IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834, p- ISSN: 2278-8735.Volume 4, Issue 6 (Jan. - Feb. 2013), PP 83-88
www.iosrjournals.org

A 3 dimensional Digital Image Skeltonization using 3x3x3 Structuring Element

P. Srinivasa Rao, Dr. M. Madhavi Latha
ECE Department, C V R College of Engineering, Hyderabad, Andhra Pradesh, India.
Professor, ECED, JNTUCEH, Hyderabad, Andhra Pradesh, India

ABSTRACT: *Image Skeletonization promises to be a powerful complexity-cutting tool for compact shape description, pattern recognition, robot vision, animation, petrography pore space fluid flow analysis, model/analysis of bone/lung/circulation, and image compression for telemedicine. The existing image thinning/skeletonization techniques using boundary erosion, distance coding, and Voronoi diagram are first overviewed to assess/compare their feasibility of extending from 2D to 3D. Previously, skeletons have been a common tool for identifying shape components in a solid object. However, obtaining skeletons of a grayscale volume poses new challenges due to the lack of a clear boundary between object and background. In this paper we propose a fast, efficient and robust algorithm to generate the skeleton of large, complex 3D images such as CT, MRI data which make use of 3X3X3 structuring elements for processing. This algorithm has been developed in the frame work of cellular logic array processing. Cellular logic array processing is a logico mathematical paradigm developed using the fundamental notions of normal algorithms and cellular automata. The algorithm provides a straightforward computation which is robust and not sensitive to noise or object boundary complexity. Because 3D skeleton may not be unique, several application-dependent skeletonization options will be explored for meeting specific quality/speed requirements.*
Keywords: *3D Image Skeleton, structuring element, cellular automata, normal algorithm.*

I. INTRODUCTION

The history of skeletonization of digital objects/ images is almost as old as digital image analysis itself. Thinning and skeletonization have numerous applications in image analysis and computer vision. The purpose is to reduce 2D discrete objects to (1D) linear representations preserving topological and geometrical information. The literature on 2D skeletonization of digital images is very rich. An outline of various thinning and skeletonization methodologies can be found in Ref. [1]. Reducing discrete structures to lower dimensions is even more desirable when dealing with (3D) volume images. The skeleton could be a promising tool for an increasing number of applications, especially in biomedical imagery. However, compared to the literature on 2D skeletonization, the articles published on 3D skeletonizations are still not very numerous, especially on 3D gray scale skeltonization. The main reason for this seems to be the difficulty to address and efficiently solve essential problems, such as topology preservation, in more than two dimensions. In fact, although many concepts such as Euler characteristics, simple points and connectivity have been studied in the past years (e.g. Refs. [2}6]), the implementation of skeletonization methods based on their use is rather complicated. The general strategy for 3D skeletonization does not differ significantly from the strategy in the 2D case. For several applications significant amount of information is lost during the process of binarization. Applying thinning directly to gray scale images is motivated by the desire of directly processing images with gray levels distributed over a range of intensity values. This will avoid shape distortions that may irremediably affect the presence of features in the binary image generated even if an optimal thresholding algorithm is used to produce the binary image. The gray skeleton is a connected subset of a gray scale pattern which consists of a network of lines and arcs centrally placed along local higher intensity regions. Unfortunately, there is no one single agreed upon definition for gray skeletons [1], [2], [8].Skeletons are classically associated as a medial axis representation that is regenerative (i.e. could be used to generate the object back exactly). Skeletons are not easily digitizable. It is not possible to have a representation that is a medial axis, preserves connectivity, preserves homotopy and exists on the square digital grid. One of these four restrictions has to be relaxed. This has opened the way to several approximations. We can group most of the published gray scale skeletonization algorithms under one of the two approaches. The first approach considers the image as a continuous surface in the 3D Euclidean space and use the first and second partial derivatives of this surface to assign the proper topographical label to each voxel [3], [15]. The second approach is based on the repeated application of a removal process that erodes the gray scale pattern until only one voxel thick object is obtained in the center of the high intensity region. The algorithm proposed in this paper is a parallel thinning algorithm that preserves connectivity and belongs to the latter family. The algorithm has been tested on a variety of images from different applications and produced satisfactory results that proved to be useful for compression and recognition applications. Aside from this introductory section, the rest of the paper is composed of 4 more sections. In section 2 we give a quick review of previously published work in this field under the heading of literature survey. Details of the suggested algorithm are presented in section 3. Section 4 shows results of applying the algorithm to 3 different images. Out of three images , two are form standard test data set and the other is real time MRI data set. We finally conclude in section 5 with observations and recommendations for future work.

