Improving shape correspondences using salient points

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Abstract

Quality of a shape matching technique is correlated to the quality of contour point correspondences obtained. Improving correspondences hence can be useful for better shape matching. In this paper we present a framework that can find salient points correspondences along the contour.The results demonstrate significant improvement for occlusion shapes, compared with inner distance.

Keywords: Inner Distance, Shape Matching, DCE, part-cutting

1. Introduction

Shape correspondence plays a key role in shape matching. The problem of partial shape matching has been extensively addressed in the literature. The earth mover's distance(EMD) has been applied to shape matching based on contours [4] successfully. They have used the shape context [8] to get contour correspondence. However the application has not given the correspondence between two different contours in occlusion cases. The inner-distance shape context is defined as the length of the shortest path between landmark points within the shape silhouette [6]. Inner distance has improved the shape context [8] through using the inner distance instead of the Euclidean distance. So for the non-rigid shape matching, the correspondence result is usually very nice. But if the two shapes have totally different structure, the inner distance cannot find the exact correspondence. Essentially inner-distance and shape context are both data points density based method. So the uniform sample rate for the entire shape contour is not very appropriate. The (Fig. 1) has shown this problem: the rider on the horse has wrong correspondence to the first horse during the global matching.

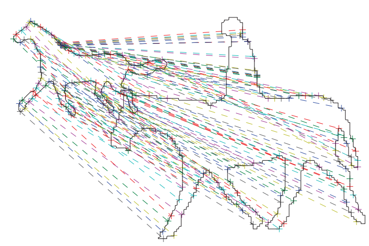

Fig. 1: Global Correspondence between two shapes from Inner distance [6].

Besides the contour based approach, skeleton branches after pruning are very useful to detect the meaningful shape structure. In Dickinson's work [2], a canonical skeleton that captures only the salient part structure of the shape is put forward.Their skeleton is very stable; however only the cases without occlusion are presented. Xie's work [10] has also used skeleton structures to find the correspondence between skeleton endpoints , which are only restricted to the the convex points of the shape.Then he used nonuniform sample rate for the shape contour segmented by the endpoint correspondences. But this is not very robust if the skeleton structures of two shapes are not very similar. This is shown in Fig. 2.

Fig. 2: Two fishes with different skeleton structure in Kimia 99 database [9] to illustrate the drawback of skeleton based matching.

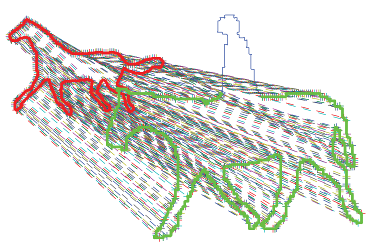

Fig. 3: The correspondences between horse and horse with a rider based on our method

Our typical results are shown in Fig. 3.The correspondences are more robust.There are two main reasons:

(1) In [10] salient regions are captured by skeleton end points which are restricted to convex points on the shape. Nevertheless a shape can have non-convex salient regions and convex regions which are not salient. We address this issue by identifying salient regions using Discrete Curve Evolution(DCE) [5] which can capture both convex and concave regions. We also developed a procedure to eliminate non-salient convex regions using "part-cutting". This also addresses the occlusion issue.

(2) Usually the skeleton branches and endpoints matching are not very robust for variant skeleton structure, just like Fig.2. But this can be improved by matching DCE points and its neighboring data points. It would be better to evaluate the matching strength of a contour part than only skeleton endpoints. The neighboring data points matching has been motivated by Kumar's paper [3] for clustering data: the similarity between two points is "confirmed" by their common (shared) nearest neighbors. Here in our work the DCE points and neighboring data points have been give different weights according to Gaussian distribution. Then the matching strength is obtained. This captures very important local information.

2. Shape matching based on salient points

The global 2D contour matching by Inner Distance [6] can find the rough matching for most points; however due to the uniform sampling method used in inner distance, some salient points have been given wrong correspondence.

The DCE method was introduced in [5]. The object contour obtained from digital images are distorted by digitization noise and segmentation errors. DCE method can eliminate the distortions while at the same time preserve the perceptual appearances sufficient for object recognition. It has treated the contour as a polygon and recursively removing least relevant vertices. In each evolution step of DCE, a pair of consecutive line segments S_1, S_2 are replaced by a single line segment joining the endpoints of $S_1 \bigcup S_2$. The key property of this evolution is the order of the substitution. The substitution is achieved according to relevance measure K given by:

$$K(S_1, S_2) = \frac{\beta(S_1, S_2) l(S_1) l(S_2)}{l(S_1 + l(S_2))}, \quad (1)$$

where line segments S_1, S_2 are the sides of the polygon incident at a vertex $\mu, \beta(S_1, S_2)$ is the turn angle at the common vertex of segments S_1, S_2 and l is the length function normalized with respect to the total length of a polygonal curve C. At last the process eliminates the less important points while keeping the important points. Through this way we obtain the DCE points. In Fig4, the red points are DCE points.

