STUDY OF SEVERAL DIRECTIONAL FEATURE EXTRACTION METHODS WITH LOCAL ELASTIC MESHING TECHNOLOGY FOR HCCR

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Abstract: This paper presents several directional features with different meshing methods for Handwritten Chinese Character Recognition (HCCR). Local elastic meshing technology is introduced in this paper, and it is found that local elastic meshing method is much better than global elastic meshing method. The performance of different directional features is studied. Experiment under a multi-classifier architecture with the five directional features shows that each feature has its own merit, and the recognition performance of a HCCR system could be improved by integrating them together.

Keywords: Feature Extraction, Directional feature

1. INTRODUCTION

Feature extraction is one of the most important problems in the field of handwritten Chinese character recognition (HCCR). Recently, it is found that the directional feature is considered suitable for both Chinese and Kanji character recognition, and directional feature has been widely used as one of the mainstream feature extraction approach in China, Taiwan, and Japan [3-11]. The general flow chart of the directional feature extraction is shown in figure 1. According to certain directional decomposition algorithm, a black pixel in a character image is firstly refined into one of the four sub-patterns (or directional patterns), namely, horizontal (一), vertical (丨), left up diagonal (丿) and right up diagonal (㇏) patterns. Then the character pattern is divided into many small meshes according to specific rules. Finally, the distribution of black pixels of four directional sub-patterns in each mesh is computed as the directional features. Two key factors in extraction of directional feature are directional decomposition algorithm and meshing method. In this paper, several directional feature extraction methods are presented. Local elastic meshing technology is introduced, and it is found that local meshing method is much better than global meshing method. The performance of different directional features is studied. Experiment under a multi-classifier architecture with voting combining rule shows that each of the five features has its own merits, and the recognition performance could be improved by integrating them together.

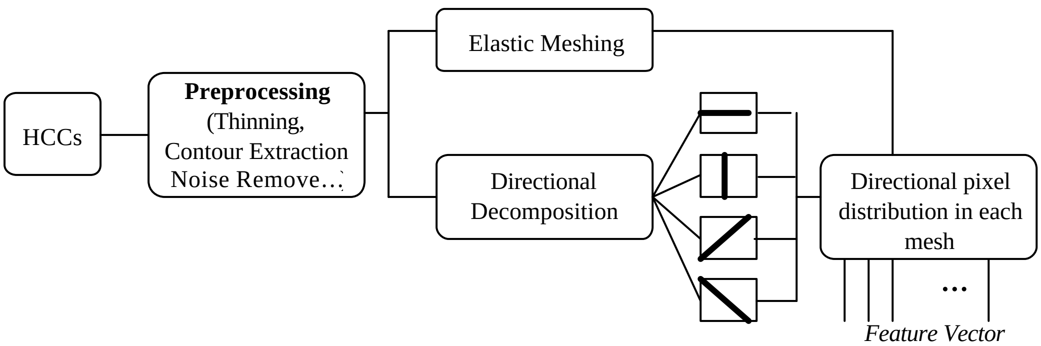


Fig. 1. Flow chart of directional feature extraction approach

2. LOCAL MESHING TECHNOLOGY

Meshing is one of the key approaches to extract the directional features[8]. Basically, there are two kinds of meshing methods, say, fixed meshing method where a set of position-fixed grids are designed, and elastic meshing method where a set of position-adaptable grids are designed according to the distribution of black pixels of a character. As there are large variations among different writing styles of handwritten characters, elastic meshing is found better than fixed meshing if no non-linear shape normalization is applied[8]. As shown in figure 2(b), global elastic meshes are constructed through equally dividing the horizontal and vertical histogram of a given character into certain number, say N, of different intervals such that each interval contains an equal number of histogram, we call this $N \times N$ elastic meshes.

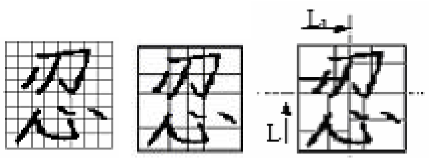


Fig. 2. *(a) 8×8 fixed meshing. (b) 2×2 global elastic meshing. (c) 2×2 local elastic meshing.*

On the other hand, local elastic meshes are obtained through two steps. A set of global elastic meshes are firstly constructed according to the global distribution of the horizontal and vertical histograms of a given character, and then, in each sub-area, the local horizontal and vertical histograms are computed again and a set of elastic meshes are constructed by equally dividing the local histograms. Figure 2 (c)~(e) show several local elastic meshes.

3. FIVE DIRECTIONAL DECOMPOSITION ALGORITHM

3.1. Thinning Directional Decomposition (TDD) [8,10]

Let p is a black pixel in a binary skeleton character image. The 8 neighborhood pixels of p are shown in figure 3. Decomposition of a black pixel p into corresponding sub-pattern is given by:

If p_1 or p_5 is black pixels, then refine p into horizontal pattern;
If p_2 or p_6 is black pixels, then refine p into left slant pattern;
If p_3 or p_7 is black pixels, then refine p into vertical pattern;
If p_4 or p_8 is black pixels, then refine p into right slant pattern.

p_4	p_3	p_2
p_5	p	p_1
p_6	p_7	p_8

Fig.3. *Eight neighborhood of pixel p.*

3.2. Contour Directional Decomposition (CDD)[4,9]

Directional decomposition based on contour of the character is similar with the method described above. The difference is that the decomposition is taken on the contour of a handwritten character instead of the skeleton of the character. It should be noted that this method is sensitive to the stroke width variations of different handwritten characters, and the contour extraction algorithm could also effect the directional decomposition result.