II. LITERATURE SURVEY

Thinning and skeletonization of binary images have been studied extensively since the early sixties. In the case of gray scale images, the literature does not provide a general agreement on the requirements for a gray skeleton in order to constitute a meaningful representation. The result of an algorithm is dependent on the definition of connectivity. Different definitions of local gray scale connectivity were presented. One definition, [14], states that the neighborhood of a voxel, p, is connected if the connective strength of any pair in the neighborhood of p is not less than p. A slightly different definition given in [4] considers the neighborhood of a voxel, p, to be connected if the connective strength of any pair in the neighborhood is not less than both values of the pair even if these values are less than the value of p. While in [1] the condition was imposed such that it is not less than both the pair and p. Another approach taken by [7] is to threshold the neighbors of p, then use the binary connectivity definition. In this section we will present some of the gray scale skeletonization and thinning algorithms documented in the literature almost in historical order. Levi and Montanari [8] presented a gray weighted skeleton based on the concept of gray weighted distance. The gray weighted distance is proportional to the sum of the gray levels along the path. The skeleton is the set of all points which do not belong to any minimal gray weighted path from any other point to the background. The skeleton resulting from this algorithm does not guarantee the connectivity. Dyer and Rosenfeld [4] presented a parallel algorithm. Their definition of connectivity does not provide global connectivity of the skeleton, moreover the skeleton does not lie along the high gray values but it is positioned in a central place determined by the boundary of the image. Peleg and Rosenfeld in [13] proposed a Min-Max medial axis transformation. Salari and Siy, [14], presented a two phase sequential algorithm. In the first phase they computed the contextual gray distance transformation (CGDT). In the second phase they removed the boundary voxels which satisfied a set of conditions. The algorithm required the input image to be segmented into zero and non-zero voxels. The resulting skeleton is one voxel wide positioned in the ridge areas. Abe et al., [1], point out the problems and resulting defects with the Salari and Siy algorithm, [14], due to its pure sequential processing nature and presented a combined sequential and parallel algorithm. Their algorithm is considered an extension of the Hilditch algorithm, [5]. Maragos and Ziff, [10], compute the gray skeleton by summing the skeletons of the binary images that result from thresholding the gray scale image at each value of the gray scale. Low, [9], defined gray skeleton in terms of gray mathematical morphology. Pal and Ghosh, [12], used three functions h(p), v(p) and f(p) which represent the horizontal, vertical membership functions and the degree of brightness respectively. The three functions are combined in different ways to define g(p) which denotes if the voxel belongs to the core line in the objects. Arcelli and Ramella, [2], presented a parallel thinning algorithm. They put two implementation based on the operations R1 and R2. R1 denote the sequence of four parallel operations, each operation remove voxels that satisfy certain conditions. Thinning is accomplished by repeatedly applying the sequence of the four operations to remove north, east, south and west border points respectively. The process terminates when no voxel is removed during a whole sequence. While R2 is a parallel operation that removes voxels which satisfy another set of conditions. The thinning is accomplished by repeatedly applying R2 until no further voxel is removed. They observed that the two operations R1 and R2 produce largely similar skeletons. Once difference is that the algorithm based on operation R1 is more prone to the creation of skeleton branches than the algorithm based on R2. Skeletonization algorithms based on a topographic approach were presented in [3] and [12]. These algorithms are aimed at avoiding object distortion, reducing deformation on junctions of a skeleton.

III. PROPOSED ALGORITHM

Skeletonization is the extended version of thinning. The given 3-D digital image is plane-wise raster- scanned by the seven-neighborhood window. On each move, the 3X3X3 sub image covered by this window is examined to see whether the gray-distance, say D, which is the difference between the maximum and the minimum gray value corresponding to that sub image is less than or equal to the user specified threshold value, say T. If D is less than or equal to T, then the gray-value 0 is assigned to all the cells other than the central cell and the corner cells in the given image. For D greater than T, the original values contained in these cells are left undisturbed. This procedure is continued till the entire image is scanned. The overall effect is that the boundary removed components of various 3-D solid regions in the given image that appear to be uniform, are obtained. This procedure is repeatedly applied till there is no component with boundary is detected.

The pseudo code for this algorithm is given below.

