*IOSR Journal of Computer Engineering (IOSR-JCE)*
*e-ISSN: 2278-0661, p- ISSN: 2278-8727Volume 13, Issue 4 (Jul. - Aug. 2013), PP 07-10*
*www.iosrjournals.org*

# Medial Axis Transformation based Skeletonzation of Image Patterns using Image Processing Techniques

Shivani Sharma[1] and Maninder Kaur[2]
[1,2](ECE Deptt., DIET, Kharar, Mohali, Punjab INDIA,

***Abstract :*** *The medial axis of an image pattern is the loci of all inscribed disks that touch two or more boundary points without crossing any of the boundaries. The medial axis transform (MAT) is a powerful representation for objects with inherent symmetry or near-symmetry. The medial axis of 2-D image patterns provides a conceptual design base, with transition to a detailed design occurring when the radius function is added to the medial axis or surface. To make such a design tool practicable, however, it is essential to be able to convert from an MAT format to a boundary representation of an object. In the proposed work, the medial axis transform has been extracted using the Euclidean distance transform based computation. The image pattern u prepared initially in binary form and then distance of each non-zero pixel to its closest zeroed pixel is computed. This process continues till the entire image pattern is scanned to its core.*
***Keywords:*** *MAT -> Medial Axis Transform, EDT-> Euclidean Distance Transform, CCD-> Charge Coupled Device*

## I. Introduction

Skeletonization is a process of extracting a skeleton from an object in a digital image. A skeleton of an image can be thought of as a one-pixel thick line through the middle of an object which preserves the topology of that object. It is a fundamental preprocessing step in many image processing and pattern recognition algorithms [5]. Skeletonized images (skeletons) are easier to process and they reduce processing time for the subsequent operations. It is a morphological operation that is used to remove selected foreground pixels from binary images. It is somewhat like erosion or opening [8]. It is particularly useful for thinning and Medial Axis Transform. It is only applied to binary images, and produces another binary image as output. This operation makes use of a structuring element [11]. These elements are of the extended type meaning they can contain both ones and zeros. The skeletonization operation is related to the hit-and-miss transform and can be expressed quite simply in terms of it.

## II. BRIEF LITERATURE SURVEY

This is complemented by special handling of non-cylindrical joint regions to obtain a centered ,topologically clean, and complete 1D skeleton. We demonstrate that quality curve skeletons can be extracted from a variety of shapes captured by incomplete point clouds. Finally, we show how our algorithm assists in shape completion under these challenges by developing a skeleton-driven point cloud completion scheme [1].

Medial representations of shapes are useful due to their use of an object-centered coordinate system that directly capturesintuitive notions of shape such as thickness, bending, and elongation. However, it is well known that an object's medial axis transform.(MAT) is unstable with respect to small perturbations of its boundary. In this paper, we propose a third, group wise approach to branch significance computation. We develop a group wise skeletonization framework that yields a fuzzy significance measure for each branch, derived from information provided by the group of shapes. We call this framework the Group wise Medial Axis Transform (G-MAT). We propose and evaluate four group wise methods for computing branch significance and report superior performance compared to a recent, leading method. We measure the performance of each pruning algorithm using denoising , classification, and within-class skeleton similarity measures. This research has ever l applications, including object retrieval and shape analysis [2].

The medial axis of a planar shape is the loci of all inscribed disks of the shape. In this paper we discuss functions that are equidistant from pairs of boundary elements when using line segments and arcs in shape boundary description. These equidistant functions can be used for medial axis extraction. Index terms - planar shape, boundary element, equidistant function, medial axis [3].

The originality of our approach is the use of the notion of a derived grid and the oversampling of the image in order to reduce the computation of the block-based medial axis transform in the original grid to the much easier task of computing the distance based medial axis transform of the oversampling of the image on the derived grid [4].

Light fires simultaneously at all points along the boundary of this region and watch the fire move into the interior. At points where the fire traveling from two different boundaries meets itself, the fire will extinguish itself and the points at which this happens form the so called `quench line'. This line is the skeleton. Under this definition it is clear that thinning produces a sort of Skelton [5].

Finding the distance transform with respect to the Euclidean distance metric is better in using, but rather time consuming. So, many approximate Euclidean distance transform (EDT) are also widely used in the computer vision and image processing fields. The chessboard distance transform (CDT) is one kind of DT which converts an image based on the chessboard distance metrics. That is, two transforms are\interchangeable through the proposed algorithms; a MAT can be found by utilizing an CDT algorithm and vice- versa. Key words: Chessboard Distance Transform, Computer Vision, Distance Transform, Image Processing, Medial Axis tranform [6].

This paper provides linear-time algorithms for solving a class of minimization problems involving a cost function with both local and spatial terms. These problems can be viewed as a generalization of classical distance transforms of binary images, where the binary image is replaced by an arbitrary sampled function.

