Shape Classification Using Regional Descriptors and Tangent Function

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Abstract— In this paper three novel hybrid regional descriptor are used for shape classification. The three descriptors are regional skeleton descriptor (RSD), regional area descriptor (RAD) and tangent function (TF). The RAD and RSD are defined by shape's skeleton as a primitive descriptor. The tangent function is generated from the contour by finding the important landmark points and gathering regional information about them. In the matching stage, optimal path searching algorithm is defined in the setting as distance measure function. These shape descriptors are tested on common datasets and the results are analyzed and compared with state of the art methods. The experimental results show that, our results are satisfactory as compared to others.

Keywords— *RAD, RSD, Tangent Function, skeleton, optimal path searching*

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I. INTRODUCTION

The shape of an object is affected by various factors. The variation of shape with protrusion. Occlusion, affine deformation and noise are called nonrigid transforms [1][2]. The good representation should be scale, transition and rotation invariant and be robust to nonrigid transform.

The procedure to find good features which can represent shape and similarity measure for classification is called shape classification. Many descriptors have been proposed, which can be categorized as 1) contour based methods 2) Skeleton based methods 3) region based methods.

The boundaries of shapes are used in contour based method. The methods which use contour based features are mostly efficient and can be easily implemented. But they are insensitive to boundaries. The contour based methods are Wavelet Descriptors [3]-[5] on boundary, Hidden Markov Models[6] etc.

The information inside the shape is used by region based method. The whole shape is considered as domain and is transformed to another domain for descriptor extraction. E.g. Radon transform. The landmark points on contour and descriptors are computed by gathering region information around those points.

Skeleton based methods uses topological information from the shape and forms shape descriptors based on it. Many methods fall into this category like Shock graph [7] etc. However skeleton is heavily affected by protrusion and occlusion. Also this category are requires to process alignment problems.

In this paper, we have proposed regional descriptor for shape classification, which includes three descriptors regional are descriptor (RAD), regional skeleton descriptor (RSD) and tangent function (TF). In next section, the framework of the proposed method and how the features are extracted from the shape are explained. We have also introduced the dynamic algorithm for classification and how the distance generated dissimilarity in Section III. The experimental results from the proposed method which are done on widely used datasets are explained in Section IV. Analyzing of the results and the comparison with other methods are done in this section. Finally, conclusions are made in Section V.

II. EXTRACTION OF SHAPE DESCRIPTORS

Our work shares similar framework with the, Belongie's Shape Context [8] and Alajlan's Triangle-Area Representation [9]. We begin with extraction of features on local points and gathering surrounding shape information. A dynamic algorithm based Optimal Path Searching (OPS) is used to find local point's correspondences and measure total distance of two shapes. Finally, the shape is classified into the category having minimum distance. In previous work, local points were used, whereas in our method local regions are used. In our proposed approach, we have defined three descriptors: 1)) regional area descriptor (*RAD*) and 2) regional skeleton descriptor (RSD), which uses the skeletons and contours and can called as skeleton based and contour based hybrid descriptors. And 3) Tangent Function, which falls into contour based category, collects the significant points from the contour according to some rules. It is assumed that the shapes are well segmented and considered as solid plate, like other shape classification methods.

A. Regional Skeleton Descriptor

The most useful primitive shape descriptor for representing as shape is the skeleton. But matching of two skeletons is too tough because the skeleton is the representation of the topological structure of the shape and as the shape changes, the topological structure changes. Hence, in our proposed approach, we have tried to take advantages of skeleton which is effective in topological structure and have tried avoiding the disadvantages of it, and we proposed the shape descriptor viz. Regional skeleton descriptor.

The RSD defines the local part of shape by calculating the perimeter of the area from the skeleton to the segment of the contour. Following the procedure given below, the regional skeleton features are extracted from the specific local region:

1) A graph of multiple base points, which are distributed along the contour, equally, is built.

2) The skeleton of the shape is found out and the point in skeleton must have radius of it maximum disk from the contour.

3) To find the closest points on skeleton from each point, skeleton is searched and accordingly, Euclidean distance is calculated between them.

