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An Analysis of Thinning & Skeletonization for Shape Representation

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***Abstract*—Skeletons are important shape descriptors in object representation and recognition. Typically, skeletons of volumetric models are computed using iterative thinning. However, traditional thinning methods often generate skeletons with complex structures that are not suitable for shape description, and appropriate pruning methods are lacking. In this paper, we present an analysis of thinning and skeletonization methods for shape representation.**

***Index Terms*—Medial Axis, Thinning, Skeletonization.**

I. INTRODUCTION

The medial axis of an object is the set of all points having more than one closest point on the object's boundary. Originally referred to as the topological skeleton, it was introduced by Blum [1] as a tool for biological shape recognition. The medial axis [5] together with the associated radius function of the maximally inscribed discs is called the medial axis transform (MAT). The medial axis transform is a complete shape descriptor, meaning that it can be used to reconstruct the shape of the original domain. The distance transform (DT) and the medial axis transform (MAT) are two image computation tools used to extract the information about the shape and the position of the foreground pixels relative to each other. The *DT* converts a binary image into an image, where each pixel has a value to represent the distance from it to its nearest foreground pixel.

The MAT is a graylevel image where each point on the skeleton [4], [10] has an intensity which represents its distance to a boundary in the original object [9]. Extensively applications of these two transforms are used in the fields of computer vision and image processing, such as expanding shrinking, thinning [2], [3] and computing shape factor etc.

Skeletonization has been a part of image processing for a wide variety of applications [6],[7]. Digital skeletons, generated by thinning algorithms, are often used to represent objects in a binary digital image for shape analysis and classification. Thinning is a process of reducing patterns to their skeleton; however, skeleton is defined as a set of thin lines, arcs and curves (usually one pixel thick), which are connected [8] with each other in such a way that the geometrical and topological properties of its originating object must be preserved

II. METHODOLOGY

A. Thinning

Thinning is a morphological operation that is used to remove selected foreground pixels from binary images, somewhat like erosion or opening. It can be used for several applications, but is particularly useful for skeletonization. In this mode it is commonly used to tidy up the output of edge detectors by reducing all lines to single pixel thickness.

The major advantages of thinning in image processing and pattern recognition are: reduction of the data amount of an input binary image, which will help decrease the data storage and the data transmission time, and preservation of the fundamental skeleton, which will facilitate the extraction of fundamental features of the object. Thinning is normally only applied to binary images, and produces another binary image as output. In everyday terms, the thinning operation is calculated by translating the origin of the structuring element to each possible pixel position in the image, and at each such position comparing it with the underlying image pixels. If the foreground and background pixels in the structuring element exactly match foreground and background pixels in the image, then the image pixel underneath the origin of the structuring element is set to background (zero). Otherwise it is left unchanged.

The thinning of a set A by a structuring element B is shown in (1).

$$A \otimes B = A - (A \otimes B)$$
$$= A \cap (A \otimes B)^C$$

(1)

A more useful expression for thinning based on a sequence of structuring elements shown in (2):

$$\{B\} = \{B^1, B^2, B^3, ..., B^N\} \quad (2)$$

where B^i is rotated version of B^{i-1} . It can be shown in (3).

$$A \otimes \{B\} = ((...((A \otimes B^1) \otimes B^2)...) \otimes B^n) \quad (3)$$

The structuring elements used in (1) are shown in figure1.

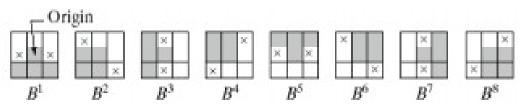

Figure 1. Sequence of rotated structuring elements used for thinning.

Matlab supports binary morphological thinning operation by the following tool.

Syntax:

Bw2= bwmorph (Bw1, 'thin')

Where Bw1 is the original binary image.

Bw2 is the resultant thinned image of Bw1.

A thinning algorithm should satisfy the following conditions in order to achieve skeletonization within feasible computation time:

1. The resulting subset of the original image should be ideally thin.
2. The resulting subset must approximate the medial axis.
3. End points must be preserved.
4. Connectivity of the object and the background must be preserved.
5. The algorithm should be computationally efficient.

The algorithm should be robust against noise.

B. Skeletonization

Skeletonization is a transformation of a component of a digital image into a subset of the original component. There are different categories of skeletonization methods: one category is based on distance transforms, and a specified subset of the transformed image is a distance skeleton. The original component can be reconstructed from the distance skeleton. Another category is defined by thinning approaches; and the result of skeletonization using thinning algorithms should be a connected set of digital curves or arcs.

The skeleton of a region is defined by means of the Medial Axis Transform (MAT) proposed by Blum. The MAT of a region R with edge b is defined as follows: Find the nearest neighbour for each point p of R, if p has more than one neighbour then p belongs to medial axis (skeleton) of R. The concept "nearest" depends on a distance, while the results of MAT depend on the selection of a distance measure. Figure 2 shows examples that use euclidean distance as measure.

