Shape Representation and Similarity Measure Based on Delaunay Triangulation

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Abstract: Shape representation and similarity measure are important and difficult problems in computer vision and have been extensively studied for decades. This paper presents an enhanced SUSAN (Smallest Univalue Segment Assimilating Nucleus) Corner Detector for shape representation and an effective algorithm to establish shape similarity measure based on Delaunay triangulation. Firstly, delaunay triangulation was constructed among corners of each shape which has been normalized in advance. Secondly, the Delaunay graph matrix was achieved from Delaunay triangulation net. Finally, the corners were matched by using spectrum of the graph matrix. Shape retrieval Experiments have been conducted on the MPEG-7 Core Experiment CE-Shape-1 database of 1 400 images which illustrate good performance of the algorithm.

Key words: shape representation; shape similarity measure; SUSAN; delaunay triangulation; graph spectrum

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Shape representation and shape similarity measure in images are necessary component of any useful image retrieval system. There is a variety of techniques that has been proposed in the literature for shape representation[1-3]. Corner is one of the most widely used in all shape representation methods. How to detect corners in an image is a classical problem and many detectors have been proposed[4,5]. Smith and Brady[4] introduced a straightforward method called SUSAN by extracting the portion of feature neighborhoods that is of similar intensity values. SUSAN is not sensitive to noise and the accuracy and speed of the algorithm are reasonable, but our experiments show that the result is still not satisfied and there are rooms for improvement. This paper presents an enhanced SUSAN for corner detection.

After corner detection, corner matching is a computationally intensive task. A number of approaches have been proposed to address the theoretical and applied issues of corner matching[6]. In this paper, we match corners between two images based on Delaunay Triangulations. Based on Delaunay Triangulations, some shape similarity measure methods have been proposed. In [2], feature point histogram which computed by counting the two largest interior angles of each individual Delaunay triangle is used for similarity measure. The distance between two shapes is then simply the L2-distance between the histograms. In [7], it first obtain the similar triangle pairs, and then extend their edges circularly until all matching corners are triangulated and mismatching corners are discarded.

1 Enhanced SUSAN corner detector

In [4], Smith and Brady introduced a straightforward method called SUSAN. Given a digital image, the USAN area will reach a minimum when the nucleus lies on a corner point. We present a new

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corner detection algorithm by improving the SUSAN corner detector in the following three aspects First, we limit the search space for corners candidates so that the algorithm becomes more efficient Second, we adopt an adaptive threshold strategy based on local brightness instead of one threshold for the whole image Third, we remove the false or the ambiguous corners according to a corner contribution measure method

Based on fact that a corner is an end of an edge, we only need to search for corners from points on edges instead of whole image Therefore, the algorithm first performs edge detection by Sobel operator Then from the edges select points whose values of measure are above a threshold as corner candidates

The selection of the threshold of brightness difference is a key to performance of the SUSAN operator because different results are obtained for different thresholds In this paper, we adopt Otsu[8] adaptive threshold algorithm which determines the threshold based on local brightness Otsu is based on a very simple idea: find the threshold that minimizes the weighted within-class variance This turns out to be the same as maximizing the between-class variance Otsu's operation is done directly on the gray level histogram, so it's very fast

All of the local minimums are considered as corner candidates, including the false corners Following criterion is used to remove them. In general, a well-defined corner should have a sharp angle and two relative long edges The process of removing false corners is done according to relevance measure R given by: $R_i = (\theta_i \times L_i \times L_{i+1}) / (L_i + L_{i+1})$. Where θ_i is the turn angle at the point P_i, L_i, and L_{i+1} are the two relative edges which have been normalized with respect to the total length of a polygonal curve C. The higher the value of R_i, the larger is the contribution to the shape of the curve If the turn angle θ_i and the two relative edges L_i and L_{i+1} are small, and R_i is below a threshold, the point P_i will be treat as a false corner, and being removed

2 Corner matching based on delaunay triangulation

The proposed corner matching algorithm is based on Delaunay Triangles The algorithm first constructs the Delaunay Triangles and Delaunay graph matrix, and then matches corners using spectrum of the graph matrix.

Let $X = \{p_1, p_2, \cdots, p_n\}$ be a set of points in the two dimensional Euclidean plane, namely the sites Partition the plane by labeling each point in the plane to its nearest All those points labeled as p_i form the Voronoi region $V(p_i)$. $V(p_i)$ consists of all the points x's at least as close to p_i to any other site[2]:

$$V(p_i) = \{x: |p_i - x| \leqslant |p_j - x|, \forall j \neq i\}.$$

The set of all points that have more than one nearest site form the Voronoi diagram $V(p)$ for the set of sites The Delaunay triangulation $D(p)$ is the embedding of the dual graph of the Voronoi diagram $V(p)$ where the nodes of $D(p)$ are the sites of $V(p)$, and two nodes are connected by an arc if their corresponding Voronoi polygons share a Voronoi edge Each face of $D(p)$ is a triangle, as shown in fig 1.