Alternatively they can be viewed in terms of the minimum convolution of two functions, which is an important operation in gray scale morphology. [7]

The relationship between both of them is first derived and proved in this paper. One of the significant properties is that CDT for 3D binary image V is equal to BB-MAT for image V' where it denotes the inverse image of V. In a parallel algorithm, a cost is defined as the product of the time complexity and the number of processors used. The presented results for the cost are reduced in comparison with those of Wang's. To the best of our knowledge, this work is the lowest costs for the 3D BB-MAT and 3D CDT algorithms known. In parallel algorithms, the running time can be divided into computation time and communication time [8].

## III. IMAGE PREPARATION

Before extracting the medial axis transform of an image pattern, the image is first converted to binary image with white as background and black as object's pixels. The image can be binarized using the Otsu algorithm. In the presented work, the image is acquired using CCD camera in jpeg format. The jpeg format is converted to gray scale image using rgb2gray command in matlab. Otsu algorithm is then applied over the gray scale image in order to get the binary image. The binary image is now ready to face the MAT algorithm in order to extract the skeleton of the image pattern under test.

## IV. EUCLIDEAN DISTANCE TRANSFORM

The Euclidean distance transform is obtained by computing the distance of a zero pixel to the nearest non-zero pixel and arranging them in a matrix of size as that of the original image. This gives a distance map of image pixels with distances as the matrix elements. Later on the distance elements are treated as gray color intensities and an image is plotted by taking the matrix row and column as pixel coordinates and distance elements as gray color intensities. This gives an image with maximum gray color intensities in the centre/core of the image. Below images show the Euclidean distance (ED) transform as computed in matlab:

Below images show the Euclidean distance (ED) transform as computed in matlab:

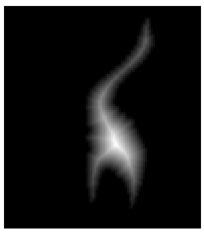

Fig. 1 Input Image Fig. 2 ED Transform

## V. TYPES OF SKELETONIZATION ALGORITHMS

There are mainly two types of algorithms-

**Sequential algorithms**- In these algorithms contour pixels are examined for deletion in a predetermined order and this can be accomplished either by raster scans or by contour following. To prevent sequentially eliminating an entire branch in one iteration, sequential algorithm usually marks the pixels to be deleted and all the marked pixels are then deleted at the end of an iteration.

**Parallel algorithms**- In these algorithms, pixels are examined for deletion based on the results of only the previous iteration. For this reason these algorithms are suitable for implementation on parallel processors where the pixels satisfying a set of conditions can be removed simultaneously.

Just as there are many different types of distance transform there are many types of skeletonization algorithm, all of which produce slightly different results. However, the general effects are all similar, as are the uses to which the skeletons are put.

The 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. Thus, for instance, we can get a rough idea of the length of a shape by considering just the end points of the skeleton and finding the maximally separated pair of end points on the skeleton. Similarly, we can distinguish many qualitatively 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.

In addition, to this, the MAT (not the pure skeleton) has the property that it can be used to exactly reconstruct the original shape if necessary. As with thinning, slight irregularities in a boundary will lead to spurious spurs in the final image which may interfere with recognition processes based on the topological properties of the skeleton. Despurring or 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.

## VI. EXTRACTION OF MAT

The medial axis transform (MAT) of an image is computed by calculating the Euclidean distance transform of the given input image pattern. The MAT is described as being the locus of the local maxima on the distance transform.

After the computation of Euclidean distance transform (EDT) of the input image, the EDT is represented in image representing the Euclidean distances as gray levels. The same is shown in above images.
The maximum Euclidean distance is represented as maximum gray level intensity in the EDT image. The pixel coordinates of the maximum gray level intensity are extracted from the EDT image by converting the EDT image into row x column matrix. The row and column of the matrix gives the coordinates of the MAT line of the image pattern.

## VII. PERFORMANCE EVALUATION PARAMETERS

**Connectivity number (CN):**

It is a measure of how many objects are connected with a particular pixel [3]. It is measured by number of color changes (black to white or white to black) in neighborhood of pixel P[i][j]

$$Cn = \sum_{k \in s} Nk - (Nk+1 \,.\, Nk+2)$$

where Nk = color of eight neighbours of pixel analyzed
N0 = central pixel
N1 = Pixel to the right of the central pixel and so on

**Thinness Measurement (TM):**

It measures the degree to which an object in an image is thinned [6].

