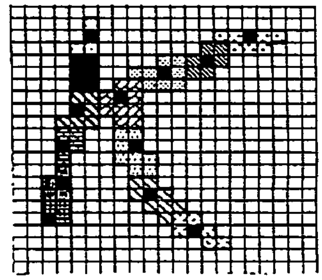

Fig.1 Example of RPs and their region.

3.3 Convergence of Learning

Efficiency of the RPs is evaluated the following mean square error.

$$E = \sum_{i} \| p_i - r_i \| / d_{max} \tag{2}$$

p_i is the selected point of the pattern, and r_i is the corresponding RP. d_{max} is a diameter of the region covered by r_i. This error function can be reduced as the RPs approach to the optimum positions. Finally, optimum allocation of all RPs will produce the minimum error.

Since the minimum value of E is slightly different for the distorted patterns. Therefore, instead of using E directly, the following relative change in E is employed to evaluate the convergence.

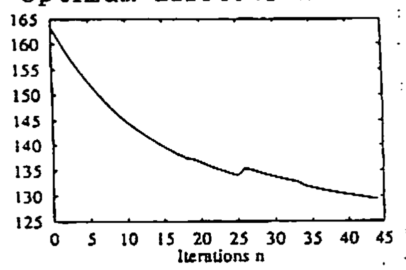

Fig.2 Example of learning curve.

$$\Delta E = \left| \frac{E(n) - E(n-1)}{E(n)} \right| < \varepsilon \tag{3}$$

E(n) is the error at n iterations. After ΔE satisfies the above condition, the learning process is regarded as to converge. ε takes a small value. Its actual value is also determined by experience. Figure 2 shows an example of a learning curve. E(n) can decrease as overall. Some increment in E(n) is caused due to RP fusion.

IV LINKAGE OF REPRESENTATIVE POINTS

The optimized RPs are linked along the pattern, at the same time, through the border of the regions. Figure 3 shows an example of linkage of the RPs.

As shown in Fig.3, a triangle is some time issued at the junction point. this is incorrect structure. This triangle is replaced by a junction point, locates at the central point.

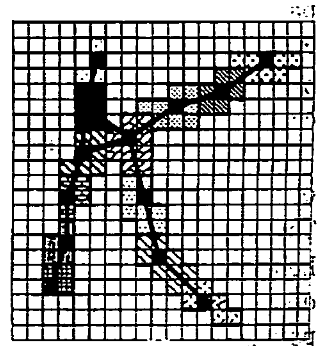

Fig.3 Example of linkages of representative points.

V SIMULATION RESULTS

5.1 Non-Uniform Line Width

Figure 4 shows a pattern with non-uniform line width, and a skeleton structure, extracted by the proposed method.

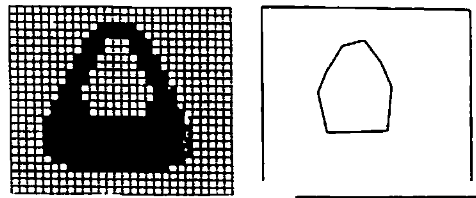

Fig.4

5.2 Alphabet and Digit Patterns

Figure 5 shows the results for 「A」, 「B」, 「0」, 「9」, including the original patterns (a1) ~ (a4), structure patterns extracted by the proposed method (b1) ~ (b4), and skeleton patterns obtained by the conventional methods [1](c1) ~ (c4) and [3](d1) ~ (d4). The proposed method can successfully extract the essential structural patterns. On the contrary, the conventional methods cannot avoid missing connections and holding whiskers.

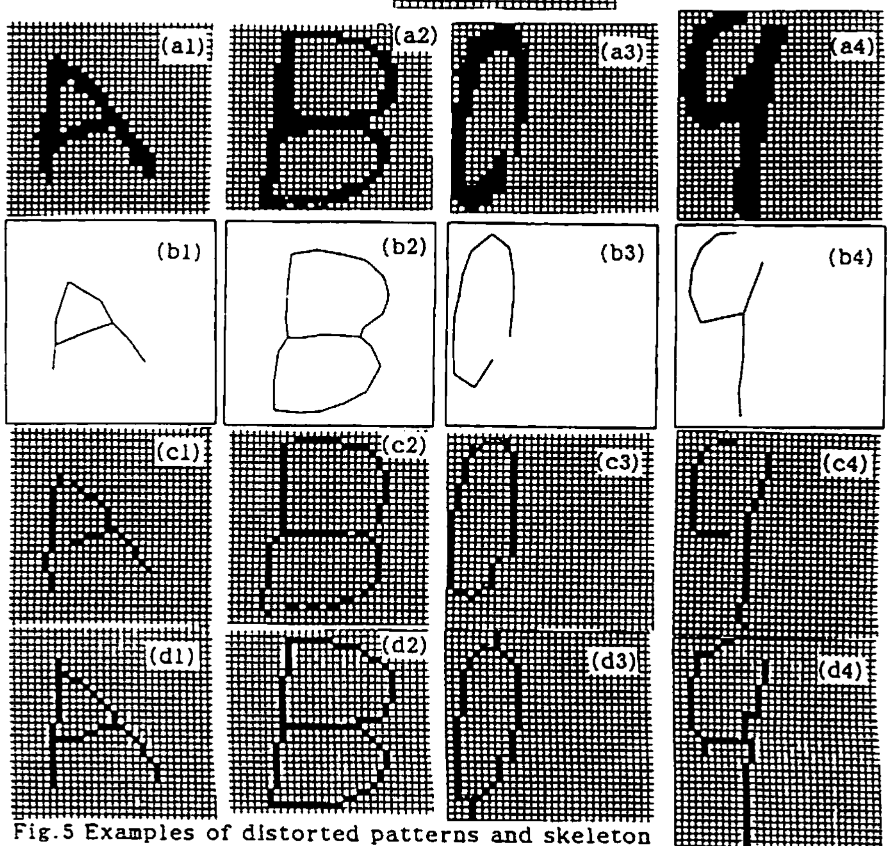

Fig.5 Examples of distorted patterns and skeleton patterns for alphabet and digit characters.

5.3 Japanese Knji Patterns

Figure 6 shows example using 「哀」. Almost the same trends can be confirmed as in Fig.5.

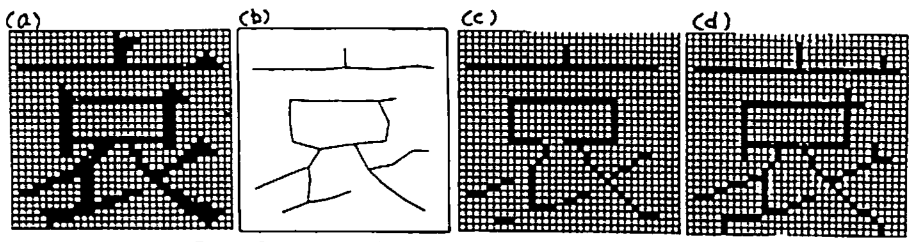

Fig.6 Examples of distorted patterns and skeleton patterns for Japanese Kanji characters.

VI CONCLUSIONS

A weighted competitive learning has been proposed to extract structural patterns. Simulation results have demonstrated efficiencies, such as insensitivity to non-uniform line width and no missing structural information.

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