4) Using depth priority search (*DPS*) algorithm, for each pair of consecutive base points, the corresponding closest points distance on skeleton is calculated by finding out the path length on skeleton.

5) The regional skeleton descriptor is obtained by adding up distances from 3) and 4).

Geometrically, this descriptor defines that how much area the part of contour between two points is included in the shape. Given two base points p_1 and p_2, and their closest points on skeleton sp_1 and sp_2 , the *RSD* of the region between these points can be mathematically defined as:

$$RSD(p_1,p_2) = D(p_1,sp_1) + D(p_2,sp_2) + length(DPS(p_1,p_2)) \quad (1)$$

where *DPS* (,) is depth priority search function which returns a discrete path . Let O be the global descriptor and it is organized into a vector as follows, supposing that we have *N* base points,

$$RSD(O) = \{RSD(p_1,p_2), RSD(p_2,p_3), \ldots, RSD(p_{N-1},p_N), RSD(p_N,p_1)\} \quad (2)$$

B. Regional Area Descriptor

Though RSD can be used for representation of shape, but it solely is not enough to justify distance between shapes. Fig. 1 is a very clear counter-example of the two local shape descriptors shown as below:

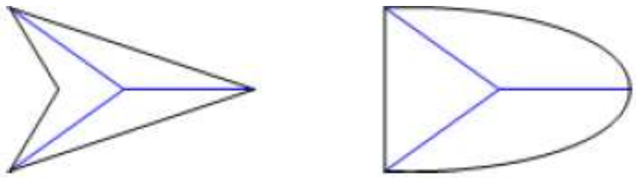


Fig. 1. Two simple different shapes have same skeleton.

Therefore, the regional area descriptor is generated by the same procedure as *RSD* that is based on local part. The Regional Area Descriptor (*RAD*) adds the maximal radii information on the skeleton segment which corresponds to the segment of contour, which is nearly equal to the quantity of area of local region. It could be expressed in mathematical form as:

$$RAD(O) = \{RAD(p_1,p_2), RAD(p_2,p_3), \ldots, RAD(p_{N-1},p_N), RAD(p_N,p_1)\} \quad (3)$$

where

$$RAD(sp_i, sp_{i(\mathrm{mod}N)+1})) = \sum_{j=1}^{length(sp_i sp_{i(\mathrm{mod}N)+1})} radius(p_j)$$

$$p_j \in [sp_i, sp_{i(\mathrm{mod}N)+1}]$$

C. Tangent Function

A very important primitive descriptor for a shape which can be used as complementary descriptor along with the skeleton based descriptors is contour, which is show in Fig. 2.

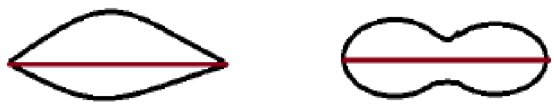
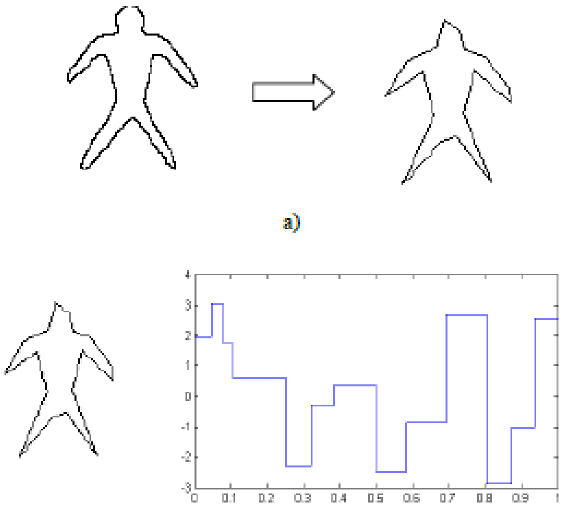


Fig. 2. Two simple shapes may have same skeleton and same size of local area.