Input: 3-D image, threshold
Output: Skeletonized version of 3-D image
Steps:
Step 1: Perform image smoothing.
Step 2: Perform hollow detection and introduce a background voxel in each hollow.
Step 3: Read the 3-D data and place voxel values in a 1-D array called *input_array*.
Step 4: Copyinput_array to output_array
Step 5: Repeat sliding the 7-neighborhood window over the image(input_array) {
Step 5(a): find the maximum gray value GMax;
Step 5(b): find the minimum gray value GMin;
Step 5(c): find the difference D = GMax -GMin;
Step 5(d): if(D <= threshold)then retain the central voxel as well as corner voxels and remove the boundary voxels in output_array else slide the 7-neighborhood } Until the structuring element spans whole of the image
Step 6: Copy output_array to input_array and repeat step 3 until there is no boundary left for removal
Step 7: Pass the output_arrayto VolumeRenderer() method

3.2 Image smoothing
This step is used to remove non-significant hollows. It is accomplished by a min-max procedure. Median filters could also be used.

3.2 Hollow detection
We use the gradient operators of Sobel or Prewitt [6] to compute the partial derivatives fx and fy in the x and y directions respectively. The gradient is calculated as $g(x,y) = |fx + fy|$. The voxel p(x,y) is declared as edge point if $g(x,y)$ exceeds a threshold value t which is selected so that less than 5 percent of the voxels are declared as edges. Each voxel detected as an edge voxel its value is subtracted from all its 4-neighbors. The neighbor voxel which result in the maximum absolute difference is changed to zero if its gray value less than p(x,y) otherwise p(x,y) itself is changed to zero. This step is necessary to introduce a background voxel inside the hollow to start eroding from the inside out.

3.3 Boundary voxel removal
The erosion operation is an iterative procedure that removes certain border voxels, i.e. change their gray level value to zero. Rules imposed on the removal or erosion operation must guarantee that it neither destroys connectivity nor reduces the gray scale connective strength. In the proposed algorithm, connectedness is accomplished by a method similar to the method used in the binary algorithm reported in [16]. The gray connectivity strength is preserved by retaining ridge voxels. As defined above, identification of ridge voxels is based on the value of gray distance.

3.4 Threshold Value Selection
The variance of the given 3D image is chosen as the threshold. It has been known that histogram produces substantial and consistent gap between object and the background. From the histogram we will select threshold value. The histograms itself is produced by the probability (frequency) of each level of grayness.

3.5 Selection of Structuring Element
The concept of the don't care voxels makes it possible to implement the arbitrarily shaped structuring element, the point set S, with an image S with fixed size and shape (3 x3 , 5x5, 3x3x3, 5x5x5 ; . . .). The choice of structuring elements are varying in most applications using mathematical morphology, like feature extraction, edge detection, skeletonization, etc, depending heavily on the image to be processed. For example, the choice of the structuring element to extract features depends on the size of the interested features and the requirement of how accurate the boundary localization is. If the size of the structuring element is too small, noise as well as unnecessary details may be extracted. If it is too large some small features may not be extracted. At the same time shape of the structuring element is also important in geometry preserving.

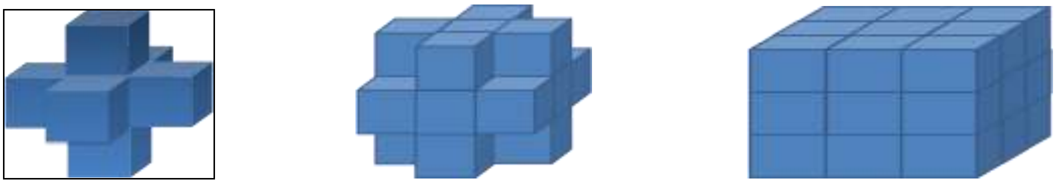

Figure (1): 3-D convex Structuring Elements

(a) 7-Neighborhood (b) 19-Neighborhood (c) 27-Neighborhood

IV. RESULTS

The algorithm has been tested on a variety of images. In this paper we report results on three test sets. The first test set is 3-D MRI image of aneurism. The second set is solid 3-D hexagonal prism. The third set is solid 3-D rectangular prism. The data set is real time MRI image where as remaining two data sets are standard test images. For the processing of these three dataset we have used seven neighborhood structuring element.

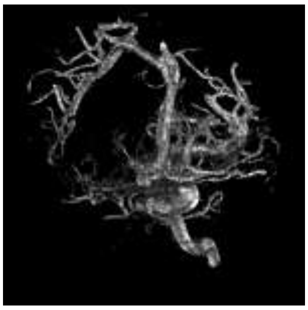
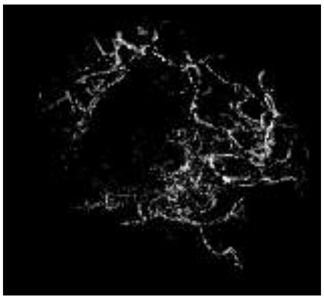

Figure2 (a) 3-D MRI image of aneurism (b) skeletonized version.

