A FUZZY STRING MATCHING METHOD FOR RECOGNIZING PARTIALLY OCCLUDED OBJECTS

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ABSTRACT

In this paper, we propose a fuzzy shortest path method to solve the occluded shape matching problems. The edit distance is formulated as a fuzzy number instead of a real number. Therefore, the edit cost is also a fuzzy number. The string matching problems were then equivalent to a fuzzy shortest path problem. The memberships for the input shape with the reference shapes are then determined as fuzzy numbers. By performing a simple ranking fuzzy numbers algorithm, the input shape is classified as the reference shape that has the minimum fuzzy edit cost.

Keywords: Occluded shape, cyclic string matching, fuzzy sets, shortest path.

1. INTRODUCTION

In order to make the machine vision system work efficiently, an ability of recognizing occluded objects must be developed. In this paper, we focus on the identification and location determination, more specifically, the occluded shapes matching.

Bhanu and Ming [1] proposed a cluster-structure algorithm to recognize occluded objects. Chung et al. [2] pointed that the neural network is useful in detecting objects. They constructed a spatiotemporal network to the problem of partially occluded objects recognition. Gorman et al. [3] solved the object recognition using a dynamic programming algorithm. Han and Jang [4] used the distance between two vertices to recognize partially occluded objects. However, the vertices may be disturbed by noise. Lai and Lin [6] recognized the objects by comparing the line segment and the angle of the corners. Lee et al. [7] developed a Hopfield neural network for occluded objects recognition. The multiscale features were used in their method. Liu and Srinath [9] used the contour matching approach to detect partially occluded objects. The distance transformation was the features in their scheme. Ogawa [11] proposed a fuzzy relaxation technique for partially shape matching. Salari and Balaji [13] utilized the B-spline representation for the object recognition. Tsai [14] proposed a modified Hough transform to extract occluded objects. Tsang and Yuen [17] used the generalized delta rule of neural network to recognize partially occluded objects. Turney et al. [19] recognized occluded objects by extracting the gradient of edges on the outline of objects. Zheng et al. [21] developed a simplified ART-2 and a two layer feed forward network to recognize partially occluded objects.

Tsai and Fu used the attributed grammar to combine statistical and syntactic methods [15]. Tsai and Yu proposed an attributed string matching with merging that involves more powerful edit operations [16]. Further, Tsay and Tsai introduced another new edit operation, i.e. split, to the attributed string matching [18]. To solve the disadvantages of linear string matching, Maes proposed a cyclic string matching technique for polygonal shape recognition [10]. Only the three conventional edit operations were needed for the cyclic string matching. However, the recognition results are not reported in the paper.

Due to the uncertainty principle, fuzzy sets describe the similarity by the membership functions instead of crisper function. Klein proposed a model based on fuzzy shortest paths [5]. He used a dynamic programming approach to solve the fuzzy shortest path problem. Okada and Soper developed an algorithm based on the multiple labeling methods for a multicriteria shortest path problem [12].

In this paper, we proposed a fuzzy shortest path method for occluded shape matching. After extract features from shapes, the cyclic fuzzy string matching was performed. The fuzzy edit distances of the input shape between all of the reference shapes are then determined. The fuzzy edit distances are then ranked by a simple fuzzy number ranking method [8]. The input shape is classified as the reference shape that has the minimum fuzzy edit distance among all the reference shapes.

2. FUZZY SHORTEST PATHS

2.1. String Matching Technique

The following notations can be found in Wu and Wang [20]. The sequence of symbols $s_1s_2...s_n$ is called the *string* s and $|s|$ is its length. The *null string*, λ, is a string of zero length.

Suppose that s and t are two strings and let $|s|$=n and $|t|$=m. The *edit network associated with s and t* can then be determined by the network G (see Fig. 1) with vertices v(i, j), for i=0, 1, …, n, j=0, 1, …, m. The weights of the three types of arcs of G are defined by an *edit cost function*ε.

(1) *Insertion*. (v(i, j), v(i, j+1)) with weight $w_{0,j+1}=\varepsilon(\lambda, t_{j+1})$, for i=0, 1, ..., n, and j 0, 1, ..., m-1.
(2) *Deletion*. (v(i, j), v(i+1, j)) with weight $w_{i+1,0}=\varepsilon(s_{i+1},\lambda)$, for i=0, 1, ..., n-1, and j=0, 1, ..., m.
(3) *Change*. (v(i, j), v(i+1, j+1)) with weight $w_{i+1,j+1}=\varepsilon(s_{i+1}, t_{j+1})$, for i=0, 1, ..., n-1, and j=0, 1, ..., m-1.

