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On a study of extracting salient points

by

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Synopsis

Segmentation problem is a critical problem in machine vision. Various approachs have been proposed in the machine vision literature. Whether or not an approach is reliable needs some criteria to justify it. In this paper, we give some criteria based on the consideration: partitioning is closed connected with intelligent action, and digitized images have themself discrete property. Almost all approachs for extracting salient points have a costly computation. For reducing the computation cost, a quick extracting method is proposed here.

Keywords : Contour,Criteria, Curve, Curvature, Hierarchy, Invariance, Salient point extracting.

1. Introduction

One of the most critical problems in machine vision is how to take apart the perceived world into coherent or meaningfull parts prior to knowing the identity of these parts. Almost all current machine vision paradigms require some form of partitioning at an early simplification step to avoid having to resolve a combinatorially lage number of alternatives in the subsequent analysis process. Given this critical role for partitioning as a functional requirement of a complete vision system, it is a major challenge to find some significant subsets of the partitioning problem for which an alogrithmic procedure can duplicate human vision[1]. Since Attneave[2] first focused attention on the importance of angles in determining the perceived shapes of outlines, salient points' extracting which plays a critical role in vision task is often used as a base for scence partitioning, image matching and recognition. For example, corners on the contours of imaged objects are often used as features for tracking the motion of these objects and for computing optical flow. Interpolations and approximations that are often adopted in bounded algebraic surface need select some control points. In cartography, computer graphics, and scene anaysis, it is often desired to diride an extended boundary or a contour into a sequence of simply represented primitives to simplify subsequent analysis and to minimize storage requirements. Usually, salient points' extracting plays an important effect to satisfy this demand[3]. The correctness, simplicity and efficiency of extracting salient points will be the basic guarantees of the successfull visual action. Whether an extracting method is reliable, it's need some criteria to justify it. In section 2, we will simply dicuss. the criterion problem. In section 3, a quick method for extracting salient points is proposed, based on the knowledge of human being. The advantage is its speed−up.

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2. Partitioning criterion

Even if we are given a problem domain in which explicit semantic cues are missing, to what extent is partitioning dependent on the purpose, vocabulary, data representation and past experience of the "partitioning instrument" as opposed to being a search for context independent "intrinsic structure" in the data? Partitioning is very closed connected with human being's intelligent action, but we didn't know well with the action's principle. So, at present, many approaches to the partitioning are independent of the next intelligent process. Althought we do not know well the releation between the partitioning and recognition, it is no doubt that the partitioning's hierarchal structure should be considered.

The digitized image is a discrete quantity described by a pixel matrix. The slight rotation of a image will caused the difference of contours between the original digitized image and the rotated digitized image. How to extract salient points from a discrete contour, these points should not be actual digit image points, is a valuable considered problem. In a word, the partitiong problem can not be considered as a separated problem from the intelligent action.

Based on the partitioning parts' intelligent action and the speciality of the digitized image, we give some criteria to the partitioning problem here (parts of criteria have been enumerated in several papers[3],[4],[5], we summarize them along with our own views):

Hierarchy: partitioning should be a hierarchichal process. The extracted parts should be assigned some labels to point out their effect in image understanding and recognition and form a hierarchichal structure. Partitioning's hierarchy can make the matching speed up and fuzzy matching be realized easily.

Invariance: partitioning should be invariant under rotation,scaling and translation. Because stereopsis requires different views of the same scene, it is necessary that these transformations not lead to different decomposition for a digitized image. This invariance usually means the decomposed parts should not be represented by its original contour points, as contour points are changeable along with the image's rotation, scaling and translation. That is also said the decomposed should be unique.

Noise Description: Parts of the contour may have to be take apart very small pieces to fit the primitive description. When these pieces become too small for an application, partitioning should stop. We call the remaining pieces λ −segments. Defining λ −segments limits the number of segments and controls the combinatorial explosion when matching segments between images.

Stability: Local perturbations in the curve should cause only local changes in partitioning. Occlusions and edge detection anomalies should not affect segmentation away from where they start.

