Efficient Shape Classification Using Adaptive Skeleton Pruning

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Abstract. In this paper, we proposed an adaptive skeleton pruning scheme for shape analysis including classification and retrieval. The new shape feature extracted by proposed scheme was a combination of two vectors generated length and thickness of internal paths based on the adaptively pruned skeleton. Experimental results showed that our method can achieve very good retrieval results. Moreover, our method is fast, simple and computational efficient.

1 Introduction

Shape analysis and retrieval is an important topic in computer science and has been studied for decades. Nowadays, researchers mainly focus on retrieving and classifying deformed shapes. Although some methods are based on machine learning, most of the methods in this field relied on features, which are extracted from shapes and used as representatives in comparison[1]. These methods or features can be divided into three categories. First, contour based methods used the information on the contours. Generally, methods in this category are involving in comparing local features. The matching of local features are sensitive to noise and occlusions, which many methods aimed to overcome. Z. Tu's generative model [2], Hidden Markov Model on the contour[3, 4] fall into this category. Second category is the region based methods which mainly employ mathematical transforms and find out the features in another space, e.g. Radon transform[5, 6], Moment[7] and shape contexts. [8] The last category of methods is the skeleton based features. The skeleton based feature could easily capture topological information of shape structure and avoid the complex computation on local feature on the boundary. Some proposed to convert a skeleton into a binary tree and find out structure similarity between trees using dynamic programming [9, 10]. However, many of skeleton based methods did not take the radii of maximal disks into account which we consider as rather useful information. Our motivation in this paper is to improve this neglect.

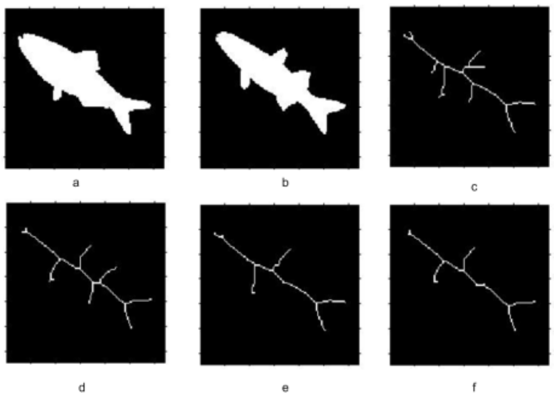

Fig. 1. (a) and (b) is different shape but similar; (c) and (d) are skeletons of (a) and (b) respective, which is not similar; After pruning, the pruned skeletons (e) and (f) became similar.

2 Adaptive Skeleton Pruning

When using a skeleton based approach, owing to some short branches exist in the skeleton, pruning is necessary. These small branches from the skeleton have very little contribution on the shape features. If we take account of tiny branches, the computational complexity sharply increases. Besides, in the later stage of proposed approach, it could cause an asymmetry of dimensions between two features vector, which makes the distance function difficult to design. Fig 1 showed how the pruning benefits classification of shapes. In our approach, we used the two sets of features as a combination for a single shape. The length of the internal path is one feature of the shape which reflects the significance of a path from one endpoint to another contributed to the shape. By calculating the lengths of the internal path between two adjacent endpoints, which are the consecutive ones in the clock-wised ordered array, the feature vector could be generated as:

$$v_1 = (L_1, L_2, ..., L_N) \quad \textbf{(1)}$$

where

$$L_i = length(E_i E_{i(\bmod N)+1}) \quad \textbf{(2)}$$

For the formula above, we can see that the dimension of the feature vector is the pre-set number of the endpoints remained. With this fixed dimension, we can employ a simpler space, i.e. Euclidean space, in the distance function.

The summation of radii of the maximal disk could differentiate different shapes which have same internal path. As the matter of fact, these summations of radii are the discrete area of different parts of the original shape which is separated by the skeleton. Like the lengths of internal path, the summations of radii were stored as a vector as well. And for the summation of radii calculates the area between two neighboring endpoints, the dimension of this vector is the same as the vector generated from the length of internal paths, which is the pre-defined number for the remaining endpoints.

$$v_2 = (S_1, S_2, ..., S_N) \quad \textbf{(3)}$$

where

$$S_i = \sum_{j=1}^{length(E_i E_{i(\mathrm{mod}\,N)+1})} radius(p_j) \quad , \; p_j \in E_i E_{i(\mathrm{mod}\,N)+1} \tag{4}$$

3 Experimental Results

We carried out the experiments on the common used database 99shapes, by Kimia et al[11], which contains 9 classes and there are 11 shapes in each class. All these shapes are solid plate shapes with no hole inside. In our experiments, every shape (query shape) was matched to all shapes in the dataset. We recorded the first 11 top closest for each shape. Each class was assigned a number N. When a query shape was about to match to others, skeleton from the query was pruned to the same N endpoints as the pruned skeletons from dataset which have been pruned. Through our experiment, we set $\beta = 1$ in (5) and tried to adjust α to reach an optimal output and found optimal result with α = 0.08. The retrieval results are shown in Table 1.

Table 1. Retrieval Results on Kamia's 99shapes Dataset

	N	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th
Quadrupeds	7	11	11	11	10	10	7	7	10	5	5	6
Humans	3	11	11	10	11	11	11	11	11	11	8	9
Airplanes	7	11	11	10	6	7	6	9	2	5	5	2
Grebes	7	11	11	11	11	11	11	10	10	10	8	2
Fish	7	11	11	11	11	10	11	11	10	10	11	5
Hands	6	11	11	11	9	9	9	8	9	6	8	2
Rays	3	11	11	11	10	11	11	10	10	8	8	4
Rabbits	4	11	11	10	9	8	9	10	7	7	10	4
Wrenches	3	11	11	11	11	11	11	11	11	11	11	11
Total		99	99	96	88	88	86	87	80	73	74	45

The numbers in Table 1 are how many queries have correctly retrieved the nth closest shape from dataset. The result showed that our method was relatively good at differentiating shapes with significant protruding lamb-like parts, for example, the human shapes, fishes and wrenches.

4 Conclusions

In this paper, we proposed an efficient adaptive skeleton pruning scheme to construct two features. One feature is built from length of internal path between pairs of clock-wised consecutive endpoints. The other one is from summation of radii of maximal disks on internal path between pairs of clock-wised consecutive endpoints. Experimental results showed that our method our method can achieve very good retrieval results in terms of accuracy and efficiency.

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