Our work improves the correspondences using DCE points. Our technique has the following three steps for two 2D shapes:

2.1. Matching DCE points of two 2D shapes

For each shape we use 20 salient points obtained using DCE [5]. Fig. 4 shows the correspondences between the salient points on two shapes. Salient points from horse on the left correspond to those in the "horse with a rider", excluding the rider. The matching strength is defined by sum of Gaussian transform of the points neighboring DCE points with peak at the DCE point as shown in Eq. 2. For example, in our work we use 10 nearest neighbors around the DCE points. If the match

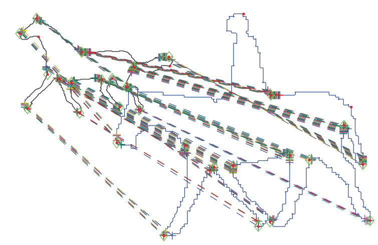

Fig. 4: The salient correspondences between horse and horse with a rider.The red points are DCE points

distance is evaluated by the number of shared neighbor matching pairs, it would be better for finding the salient points correspondence pair. Inside this neighborhood, the points matched to the other shape will be input into the Gaussian function($\sigma = 5, \mu = 0$) and obtain the weight to strengthen the local information. Then match cost multiplied by the Gaussian weight are summed to obtain the strength from shape1:

$$S1_i = \sum_{p=1}^{N} w_p * cost_p \qquad (2)$$

$w_p, (1 \leq p \leq N)$ is the weight of salient points' N nearest neighbor. $cost_p, (1 \leq p \leq N)$ is the matching cost of these points to the other shape. $\{S1_1, ..., S1_i, ..., S1_M\}, \{S2_1, ..., S2_j, ..., S2_M\}$ are the strength sequence for all the M correspondence points in S1 and S2. The local matching strength/distance function for two shapes are:

$$Strength(S1, S2) = S1_i * S2_i \qquad (3)$$

If the data points are sparser or fewer, the strength between the DCE point correspondence pair will be weaker and vice versa. We have set a threshold to eliminate the weak salient correspondence pair.

2.2. Salient Structure Matching

The salient rider part is represented by the convex DCE point (it is also skeleton endpoint from [1]) and its neighbor concave DCE points on the left and right hand side. The group of convex point and its neighboring pairs of concave points can capture the salient part structure correspondence. Here the concave points have local minimum curvature. Fig. 5 from [7] has considered all the possible cases in our current work. But one more restriction is given in our work: between the cut positions, there are no convex DCE point correspondence between two shapes. If there is no neighboring concave points, the short-cut rule will be used.

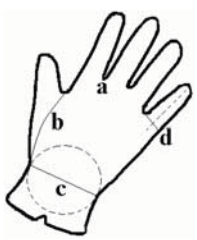

Fig. 5: (a)Minima Rule: Points of minimum curvature are good places to begin a part cut.(b) Limbs: Part cuts are made between two points of minimum curvature when there is evidence for "good continuation".(c) Necks: Part cuts are made between two points. (d) Short-Cut Rule: All else being equal, a part cut is made from a point of minimum curvature to the nearest boundary point, crossing a local axis of symmetry[7]

If the DCE points and their nearest neighbor can not correspond to the convex DCE points from the other shape, then those are likely to be the non-salient or occluded part of the object. However this needs to be verified by matching the neighboring concave DCE points. Inside each pair of concave DCE points, if the convex DCE points cannot find corresponding DCE convex points in the other shape, the contour part between these two concave points could be removed or cut. This is proved by minima rule and short-cut rule used in [7]. Finally the matched and unmatched contour parts in a shape are found.

2.3. Shape matching based on "part-cutting"

Based on the Inner Distance Shape Context (IDSC)+Dynamic Programming(DP)[6], matching is strengthened through matched segments. The unmatched segments are skipped. We call this method **"part cutting"**. The distance Dist in Eq.4,is computed through IDSC for matched parts. Since the endpoints of parts are registered by pair of salient DCE points, the correspondences between them are also more accurate.

$$Dist(S1, S2) = \sum_{i=1}^{p-1} IDSC(Seg1_i, Seg2_i) \tag{4}$$

$Seg1_i, Seg2_i, (1 \leq i \leq p-1)$ are matched parts from shape S1 and S2. As in [10] we sample equal number of points from contour parts. "part cutting"is crucial for establishing our final correspondences. Thus two shapes from different classes might have more similar global matching. So in our experiments we combined the distance from IDSC+DP and "part cutting".

3. Experiments

Kimia 99 database contains 99 images from 9 categories of shape. Each cate-

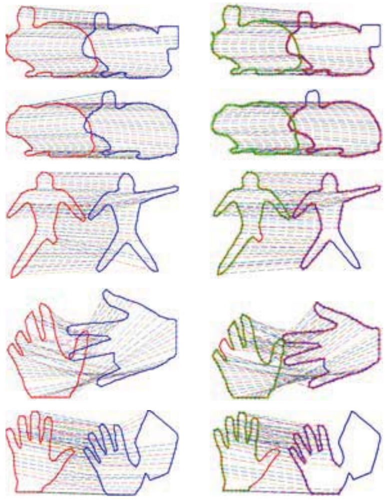

Fig. 6: some experiments results (Results from [6] are shown on the left; and our results on the right)

gory has 11 shapes. We compared our results with the best performing technique of [6] on Kimia99 [9]. In Fig.6, the occluded rabbit's tail can be detected by our method; the occluded hand can be also detected.

In the experiment, each shape is used to match against all other shapes. The 10 nearest neighbors retrieval results are shown in Table 1.Our final method has combined the IDSC+DP [6] and "part cutting". It performs better than IDSC+DP on Kimia 99 database.

4. Conclusions

We presented a technique for improving shape correspondences by identifying salient regions of shapes in context. Our approach demonstrates the improvement in correspondences obtained by inner distance. Especially for occluded cases, the proposed method can find the correct correspondences between salient parts. "part cutting" can be used to decompose the shape information for global matching and then local part matching has been combined with IDSC+DP for the final retrieval. The results show its better performance than IDSC+DP [6] for database with occluded shapes, Kimia99.

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Table 1: Retrieval results on Kimia Data Set [6]

Distance Type	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
IDSC+DP	99	99	99	98	98	97	97	98	94	79
IDSC+DP,Cut	99	99	99	99	99	99	99	99	91	79

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