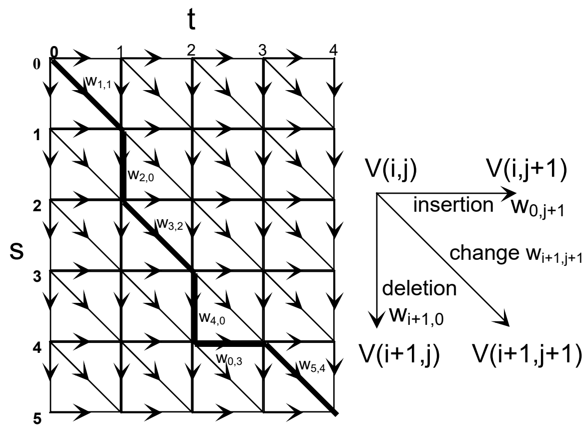

Fig. 1. The edit network **G** for |**s**|=5 and |**t**|=4.

The problem of finding a *minimum cost edit sequence* between s and t is now equivalent to find a *shortest path* in **G** from v(0, 0) to v(n, m). The thick lines in Fig. 1 show the shortest path and its corresponding edit sequence. The above method solves the *linear string-to-string correction* *problem* by finding the edit distance and its corresponding edit sequence. Here the problem is to find the *edit distance* δ([*s*], [*t*]) as well as its corresponding edit sequence, where [*s*] and [*t*] are the *cyclic strings* of *s* and *t*, respectively. It becomes the *cyclic string-to-string correction problem*. We can assume that $m \leqq n$ without losing the generality, and the strings *s* and *t* are the cyclic strings. Then the edit distance proposed by Maes [10] is

$$\delta([s], [t]) = \min\{\delta(s, \sigma^j(t)) : j = 0, 1, \ldots, m-1\}, \tag{1}$$

where $\sigma^j(t)$ is the string obtained from *t* after j cyclic shifts.

To calculate the edit distances, let $tt = t_1t_2\ldots t_m t_1 t_2 \ldots t_m$ be the string which concatenates *t* with itself. We can first construct the edit network *H* associated with *s* and *tt* (see Fig. 2). Then we can determine the edit distance $\delta(s, \sigma^j(t))$ by finding the shortest path from v(0, j) to v(n, m+j), for j = 0, 1, ..., m-1.

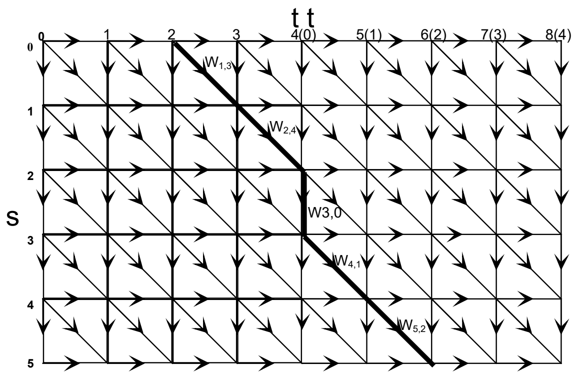

Fig. 2. The edit network **H** associated **s** and **tt.**

2.2. Fuzzy Edit Distance

Let *I* and *R* be the input shape and the reference shape, respectively. The problem of matching two shapes is therefore identical to the cyclic string matching between strings *s* and *t*. Given an edit cost function ε, then we can construct the edit graph *H* associated with *s* and *tt* to find the shortest path. The paired symbols of *I* and *R* can then be found by tracing the minimum cost edit sequence. Thus, the matching relation between the vertices of *I* and *R* can be determined. These two ordered sequences are called the *best-matched pair* of *I* and *R*. The minimum edit distance in the string matching is called *matching cost*. Therefore, the dissimilarity of two shapes can then be defined as the matching cost between them.

It is important to define a cost function in string matching. Suppose that the value of λis zero. We can define the edit cost function that is both suitable for the one-dimensional or higher dimensional features.

$$\varepsilon(s_i \rightarrow t_j) = \left\| s_i - t_j \right\|, \tag{2}$$

where $\|*\|$ is the norm of the vector *.

In the conventional string matching approach, the input shape can then be classified as the reference shape with the minimum matching cost. However, due to the uncertainty principle, the edit costs can be defined as the triangular fuzzy numbers as seen in Fig. 3. The triangular fuzzy number A=(r, a, b) is a fuzzy number with membership function f_A defined as

$$f_A(x) = \begin{cases} (x - r + a)/a, & r - a \le x \le r \\ -(x - r - b)/b, & r \le x \le r + b \\ 0, & otherwise \end{cases} \tag{3}$$

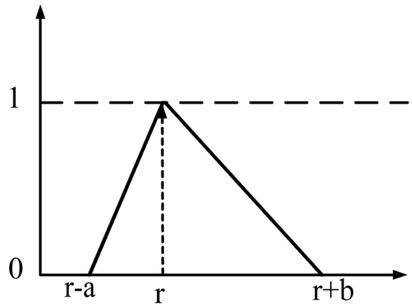

Fig. 3. A triangular fuzzy number A=(r, a, b).