A segmented shape, generally, contains some noise which affects its shape descriptors to some extent and cause high computational cost. The insignificant information on the boundary noise and should be removed and those important points on the large turning corners should be preserved. We have used the turning angles and considered that other two shape descriptors will compensate the loss of information in the segment on simplified contour in the whole system. For simplifying it: we replace two consecutive line segments on the contour with one line segment which will join their endpoints, if joint 'condition' of two line segments that are consecutive is lower than a pre-defined threshold. The joint 'condition' is a function which is defined to compute that how much the two consecutive line segments and their angle is contributing to the whole shape. And our approach reduces each and every shape to a minimum fixed number of points. We first define the relevance function [11], [12], to achieve this:

$$K(s_1,s_2)=\frac{\beta(s_1,s_2)\bullet L(s_1)\bullet L(s_2)}{L(s_1)+L(s_2)} \qquad (4)$$

The relevance function which is defined on two consecutive vectors and gives a value which represents how importance the triangle consist of s_1 and s_2 contributes to the whole shape. The higher value of K ($s1$, $s2$) , the more significant. The two vectors that connects the endpoints, are to be replaced, and number of points is more than the pre constant which is predefined and if there is an i, such that it is minimum. By applying such operation iteratively, the shape boundary is traversed until number of points gets equal to our pre-defined value.



a)

b)

Fig. 3. a) An image boundary and corresponding simplified one. b) A simplified boundary and its tangent function.

After simplification, as Shown in Fig. 3, a simplified shape is generated which has less noise and preserves shape information as well. The tangent function(*TF*), also called a turning function is as shown in Fig. 4 which is a multi-valued function defined $T(C)$:[0,1]- > [by $T(C)(s)$ $=C\_'$ (s) and $T(C)(s)=C'_+$ (s) , where $T(C)(s)$ = $C'\_$ (s) and $T(C)(s)$ = C'_+ (s) are left and right derivatives of C. The value of $T(\ p)$, p is a point on C, is angle between the line segment vector and a reference vector . The tangent function $T(C)(s)$ specifies wherever there is turning on the contour, decreasing with right turns and increasing with left turns is used as a shape descriptor. To achieve rotation invariance, we pick up the pixel which is farthest from centroid in the shape to start simplification.

D. *Rotation, Scale, Transition Invariance*

The proposed descriptors can achieve *RST* invariance. Firstly, the transition invariant can be naturally satisfied. After the contour and skeleton are extracted, our descriptors have nothing to do with the position of the shape. As for rotation invariant, our descriptors are arranged in vector form in which the local features are kept in clock-wised form. Therefore, the invariant property can easily solved by a circular shift on the vector in matching. Finally, by normalizing the global vector or the vectors divided by the sum of local features, the scale invariant can be achieved.

III. CLASSIFICATION AND DISTANCE MEASURE

The Optimal Path Searching (*OPS*), which is extended from dynamic algorithm, was used in our matching stage. The most important advantage of OPS is that it can handle two descriptor vectors with different dimensions. The local point on one shape is not necessary matched to a fixed point on another shape, but could be matched to the neighbors of a point on the other shape. This is useful in handling deformed shapes which global similarity is exist while some significant differences on local parts. The total distance of two shapes is computed during *OPS* as cost of the optimal path to obtain the optimal path, searching all the possible paths is a conventional approach. However, the time and space complexities are prohibitive. To solve this problem, we adopt the dynamic programming algorithms based on Bellman's principle to reduce the time and computational cost. In other words, the Bellman's principle tells us that the concatenation of its two optimal sub-paths will be considered as the optimal path. Therefore, to search the optimal path, we could cast the problem into searching its two optimal sub-paths. The proposed descriptors have different capability in classifying shapes because of different natures and different origins. A combination might be a good idea to take all use their advantages. In order to avoid complicated combination of distance measures, we use a simple linear combination of the distances from three shape descriptors.

IV. EXPERIMENTAL RESULTS

A.

B. A. *Classification*

Our classification employed the traditional distance measure based approach which determined by the minimal distance between sample shape and shapes in the dataset. The distance is the dissimilarity of two shape and distance functions are usually defined for the feature that proposed. The distance measure function takes in two descriptors vectors from a pair of shapes respectively and calculates dissimilarity. The larger is the output distance, the less similar are the two shapes. Every shape in dataset is labeled with a known class. A sample from dataset is to be matched with every shape in the same dataset except for itself and the distances are also calculated. We find out the shape in dataset with minimal distance and consider the sample and *this* retrieved shape are in the same class.