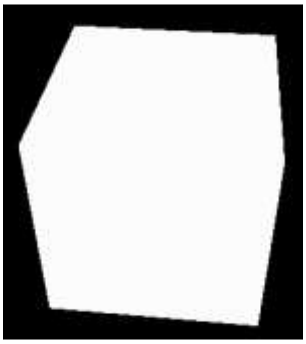
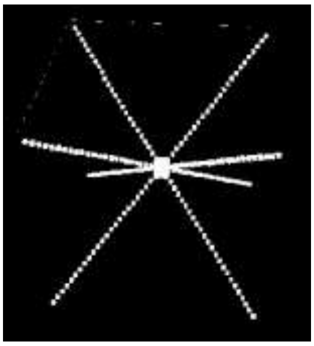

Fig 3 (a) solid 3-D Hexgonal prism (b) skeletonized version

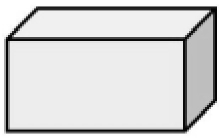
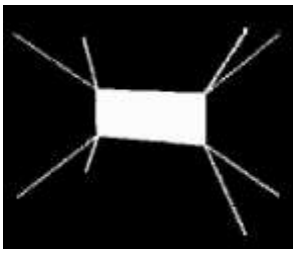

Figure 4 (a) solid 3-D rectangular prism (b) skeletonized version

V. CONCLUSION

No doubt that for several applications there are several advantages to be able to thin the gray level objects without converting the image into a binary image. In this paper we have proposed a robust parallel thinning algorithm for 3D gray scale images. The algorithm is based on eroding objects iteratively by removing certain border voxels without affecting the connectivity. The algorithm was tested on images from different domains and produced satisfactory results.

REFERENCES

[1] Abe, K., Mizutani, F. and Wang, C., "Thinning of grayscale images with combined sequential and parallel conditions for voxel removal", *IEEE Trans. on Systems Man Cybernetics*, vol. 24, no. 2, pp. 294-299, Feb. 1994.

[2] Arcelli, C. and Ramella, G., "Finding grey-skeletons by iterated voxel removal", *Image and Vision Computing*, vol.13, no. 3, pp. 159-267, Apr. 1995.

[3] Chen, S. and Shih, F., "Skeletonization for fuzzy degraded character images", *IEEE Trans. on Image Processing*, vol. 5, no. 10, pp. 1481-1485, Oct. 1996.