3.3. EDGE Directional Decomposition directly from the original character (EDD) [8]

Another strategy to decompose a character is to examine its edge boundary to obtain a set of directional images [8]. As shown in figure 4, four directional operators are designed to refine a Chinese character into four directional image sub-patterns.

(a)

-1	-1	-1
0	0	0
1	1	1

(b)

-1	0	1
-1	0	1
-1	0	1

(c)

-1	-1	0
-1	0	1
0	1	1

(d)

0	1	1
-1	0	1
-1	-1	0

Fig. 4. Four edge directional operators.

3.4. Modified Contour Directional Angle Decomposition (CDAD)

Decomposition based contour directional angle is first introduced in [3]. A black contour pixel in a character image is refined into one of the four directional sub-patterns according to its **directional angle,** which is defined by:

$$q(p) = \tan^{-1}\left(\frac{D_x}{D_y}\right)$$

where D_x、D_y are given by:

$$D_x = (p_6 + 2p_7 + p_8) - (p_1 + 2p_2 + p_3)$$
$$D_y = (p_3 + 2p_5 + p_8) - (p_1 + 2p_4 + p_6)$$

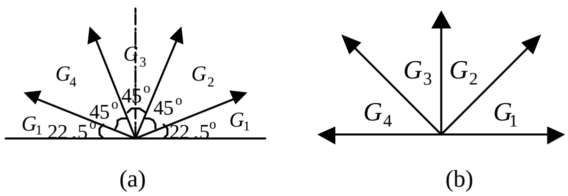


Fig. 5 (a) Original CDAF *(b) Modified CDAF: G1 stands for both horizontal and vertical sub-patterns; G2 stands for both vertical and left diagonal sub-patterns; G3 stands for both vertical and right diagonal sub-patterns; G4*

stands for both right diagonal and horizontal sub-patterns.

The ranges of contour angles are from 0 to 180, which are partitioned equally into four groups, G1, G2, G3, G4, as shown in figure 6(a)[3], and each group stands for one directional sub-pattern. From our experiments, we found that refine a black pixel in four directional sub-patterns according to figure 6 (b) instead of figure 6 (a) is more efficient.

3.5. A New Stroke-based Directional Decomposition (SDD)

Let $DN^l\ (l=1,2,3,4)$ denotes the four directional pixel length of a pixel in a binary image, where l represents horizontal, vertical, left up diagonal and right up diagonal direction respectively, as shown in figure 6. And the a −neighbor of a black pixel (m, n) in the character image is defined as follows:

$$L_a(m,n)=\{(i,j)\mid \max[\,abs(i-m), abs(j-n)]\le a\}$$

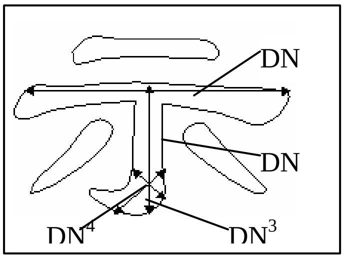


Fig. 6. *Directional pixel length* DN^l

The directional characteristic number $DN_a^l(m,n)$ for each point (m,n) in the character pattern area is given by the following equation,

$$DN_a^l(m,n)=\max_{(i,j)}\{DN^l(i,j),\ \ (i,j)\in L_a(m,n)\}$$

where $l=1,2,3,4$ and a is a small integer constant determined by experiment.

Based on the definition described above, the decomposition algorithm are given below:

For *a black pixel (i,j) in the pattern area,*

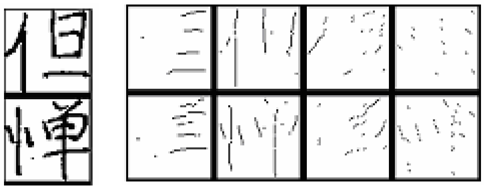
If $DN_a^k(i,j)=\max_l\{DN_a^l(i,j)\},\quad l=1,2,3,4$ ***OR,***

$DN_a^k(i,j)>W$ AND $DN_a^k(i,j)<\max_l\{DN_a^l(i,j)\}$

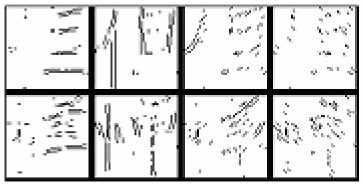
Then*, the pixel (i, j) is refined into the* k^{th} *sub-image.*

Where W denotes up-boundary for the width of the strokes in a Chinese character.