Instead of the crisper definition in Eq. 2, the edit cost is represented as a fuzzy number in this paper. In fact, the fuzzy edit cost is defined as

$$\varepsilon(s_i \rightarrow t_j) = (r, a, b) \tag{4}$$

where $r = \left\| s_i - t_j \right\|$ and a=b=r/100.

In addition, an addition of two triangular fuzzy numbers can be defined as follows [12]:

$$(r_1, a_1, b_1) \oplus (r_2, a_2, b_2) = (r_1 + r_2, a_1 + a_2, b_1 + b_2). \tag{5}$$

The fuzzy edit costs in Eq. (4) are defined as fuzzy numbers. They represent the weights of the arcs on the network in Fig. 2. Therefore, the edit distances are also the fuzzy numbers. In each stage of finding the shortest path, the fuzzy edit distances should be ranked to find the shortest path. Thus, the fuzzy shortest paths can be found by ranking fuzzy numbers.

The method for ranking fuzzy numbers can be done by a simple method proposed by Liou and Wang [8]. They used the integral values of the inverse of membership functions to rank fuzzy numbers. For a fuzzy number A=(r, a, b), the total integral value can be constructed from the left integral value and the right integral value are two values. The total integral value $I_T(A)$ with index of optimism α is then defined as

$$I_T(A) = \alpha\, I_L(A) + (1-\alpha)\, I_R(A) \tag{6}$$

The left integral value $I_L(A)$ and the right integral value $I_R(A)$ of a triangular fuzzy number A=(r, a, b) can be found as

$$I_L(A) = r - a/2 \tag{7}$$
$$I_R(A) = r + b/2. \tag{8}$$

From Eqs. (6) to (8), the total integral value is defined as

$$I_T(A) = r + (b - (a+b)\alpha)/2 \tag{9}$$

For two triangular fuzzy numbers, they can be ranked by finding their integral values for the inverses of the membership functions. For triangular fuzzy numbers, it is very effective to find the inverse of the membership functions. Therefore, the integral values can be found effectively.

2.3. Occluded Shape Matching Using Fuzzy Shortest Path

The proposed fuzzy shortest path algorithm for occluded shape matching can be summarized as follows:

Step 1. Repeat steps 2 to 4 until there is no input shape to be recognized.

Step 2. Extract features from the shapes and construct the fuzzy network using the fuzzy edit costs.

Step 3. Find the fuzzy edit distances between the input occluded shape and each of the reference shapes by the fuzzy shortest paths technique.

Step 4. Classify the input shape as the two reference shapes with the minimum fuzzy edit distance.

3. RESULTS AND DISCUSSIONS

Nine different tools were used for evaluation in the experiment (see Fig. 4). A good shape matching approach should be robust under different orientations and scales. For each tool image, there were 16 different orientations and 4 different scales conducted. The 16 different orientations were arbitrary chosen by rotating the tools and the positions of the tools were changed at the same time. For each orientation, three additional images were generated by reducing the image to 90%, 70%, and 50% of original in both the horizontal and vertical directions. Thus, 64 (=16×4) testing images for each tool were used for matching, and there were a total of 576(=9×64) testing images.

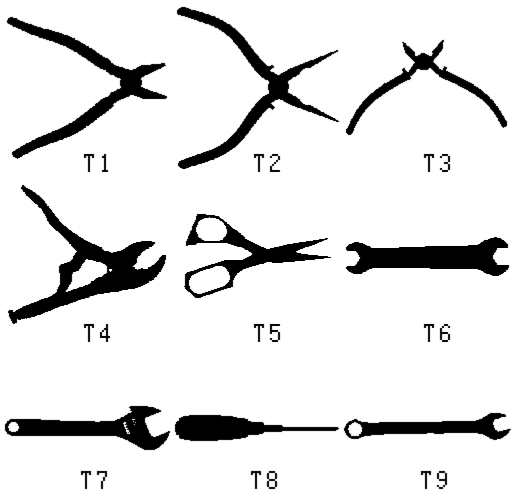

Fig. 4. The testing hand tools: nine original tools.