Robustness: Measurements on discrete curves are inherently noisy due to the quantization and it is impossible to avoid using thresholds at some point. Although thresholds cannot be eliminated entirely, the algorithm should respond to parameter variations smoothly with little change in performance; it must not be overly sensitive to empirically selected constants.

Efficiency: The algorithm should be computationally efficient. Machine vision is a real time task, it demand the algorithm should be simpler, quicker and pracricl under a lower capicity.

3. A quick method for extracting salient points

Attneave pointed out that the points at which a curve bends most sharply are good partitioning points. This idea has been the starting point for most of the subsequent efforts in curve partitioning, but attempts to convert this abstract concept into a computationally executable procedure, one of them gives intuitively acceptable results, have met with limited success [1]

Many methods used the conventional definitions of curvature to extract salient points. The mathematical definition is based on the properties of a curve in infinitesimal neighborhood about the point at which the curvature is being measured. For the finite precision quantized curves, it has been difficult to find a suitable approximation to the limiting procss originally intended for use on mathematically continuous curves and the computation cost is very high.

Fischler and Bolles [4] provided an elegant discussion of the salient points of the curve partitioning problem and present two algorithms. they are robust for resisting noise. Althoug these algorithms appear to satisfy many of their criteria and can perform the human level of competence for a significant subset of the partitioning task, neither is directed in its approach. This is largely because,as they pointed out, contour partitioning is not a domain-independent procedure [3]. At the same time the computation process is too complicated.

No matter Fischler's method or other methods based on the mathematical definition of curvature, the computation cost is too much. Here we provide a quick method for extracting salient points based on the knowledge which has been used by human being. The advantage is its speed-up and flexibilty. At the local extracting effect, it is the best because of using the human being's knowledge.

The algorithm is as follows: Whether or not a point on a contour is a salient point is examined by human being, considering the shape of it and several neighbouring points on the contour. This examining knowledge forms a search table. When the algorithm is extracting salient points, it searches the table by using the shape of examined point and its neighbouring points. We simply discuss how to obtain and represent the justifing knowledge and the searching method.

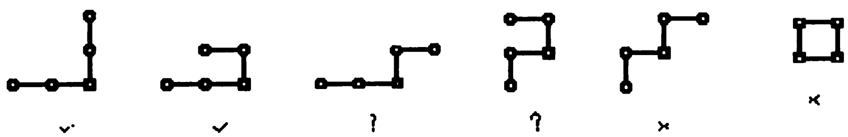
A: Obtaining the knowledge:

Considering the computation quantity and error, many methods based on the mathematical curvatue concept used 5-9 points for extracting salient points. For the local examining, the number of observed points is enough. Here we observed 9 or 11 points. If we inspected every shape of 9 or 11 points, the working quantity would be too high. But using the hierarchical method, we can simplify the working. For example, at first we consider $n=3$'s all shapes (supposing n is the number of observed curve's points), the observed shape in Fig.1 (a) does not form a salient point, but Fig.1(b) need more connected points to be observed. So adding two points to it, six shapes were got (see Fig.2). Among them some can be fixed as forming a salient point or not, the others need more points to be observed. Repeating the process, we can get all judging knowledge among 9 or 11 points scope.

(a) (b)

(√ is a salient point, X is not a salient point, ? need to test more points)

Fig.1. 3 points' shapes



(a) (b) (c) (d) (e) (f)

(√ is a salient point, X is not a salient point, ? need to test more points)

Fig.2. 5 points' shape

B: Expressing the knowledge and searching

Here we adoped 2 bits Freeman's chain code to represent curve. Coding model is showed as Fig.3. Two jointed points need two bits to code. For n points' curve, the length of Freeman's chain code is $(n-1)*2$ bits, this is also the search table's capacity. In our method, the capacity is about 128k bytes ($n=11$). Because some curves have mirror symmetry, centry symmetry and so on, (though the codes are different, the shapes are same as described in Fig.4), for reducing the capacity, we only store the shape into the table that the shape is represented by a deputy code of all codes. The next problem is how to change a code into its deputy code. First, we change the coding method, taking the examined point as a centry and coding the curve from it to two sides (called it "centry Freeman's chain code"). Second, we get the code of mirror symmetry. Third, we rotate the curve and the mirror symmetry curve and get the minimal "centry Freeman's chain code", that is, the deputy code. The process of transforming a Freemain's chain code to its deputy code is showed as below:

$$(N_{k1}N_{k2}).......(N_{11}N_{12})|(M_{11}M_{12}).......(M_{k1}M_{k2}) \Rightarrow (\overline{N}_{11}\overline{N}_{12})......(\overline{N}_{k1}\overline{N}_{k2})|(M_{11}M_{12})......(M_{k1}M_{k2})$$
$$\Rightarrow (\overline{N}_{12}\overline{N}_{11}).......(\overline{N}_{k2}\overline{N}_{k1})|(M_{12}M_{11})......(M_{k2}M_{k1})$$
$$A_1 = (00).......(\overline{N}^1_{K1}\overline{N}^1_{K2})|(M^1_{11}M^1_{12}).......(M^1_{K1}M^1_{K2}); A_2 = (00).......(M^2_{K1}M^2_{K2})|(\overline{N}^2_{11}\overline{N}^2_{12}).......(\overline{N}^2_{K1}\overline{N}^2_{K2});$$
$$A_3 = (00).......(\overline{N}^3_{K1}\overline{N}^3_{K2})|(M^3_{11}M^3_{12}).......(M^3_{K1}M^3_{K2}); A_4 = (00).......(M^4_{K2}M^4_{K1})|(\overline{N}^4_{12}\overline{N}^4_{11}).......(\overline{N}^4_{K2}\overline{N}^4_{K1}); \quad \cdots\cdots(1)$$

The deputy code A = is min (A_1, A_2, A_3, A_4) ·····(2)

Fig. 5. shows an example of how to get the deputy code of a 5 point curve.

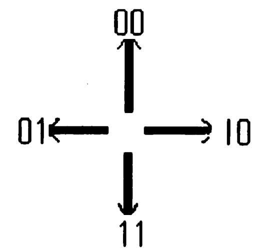


Fig.3. curve's coding

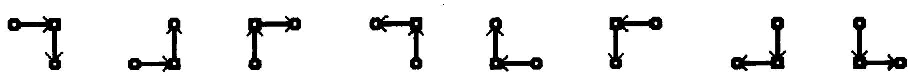
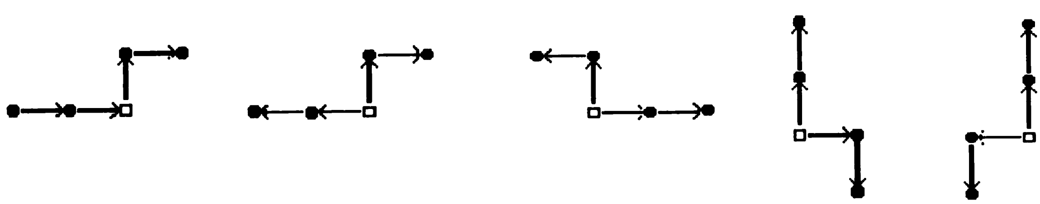


Fig.4. 2 points' coding shapes



(a) (b) (c) (d) (e)

(f) (g)

10100010 01010010 1010C001

A_2=01010010 A_4=00011010 A_1=00001011 A_3=00000111

Deputy code is A = is min(A_1, A_2, A_3, A_4)

(a) is a 5 points Freeman's code curve. (b) is the centry Freeman's chain code of (a). (c) is the centry Freeman's chain code of (a)'s mirror symmetry curve. Rotating (b) smallest (seeing (seeing (d), (e), (f), (g)), we get A_1, A_2, A_3 and A_4. The deputy code is obtained as the minimumu of A_1, A_2, A_3 and A_4.

Fig.5. an example of getting the deputy code of a 5 points curve.

4. Conclusion

The method provided in this paper can speed up matching. The efficiency is good, but the extracted points don't form a hierarchal structure. The reason is the justifying knowledge is local. For getting a hierarchal structure, the global analysis knowledge is need. The next work is as follows:

(1) How to extract and express the knowledge of releation between smoothing and scale change.

(2) How to extract and organize the salient points into a hierarchial structure.

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