$$TM = 1 - (TM1 / TM2)$$

$$TM1 = \sum_{i=0}^{n} \text{Triangle Count } (P[i][j])$$

$$TM2 = 4 \times [\max(m,n) - 1]^2$$

Where Triangle Count (P[i][j]) = P[i][j] × P[i][j-1] × P[i-1][j-1] +
P[i][j] × P[i-1][j-1] × P[i- 1][j] +
P[i][j] × p[i-1][j] × P[i-1][j+1] +
P[i][j] × P[i-1][j+1] × P[i][j+1]

And TM1 = Total number of black triangles in an image.
TM2= Maximum number of black triangles an image could have

**Connectivity Measurement (CM):**

It is used to measure the connectivity of output skeleton. An object in an image is said to be disconnected if it has broken pieces. [6]

$$CM = \sum_{i=0}^{n} S(P[i][j])$$

Where $S(P[i][j]) = \begin{cases} 1 & if\ CN(P[I][J] < 2 \\ 0 & Otherwise \end{cases}$

**Sensitivity Measurement (SM):**

It is used to measure the noise in an image. This noise is mainly the perturbations in an outline of an object, not unwanted extra parts in an image. [6]

$$SM = \sum_{i=0}^{n} \sum_{j=0}^{m} S(P[i][j])$$

Where $S(P[i][j]) = \begin{cases} 1 & if\ TransP[i][j] > 2 \\ 0 & otherwise \end{cases}$

## VIII. RESULTS

Following images show the input image pattern and the corresponding MAT.

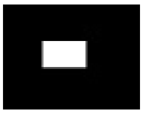

Fig.3

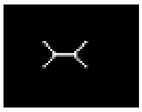

Fig. 4

Fig. 5

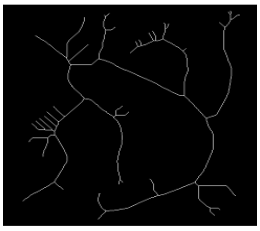

Fig. 6

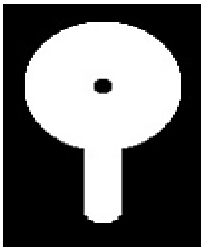

Fig. 7

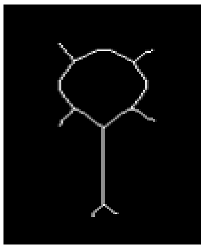

Fig. 8

Input Images – Fig. 3, 5 and 7
MAT Images – Fig. 4, 6 and 8

Following table shows the performance measure of the skeletonized image:

| Image No. | CN | TM | CM | SM |
|---|---|---|---|---|
| Fig. 3 | 0.0117 | 0.980 | 0.00023 | 0.002 |
| Fig. 5 | 0.0212 | 0.784 | 0.00035 | 0.098 |
| Fig. 7 | 0.0332 | 0.796 | 0.00040 | 0.010 |

## IX. CONCLUSION

The result table shows the results after implementing the discussed medial axis transform based skeletonzation of image patterns. The Skeletonized images are shown above figures. Higher the thinness factor, better is the skeletonzation or thinning. The discussed algorithm has been implemented on matlab version 7.5 and a text file is generated after every skeletonization.The performance parameters are normalized with respect to size of the image. This removes the ambiguity of the image if zoomed or compressed. Euclidean transform based medial axis transformation extraction of image patterns give a good speedy skeleton of image patterns. This serves good purpose in terms of computational speed as well.

## REFERENCES


[1]. Andrea Tagliasacchi, Hao Zhang, Daniel Cohen-Or, "Curve Skeleton Extraction from Incomplete Point Cloud", ACM Transaction.

[2]. G. Hamarneh is with the School of Computing Science, Simon Fraser,University, 8888 University Drive, Burnaby, BC V5A Canada.E-mail: hamarneh@cs.sfu.ca.

[3]. H. Blum, "A transformation for extracting newdescriptors of shape". Symposium Models forSpeech and Visual Form, Weiant Whaten-Dunn(Ed), Cambridge, MIT Press (1967)

[4]. G. Bertrand, "Skeleton in Derived Grids," Seventh ICPR, pp. 326-329,Montreal, 1984. G. Bitz and H.T. Kung, "Path Planning on the Warp Computer: Using a Linear Systolic Array in Dynamic Programming," Int',l J. Computer Mathematics, vol. 25, pp. 173-188, 1988.

[5]. D. Ballard and C. Brown Computer Vision, Prentice-Hall, 1982.

[6]. C. Arcelli and G. Sanniti di Baja, "Ridge points in Euclideandistance maps," Pattern Recognition Letters, 13, 1992.

[7]. R. Bellman and W. Karush. Functional equations in the theorey of dynamic programming XII: An application of the maximum transform. Journal of Mathematical Analysis and Applications, 6:155–157, 1963.

[8]. Amenta, N. and Bern, M.W., Surface reconstruction by Voronoi filtering. Discrete & Computational Geometry. v22 i4. 481-504.