[4] Dyer, C. R. and Rosenfeld, A., "Thinning algorithms for grayscale pictures", *IEEE Trans. Pattern Anal and Machine Intell.,* vol. 1, no. 1, pp. 88-90, Jan. 1979.
[5] Hilditch, C., "Linear skeletons from square cupboards", *Machine Intelligence IV,* Edinburgh University Pres , pp. 403-420, 1969.
[6] Jain, A., *Fundamentals of digital image processing,*Prentice Hall, 1989.
[7] Kundu, M., Chaudhuri, B. and Dutta-Majumder, D., "A parallel greytone thinning algorithm (PGTA)", *Pattern Recognition Letters,* vol. 12, no. 8, pp. 491-494, 1991.
[8] Levi, G. and Montanari, U., "A gray-weighted skeleton", *Information and Control,* vol. 17, pp. 62-91, 1970.
[9] Low, A., *Introductory computer vision and image processing,* 1991.
[10] Maragos, P. and Ziff, R., "Threshold superposition in morphological image analysis systems", *IEEE Trans. On Pattern Analysis and Machine Intelligence,* vol. 12, no. 5, pp. 498-504, May 1990.
[11] Mersal, S., *Mathematical morphology techniques for gray level image processing,* Ph.D. Dissertation, Cairo University, in progress.
[12] Pal, S. and Ghosh, A., "Fuzzy geometry in image analysis", *Fuzzy Sets and Systems,* vol. 48, pp. 23-40, 1992.
[13] Peleg, S. and Rosenfeld, A., " A min max medial axis transformation", *IEEE Trans. PAMI,* vol. PAMI 3, no. 2, pp. 208-210, March 1981.
[14] Salari, E. and Siy, P. "The ridge seeking method for obtaining the skeleton of digital images", *IEEE Trans. On Systems Man and Cybernetics,* vol. SMC-14, no. 3, pp. 524-528, May/June 1984.
[15] Wang, L. and Pavlidis, T., "Direct gray-scale extraction of features for character recognition", *IEEE Trans. on Pattern Anal. And Machine Intell.,* vol. 15, no. 10, pp. 1053-1067, Oct. 1993.
[16] Zhang, Y. and Wang, P., "New parallel thinning methodology", *Intr. Journal of Pattern Recog. & Artificial Intell.,* vol. 8, no. 5, pp. 999-1011, 1994.
[17] N. Ahuja and J. Chuang. Shape representation using a generalized potential _eld model. *IEEE Trans. Pattern Anal. Mach. Intell.*, 19(2):169.176, 1997
[18] G. Bertrand. A parallel thinning algorithm for medial surfaces. *Pattern Recognition Letters,* 16(9):979.986, 1995.
[19] H. Blum. A transformation for extracting new descriptors of shape. *Models for the Perception of Speech and Visual Form*, pages 362.380, 1967
[20] A. Bonnassie, F. Peyrin, and D. Attali. Shape description of threedimensional images based on medial axis. In *ICIP*, volume 3, pages 931.934, 2001.
[21] G. Borgefors. Distance transformations in digital images. *Comput. Vision Graph. Image Process.*, 34(3):344.371, 1986.
[22] T. K. Dey and W. Zhao. Approximate medial axis as a voronoi subcomplex. In *SMA '02: Proceedings of the seventh ACM symposium on Solid modeling and applications*, pages 356.366, New York, NY, USA, 2002. ACM Press.
[23] P. Dokladal, C. Lohou, L. Perroton, and G. Bertrand. A new thinning algorithm and its application to extraction of blood vessels. *Proc. Of Biomedsim*, pages 32.37, 1999.
[24] K. Fu and J. K. Mui. A survey on image segmentation. *Pattern Recognition*, 13(1):3.16, 1981.
[25] T. Ju, M. Baker, and W. Chiu. Computing a family of skeletons of volumetric models for shape description. *Computer-Aided Design*, 39(5):352.360, 2007.
[26] T. Ju, Q.-Y. Zhou, and S.-M. Hu. Editing the topology of 3d models by sketching. In *SIGGRAPH '07: ACM SIGGRAPH 2007 papers,* page 42, New York, NY, USA, 2007. ACM.
[27] G. Kindlmann, X. Tricoche, and C.-F. Westin. Anisotropy creases delineate white matter structure in diffusion tensor MRI. In *Ninth International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI'06),* Lecture Notes in Computer Science 4190, pages 126.133, Copenhagen, Denmark, October 2006.
[28] A. L´opez, D. Lloret, J. Serrat, and J. Villanueva. Multilocal creaseness based on the level-set extrinsic curvature. *Computer Vision and Image Understanding*, 77(2):111.144, 2000.
[29] A. L´opez, F. Lumbreras, and J. Serrat. Evaluation of methods for ridge and valley detection. *Evaluation,* 21(4):327.335, 1999.
[30] S. Mersa and A. Darwish. A new parallel thinning algorithm for gray scale images. *Proceedings of the IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing,* pages 409.413, 1999.
[31] K. Pal´agyi and A. Kuba. A parallel 3d 12-subiteration thinning algorithm. *Graphical Models and Image Processing*, 61(4):199.221, 1999.
[32] P. Saha, B. Gomberg, and F. Wehrli. Three-dimensional digital topological characterization of cancellous bone architecture. *IJIST*, 11(1):81.90, 2000.

[33] P. K. Sahoo, S. Soltani, A. K. Wong, and Y. C. Chen. A survey of thresholding techniques. *Comput. Vision Graph. Image Process.*, 41(2):233.260, 1988.
[34] D. J. Sheehy, C. G. Armstrong, and D. J. Robinson. Shape description by medial surface construction. *IEEE Transactions on Visualization and Computer Graphics*, 2(1):62.72, 1996.
[35] S. Svensson, I. Nystrom, C. Arcelli, and G. S. di Baja. Using greylevel and distance information for medial surface representation of volume images. *icpr*, 02:20324, 2002.
[36] S. Svensson, I. Nystr¨om, and G. Sanniti di Baja. Curve skeletonization of surface-like objects in 3d images guided by voxel classi_cation. *Pattern Recognition Letters*, 23(12):1419.1426, October 2002.
[37] J. Weszka. A survey of threshold selection techniques. *Pattern Recogn*, 7:259.265, 1978.
[38] Z. Yu and C. Bajaj. A structure tensor approach for 3d image skeletonization: Applications in protein secondary structure analysis. *Image Processing, 2006 IEEE International Conference on*, pages 2513-2516, 8-11 Oct. 2006.
[39] S. Zhang, C¸ agatay Demiralp, and D. H. Laidlaw. Visualizing diffusion tensor mr images using streamtubes and streamsurfaces. *IEEE Transactions on Visualization and Computer Graphics*, 9(4):454.462, 2003.