The access the ability of the proposed method in recognizing partially occluded objects, 36 types of partially occluded objects tested as shown in Fig. 5. Each type of partially occluded objects has been tested on two levels of sizes (100% and 50%), and 4 levels of orientations (0^0, 90^0, 180^0, 270^0). Therefore, each partially occluded object has eight test images. The number of test images is 288. Table 1 shows the experimental results of the proposed method. It is seen that the proposed method can recognize the partially occluded objects correctly.

In order to extract the features from the shapes, the dominant points on the boundary of the object can be detected by the curvature-based polygonal approximation method [20]. The compactness of an object is defined as p^2/a, where p and a are the perimeter and the area of the objects, respectively. However, the area of the triangle formed by the two adjacent dominant points and the centroid will be zero, when these three points are on the same line. Therefore, the modified compactness, c_i, can be defined as (see Fig. 6)

$$c_i = p_i^2/(a_i+e), \tag{10}$$

where p_i is the perimeter, a_i is the area of the triangle, and e is a small positive real number.

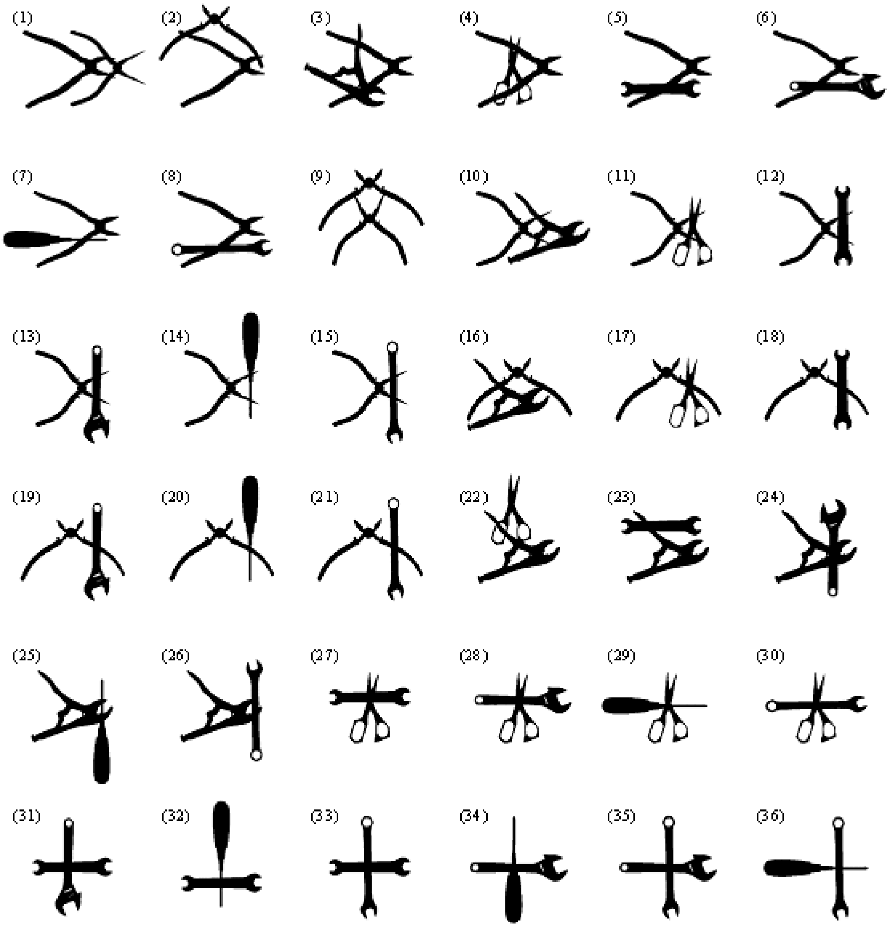

Fig. 5. The testing hand tools: 36 occluded objects to be recognized.

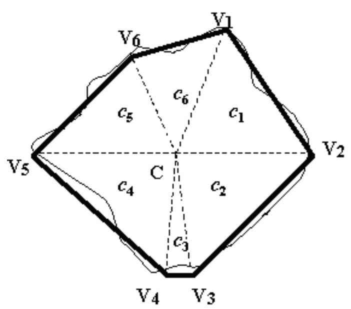

Fig. 6. The modified compactness $c_i = p_i^2/(a_i+e)$.

In order to make the features to be independent of position, orientation, and scaling, these features should be normalized. In this paper, all the features are divided by the maximum value. The e value in computing the modified compactness is set to 0.00001. The matching algorithm was applied to each testing image for matching. If a wrong classification was made, an error was recorded. And the recognition rate can be computed. The index α was set to 0.3. It is seen that the fuzzy string matching algorithm has better recognition rates than that of the string matching algorithm.