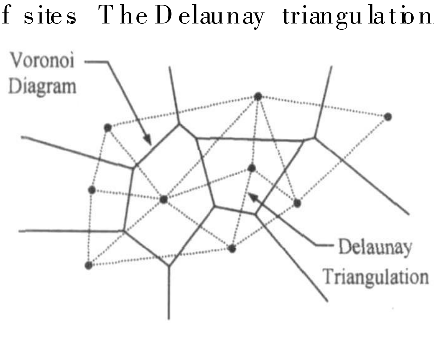


Fig. 1 Voronoi diagram and delaunay triangulation

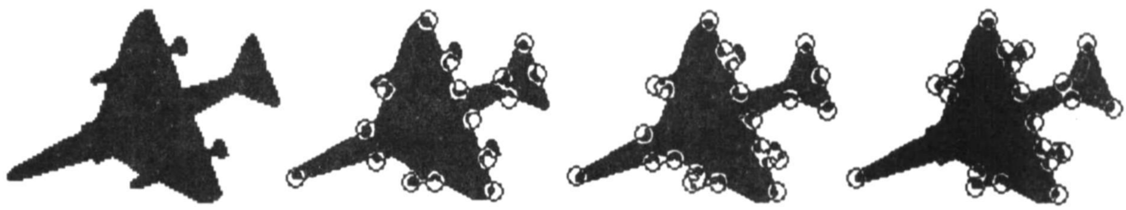
With the Delaunay triangulation, we construct Delaunay graph matrix. The graph is denoted by $G = (V, E)$, where V is the set of corner nodes, and $E \subseteq V \times V$ is the edge-set For the graph G, we compute the adjacency matrix A. This is a $|V| \times |V|$ matrix whose element with row index i and column index j is

$$A(i,j)=\begin{cases}1 & \text{if}(i,j)\in E\\ 0 & \text{otherwise}\end{cases}$$

Based on the Delaunay graph matrix, the corner feature can be derived and described as follows. From the adjacency matrix A, we can calculate the eigenvalues λ by solving the equation $|A-\lambda I|=0$ and the associated eigenvectors X by solving the system of equations $AX^{w}=\lambda^{w}X^{w}$, where w is the eigenmode index. We order the eigenvalues according to the decreasing magnitude of the eigenvalues, i.e. $|\lambda^{1}|>|\lambda^{2}|>\cdots>|\lambda^{|V|}|$. The spectrum Feature for the corner representation is constructed from the first ten ordered eigenvalues of the adjacency matrix.

3 Experimental results

3.1 Corner detection



(a) Plane image (b) Harris detector (c) SUSAN detector (d) Improved SUSAN detector

Fig. 2 Example of corner detection

We attempted many different images, but only one sample is being depicted here. Fig. 2 shows the corner detection results by Harris detector[9], SUSAN[4] and our improved SUSAN algorithm. Corners are indicated by small circle. 3 and 4 false corners were detected by Harris and SUSAN detectors, while 8 and 3 corners were missed. However, no false corner was detected or any corner was missed by improved SUSAN algorithm we proposed here. Table 1 shows the comparisons of corner detection.

3.2 Shape image retrieval

We perform shape image retrieval experiment using the MPEG-7 Core Experiment CE-Shape-1 database to evaluate the performance of DTM algorithm. The database consists of 70 different classes of shapes, each class containing 20 similar objects, usually (heavily) distorted versions of a single base shape. The whole data set therefore consists of 1 400 shapes. Each image was used as a query, and the retrieval rate is expressed by the Bull's Eye Percentage (BEP): the fraction of images that belong to the same class in the top 40 matches. Since the maximum number of correct matches for a single query image is 20, the total number of correct matches is 28 000. The overall retrieval rate is computed as the ratio of the total number of actual correct matches and the total number of possible correct matches.

Tab.1 Comparisons of corner detection

Evaluations	Harris	SUSAN	Improved SUSAN
False Corners	3	4	0
Miss Corners	8	3	0

Tab.2 Performance of similarity measures

Evaluations	Histogram	DTM
BEP	47	49

We compare our method (short in DTM) with Delaunay triangulation shape representation with histogram[2] (short in Histogram). The retrieval performance is shown in table 2. It is observed that our method outperformed by both the Histogram method.

4 Conclusions

This paper proposed an enhanced corner detector based on SUSAN algorithm. The improvements include three aspects A comparison experiments demonstrated that this enhanced SUSAN gives more accurate and stable results.

This paper also proposed an algorithm to establish shape similarity measure based on Delaunay triangulation (DTM). Since the spectrum of Delaunay graph matrix robust to noises and can describe shape images better, the proposed algorithm is robust and effective in shape image retrieval.

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基于 Delaunay 三角化的形状表示与相似性衡量

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摘　要: 在计算机视觉中, 形状的表示和相似性衡量是重要且复杂的问题, 提出了一种改进的 SUSAN (最小一致性区域)拐点检测算法并用于形状表示, 同时基于 Delaunay 三角化给出了一个用于形状相似性衡量的有效算法。首先, 对形状的拐点进行 Delaunay 三角形构造, 然后从 Delaunay 三角网中获得 Delaunay 图矩阵, 最后使用矩阵的谱对拐点进行匹配。在含有 1 400幅图像的MPEG-7CE-Shape-1数据库中的检索实验进一步验证了算法的有效性。

关键词: 形状表示; 形状相似性衡量; SUSAN; Delaunay 三角化; 图谱

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