C. B. *Datasets for Experiments*

In order to evaluate which approach is better in this field, some standardized databases and benchmarks for experiment are designed. Many databases are designed for different kinds of methods, owing that different methods may have different assumptions on shapes. A commonly used database is 99shapes, by Kimia *et al.* It contains ninety nine planar shapes which classified into nine classes, with eleven shapes in each. Shapes in the same class are in different variant form, including occluded, noised, rotated, etc. Other databases including MPEG-7 Shape Dataset [5], Articulated Dataset, Swedish Leaf Dataset and Brown Dataset are used to have further experiments. Precision and Recall is used for benchmark for the reason of fair comparisons.

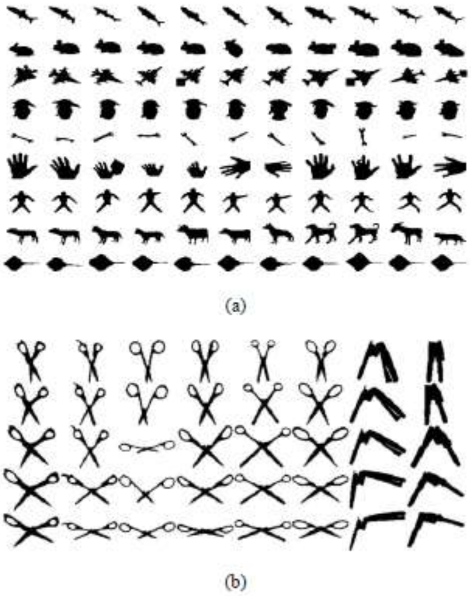


Fig. 4. Common used test material (a) Image dataset of 99 testing shapes provided by Kimia *et al.* (b) Image dataset of articulated testing shapes.

D. Results and Discussion

Table I shows the optimal result from test on 99shape dataset. The numbers of points we sampled from the shapes are 50, 50 and 25 for *RSD*, *RAD* and *TF* respectively.

TABLE I: Retrieval Result of Combined Descriptors on 99 Shape Dataset for Each Class

Rank	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Quadrupeds	11	11	11	11	8	8	6	5	6	3
Humans	11	11	11	11	11	11	11	11	11	10
Airplanes	11	11	8	5	6	6	2	4	4	2
Grebes	11	11	11	11	10	11	10	8	10	3
Fish	11	11	11	11	10	11	10	7	6	5
Hands	11	11	11	11	9	8	6	8	4	1
Rays	11	11	10	11	11	11	9	7	5	3
Rabbits	11	11	11	10	10	10	11	5	8	5
Wrenches	11	11	11	11	11	11	11	11	11	11

For the articulated dataset, 45, 35 and 45 points are sample for *RSD*, *RAD* and TF. Retrieval result on articulated dataset was presented in Table I. We have noticed that result on 99shape from *RAD* is slightly better than *RSD*, while on articulated dataset *RSD* performs slightly better than *RAD*. During the above experiment, we tried to normalize the descriptors and found that experiment on 99 shapes received little influence from normalization while result from articulated dataset has some improvement.

TABLE II: Comparison of Results of 99 Shape Dataset with Shape Context [16]

Method	Shape context	Ours
1st	97	99
2nd	91	99
3rd	88	95
4th	85	93
5th	84	85
6th	77	87
7th	75	74
8th	66	68
9th	56	63
10th	37	45

TABLE III: Comparison of Results of Articulated Dataset with State-of-the-Art

Descriptor	1st	2nd	3rd	4th
L_2 (baseline)	25	15	12	10
SC + DP[16]	20	10	11	5
MDS + SC + DP[16]	36	26	17	15
Contour Distance[10]	36	31	28	23
Center of mass-based[10]	25	12	9	11
Our method	**39**	**36**	**30**	**22**

From the Table I, our algorithm has a almost 100% correct classified rate for Human and Wrench. We noticed that the Airplanes class is of the lowest correct rate except for the top 3 ranks. And the hit rate declined rapidly which make it singled out from the Table I. The matching distance in this class is carefully investigated and the distance revealed that our descriptors have difficulties in classifying sampled with a large part of protrusion in proportion to its main part. Another reason leads to the low correct rate in Airplanes class is the different numbers of sharp protrusions in different samples in same class and the numbers are various. Since the sharp protrusions influence the branches in skeleton, different numbers of protrusion affect the skeletons' stability within the class and diversify the descriptors of this class.