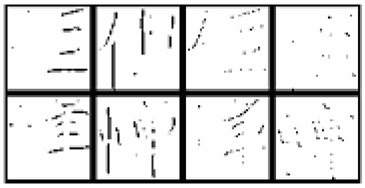
Figure 7 shows some decomposition results using the five algorithms described above.



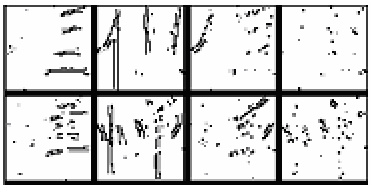
(a) (b)



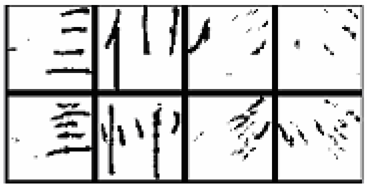
(c)



(d)



(e)



(f)

Fig. 7. *Five directional-decomposition-results. (a) Original HCCrs. (b) The corresponding four directional sub-patterns with TDD algorithm. (c) CDD algorithm. (d) EDD algorithm. (e) CDAD algorithm. (f) SDD algorithm.*

4. Feature Extraction

After a character is decomposed into four directional sub-patterns, the distribution of black pixels in each mesh is computed as the cellular features. The number of meshes is equal to the dimension of the feature vector. According to the five different directional decomposition methods, we got the following five feature extraction methods:

- Thinning Directional Feature (TDF);
- Contour Directional Feature (CDF);
- *EDGE* Directional Feature (EDF);
- Contour Directional Angle Feature (CDAF);
- Stroke Directional Feature (SDF).

5. EXPERIMENTS

5.1. Experimental data

Our experiments are carried out on the 863 National Standard Handwritten Chinese Character Database " HCL2000" . 100 sets of 3755 categories of the samples from the corpus are used as training data and another 20 sets of samples are taken as testing data.

5.2. Performance of local elastic meshing against global elastic meshing

The recognition performance for 1034 categories of characters with different meshing methods is shown in table 1. It could be seen that local elastic meshing is much better than global elastic meshing for TDF, CDF, EDF, and CDAF. For SDF, the recognition rate is similar for both local and global elastic meshing. From table1, it could also been seen that for low dimensional features (less meshes), the recognition rate is not promising. With the increase of meshes, the recognition rate is improved accordingly. The recognition rate reaches optimal result at certain dimension, say, Local 4×2, and too much meshes (for example, Global 10×10) is not always helpful for recognition.

5.3. Performance of the five directional features

The recognition performance for large vocabulary Chinese character recognition (3755 categories of characters) with the five features described above is shown in table 2. The meshing method we used is local 4×2 elastic meshes.

From table2, it could be seen that CDAF produced the best recognition performance, where CDF produced the lowest recognition rate. However, from our point of view, we don't think that the recognition rate is the only way to judge the goodness of a feature extraction approach. In fact, under a multi-classifier environment, we pay more attention on the complementary of different features. For large vocabulary recognition of handwritten Chinese characters, it is now clear that no single feature for classification is "optimal" and thus multiple methods have to be used in a practical HCCR system. To testing the performance and the complementary of the five features, a multi-classifier with adaptive voting combining rule is designed to integrate three of them together. Five kinds of combination experiments are conducted. The recognition result is shown in table 3.

From table 3 and table 2, it could be seen that the recognition rates of all the five kinds of integrated system are improved significantly under the simple voting combining rule. This indicates that good complementary characteristic exists in the five features. With a suitable design of combining scheme, the recognition rate could be improved furthermore.

Table 1. Recognition performance against different meshes

Meshing Methods	Recognition Rate (%)				
	TDF	**CDF**	**EDF**	**CDAF**	**SDF**
Local 2×2	84.38	78.10	84.42	87.49	76.27
Local 3×2	91.69	89.28	92.56	93.65	88.77
Local 4×2	**92.92**	**91.26**	**93.82**	**94.89**	**92.24**
Local 5×2	92.51	91.05	93.80	94.89	93.05
Global 4×4	84.09	78.55	85.07	88.23	78.45
Global 6×6	91.56	88.71	91.68	93.52	89.70
Global 8×8	**92.71**	**90.82**	**92.71**	**93.82**	**92.35**
Global 10×10	92.36	90.60	92.16	93.36	92.76

Table 2. *Recognition rate of different features for 3755 categories of characters*

Features	Recognition Rate (%)

TDF	86.0
CDF	81.5
EDF	83.7
CDAF	87.6
SDF	82.0

Table 3. *The recognition rate of different combination of the features*

Combination	Recognition rate
CDAF + SDF + TDF	91.94
CDF + TDF + SDF	92.10
TDF + EDF + CDAF	91.86
SDF + EDF + CDF	90.10
EDF + CDF + CDAF	90.88

6. CONCLUSIONS

Five kinds of directional feature extraction approaches are presented in this paper. Local elastic meshing techniques is applied to all the five directional feature extraction approaches. Experiments show that local elastic meshing is better than global meshing method for most of the directional features. The complementary and recognition performance of the five features are studied under a multi-classifier architecture and it is found the recognition rate could be improved significantly to integrate them together.

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