4. CONCLUSIONS

String matching is a useful tool for shape matching, but it tends to be affected by uneven segmentation problem. In this paper, we propose a fuzzy shortest path method to solve the occluded shape matching problems. The edit cost is formulated as a fuzzy number instead of a real number. In fact, the fuzzy edit costs are represented by the triangular fuzzy numbers. Therefore, the edit distance is also a fuzzy number. The string matching problem was then equivalent to a fuzzy shortest path problem. The memberships for the input shape with the reference shapes are then determined as fuzzy edit distances. By ranking the fuzzy edit distances, the input shape is classified as the reference shape that has the minimum fuzzy edit distance. The experimental results indicate that the use of the fuzzy string matching method has superior recognition performance to the use of the conventional one.

REFERENCES

1. B. Bhanu, J. Ming, Recognition of occluded objects: a cluster-structure algorithm, Pattern Recognition, 20(2) (1987) 199-211.
2. P. C. Chung, E. L. Chen, J. B. Wu, A spatiotemporal neural network for recognizing partially occluded objects, IEEE Trans. Signal Processing 46 (1998) 1991-2000.
3. J. W. Gorman, O. R. Mitchell, F. P. Kuhl, Partial shape recognition using dynamic programming, IEEE Trans. Pattern Analysis and Machine Intelligence, 10(2) (1988) 257-266.
4. M. H. Han, D. Jang, Use of maximum curvature points for the recognition of partially occluded objects, Pattern Recognition, 23 (1990) 21-33.
5. C. M. Klein, Fuzzy shortest paths, Fuzzy Sets and Systems, 39 (1991) 27-41.
6. J. Z. C. Lai, J. M. Lin, Recognizing partially occluded 2-D parts based on the tracing of feature points, Proceedings on IEEE International Conference on Robotics and Automation, Piscataway, NJ, USA, 1991, pp.1796-1801.
7. J. S. Lee, C. H. Chen, Y. N. Sun, G. S. Tseng, Occluded objects recognition using multiscale features and Hopfield neural network, Pattern Recognition, 30(1) (1997) 113-122.
8. T. S. Liou, M. J. Wang, Ranking fuzzy numbers with integral value, Fuzzy Sets and Systems, 50 (1992), 47-255.
9. H. C. Liu, M. D. Srinath, Partial shape classification using contour matching in distance transformation, IEEE Trans. Pattern Analysis and Machine Intelligence, 12 (1990) 1072-1079.
10. M. Maes, On a cyclic string-to-string correction problem, Information Processing Letters, 35 (1990) 73-78.
11. H. Ogawa, Fuzzy relaxation technique for partial shape matching, Pattern Recognition Letters, 15(1994) 349-355.
12. S. Okada, T. Soper, A shortest path problem on a network with fuzzy arc lengths, Fuzzy Sets and Systems, 109 (2000) 129-140.
13. E. Salari, S. Balaji, Recognition of partially occluded objects using B-spline representation, Pattern Recognition, 24(7) (1991) 653-660.
14. D. M. Tsai, An improved generalized Hough transform for the recognition of overlapping objects, Image and Vision Computing, 15(1997) 877-888.

ISSN 2056-5860

15. W. H. Tsai, K. S. Fu, Attributed grammar- a tool for combining syntactic and statistical approaches to pattern recognition, IEEE Trans. System, Man, and Cybernetics, 10 (1980) 873-885.
16. W. H. Tsai, S. S. Yu, Attributed string matching with merging for shape recognition, IEEE Trans. Pattern Analysis and Machine Intelligence, 7 (1985) 453-462.
17. P. W. M. Tsang, P. C. Yuen, Recognition of partially occluded objects, IEEE Trans. Systems, Man and Cybernetics, 23(1993) 228-236.
18. Y. T. Tsay, W. H. Tsai, Model-guided attributed string matching by split-and- merge for shape recognition, International Journal of Pattern Recognition and Artificial Intelligence, 3 (1989) 159-179.
19. J. L. Turney, N. T. Mudge, R. A. Volz, Recognizing partially occluded parts, IEEE Trans. Pattern Analysis and Machine Intelligence, 7 (1985) 410-421.
20. W. Y. Wu, M. J. Wang, Two-dimensional object recognition through two-stage string matching, IEEE Trans. Image Processing, 8 (1999) 978-981.
21. N. Zheng, Y. Li, Y. P. M. Houwers, Local feature-based recognition of partially occluded objects using neural network, Proceedings of the Industrial Electronics Conference, Los Alamos, CA, USA, 1995, pp.1301-1306.