Comparison with Shape Context is listed in Table II. Compared to Shape Context our proposed shape descriptors have the advantageous property of scale and rotation invariant. Our method enjoy a high hit rate from 1st to 5th rank however, unfortunately, it slightly falls behind from 6th to 10th rank.

A comparison of the results on articulated dataset with other state-of-the-art methods shows that our method is highly articulation insensitive. The articulated dataset is a challenging dataset for shape classification owing that most samples in the dataset are segmented from real images of same type of object, for instance, the scissors and samples in the same class are from the same object but with some degree of articulation at some branch points. Results data listed in Table III shows that the proposed method outperformed others on this dataset.

V. CONCLUSIONS

In this paper, we proposed hybrid regional and global descriptor for shape classification. By combining the descriptors, the drawbacks of each descriptor are overcome. In the matching stage, a dynamic programming based Optimal Path Searching is integrated into our method. The matching algorithm successfully handled the challenge of matching two different descriptors in different lengths. The proposed methods are tested on the widely used 99shape and articulated dataset. The experimental results are satisfactory. Data of result is presented in table form and compared to other the-state-of-art methods in literature as well.

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REFERENCES

[1] L. Latecki, R. Lakamper, and U. Eckhardt, "Shape descriptors for non-rigid shapes with a single closed contour," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2000, vol. 1, pp. 424-429.

[2] T. Schoenemann and D. Cremers, "Matching non-rigidly deformable shapes across images: A globally optimal solution," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, CVPR 2008, pp. 1-6.

[3] D. Huang and G. Lu, "Review of shape representation and description techniques," *Pattern Recognition*, vol. 37, 2004.

[4] Y. W. Chen and Y. Q. Chen, "Invariant description and retrieval of planar shapes using radon composite features," *IEEE Transactions on Signal Processing*, vol. 56, pp. 4762-4771, 2008.

[5] W. l. Yao and C. M. Pun, "Invariant shape representation by radon and wavelet transforms for complex inner shapes," in *Proc. International Conference on Information and Automation*, 2009, pp. 1144-1149.

[6] M. Bicego and V. Murino, "Investigating hidden markov models' capabilities in 2d shape classification," *IEEE Transactions on Pattern Analysis And Machine Intelligence*, vol. 26, pp. 281-286, Feb. 2004.

[7] T. B. Sebastian, P. N. Klein, and B. B. Kimia, "Recognition of shapes by editing their shock graphs," *IEEE Transactions on Pattern Analysis And Machine Intelligence*, vol. 26, pp. 550-571, May 2004. [8] H. Ling and D. W. Jacobs, "Shape classification using the inner-distance," *IEEE Transactions on Pattern Analysis and Machine Intelligence* , vol. 29, pp. 286-299, 2007.

[8] S. Belongie, J. Malik, and J. Puzicha, "Shape matching and object recognition using shape contexts," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, pp. 509-522, 2002.

[9] N. Alajlan, I. E. Rube, M. S. Kamel, and G. Freeman, "Shape retrieval using triangle-area representation and dynamic space warping," *Pattern Recognition*, vol. 40, pp. 1911-1920, 2007.

[10] L. J. Latecki and R. Lakämper, "Convexity rule for shape decomposition based on discrete contour evolution," *Computer Vision and Image Understanding*, vol. 73, pp. 441-454, 1999.

[11] L. J. Latecki and R. Lakämper, "Shape similarity measure based on correspondence of visual parts," *IEEE Transactions on Pattern Analysis And Machine Intelligence*, vol. 22, pp. 1185-1120, 2000.

[12] D. Sharvit, J. Chan, H. Tek, and B. Kimia, "Symmetry-based indexing of image databases," *J. Vis. Commun. Image Represent*, vol. 12, 2004.