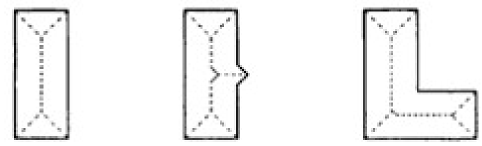

Figure 2. Medial axis of some simple geometrical shapes.

The skeleton of a region should fulfill the following conditions:

1. Be a connected subset of points from the original region.
2. Represent the geometric characterstics of the original region.
3. Preserve some topological characterstics of the original region, such as connectivity and holes.

In general, all skeletonization methods of binary images can be classified into two groups:

- Pixel-based methods.
- Non-pixel-based methods.

In a pixel-based method, every pixel belonging to an object in the image is used for computation of the skeleton (thinning and distance transformations). So, all pixels inside a shape are used in the skeletonization process. Pixel based methods often use thinningtechniques or distance transforms . On the other hand, a non-pixel-based method attempts to determine analytically the symmetric points of a shape from opposite points in the shape edge, so only the contour pixels of a shape are used for skeletonization.

Skeletionization is an important technique used in many areas in digital image processing. Its goal is to reduce an object R within an image in order to generete an object S (commonly called as skeleton) whose thickness is just one pixel and it is generally connected, preferable on a specific metric. It is known that the genereal topological characteristics based on connectivity are not sufficient to describe a given object, because the skeleton of a simple connected object can be just a point, and it has become useless in many aplications. For this reason, the objects geometric properties are considered and those properties helps to preserve the "geometric form" of the object in the final skeleton.

Morphological skeleton can be obtained in (4).

$$S(A) = \bigcup_{K=0}^{K} S_K(A) \tag{4}$$

Where $S_k(A)$ can be given by (5):

$$S_K(A) = (A \ominus KB) - (A - KB) \circ B$$
$$(A \ominus$$

(5)

K successive erosions are carried out and k is the last iterative step before A erodes to an empty set. The set A can be reconstructed by using (6).

$$A = \bigcup_{K=0}^{K} (S_K(A) \oplus KB) \tag{6}$$

Where k successive dilations are carried out in the same manner. It is given by (7).

$$(S_K(A) \oplus KB) = ((...(S_K(A) \oplus B) \oplus .....) \oplus \tag{7}$$

Matlab supports binary morphological skeleton by the following tool.

Syntax:

Bw2= bwmorph (Bw1, 'skel')

Where Bw1 is the original binary image.

Bw2 is the resultant skeleton of image Bw1.

III. RESULTS AND DISCUSSIONS

In general, the thinning algorithm is an iterative edge-point erosion technique, where a small window (e.g. 3 x 3 window) is moved over the entire image with a set of rules applied to the contents of the windows.

Skeletonization is a process for reducing foreground regions in a binary image to a skeletal remnant that largely preserves the extent and connectivity of the original region while throwing away most of the original foreground pixels.

Figure 3. (a) (b) (c)

Figure 4. (a) (b) (c)

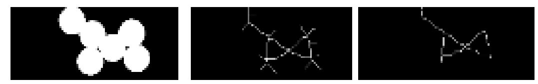

Figure 5. (a) (b) (c)

Figure 6. (a) (b) (c)

Figure 3(a), 4(a), 5(a), 6(a) - original binary images. Figure 3(b), 4(b), 5(b), 6(b) - thinned results. Figure 3(c), 4(c), 5(c), 6(c) – skeletonization results respectively.

With thinning operation, slight irregularities in a boundary will lead to spurious spurs in the skeleton which may interfere with recognition processes based on the topological properties of the skeleton. Pruning can be carried out to remove spurs of less than a certain length but this is not always effective since small perturbations in the boundary of an image can lead to large spurs in the skeleton.

Whereas, skeleton is useful because it provides a simple and compact representation of a shape that preserves many of the topological and size characteristics of the original shape. Similarly, we can distinguish many different shapes from one another on the basis of how many `triple points' there are, *i.e.* points where at least three branches of the skeleton meet.

IV. CONCLUSION

Shape representation is a fundamental step in image processing which is used for object recognition. The present paper has carried out an analysis of thinning and skeletonization for shape representation. The thinning operation produces connected skeleton but has spurious branches which requires pruning technique for removing the obtained spurs in the skeleton. The skeletonization operation results unconnected skeleton which requires further operations for improving connectivity. Thus, thinning can be used for character representation which provides better connectivity followed by pruning and skeletonization is used for shape representation of an image which can be improved by various morphological operations.

V. ACKNOWLEDGMENT

The auth

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would like to

valuable comments.

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