FAST CENTER-LINE EXTRACTION FOR QUANTIFICATION OF VESSELS IN CONFOCAL MICROSCOPY IMAGES

Mahnaz Maddah,[a,b] Ali Afzali-Kusha,[a] Hamid Soltanian-Zadeh[a,b,c]

[a]Elec. and Comp. Eng. Dept., Faculty of Eng., University of Tehran, Tehran, Iran
[b]Institute for Studies in Theoretical Physics and Mathematics, Tehran, Iran
[c]Radiology Dept., Henry Ford Health System, Detroit, Michigan, USA

ABSTRACT

In this paper we present a novel method for the 3D centerline extraction of elongated objects such as vessels. This method unites the basic ideas in distance transform-based, thinning, and path planning methods to extract thin and connected centerlines. This fast approach needs no user interaction or any prior knowledge of the object shape. Centerline extraction is the first and most important step towards the quantification of vascular images which is beneficial for research, diagnosis, surgery planning, and therapy. The results confirm the superiority of our proposed method when applied to the complex branching structures of vessels in the confocal microscopy images of a rat brain.

1. INTRODUCTION

Numerous 3D visualization tools exist to handle and visualize thin 3D structures like vessels. The most common tool is maximum intensity projection (MIP), which is a very simple ray tracer. It generates a 2D projection of 3D object along a single direction, and presents many drawbacks such as visual occultation of vessels and artificial crossing that can only be detected by matching on several other projections [1]. Through MIP approach, quantitative parameters such as diameter, length and volumes of vessels, which is beneficial for diagnosis, planning surgery and therapy, is not accurately estimated. So a processing of the 3D images is required to properly extract vessel parameters and for reliable visualization. In 3D imaging, obtaining the 3D main structure or the center-line of objects has received a great attention in recent years for its vast application in data compression, medical imaging, path planning, etc. Centerline extraction is the first and the most important step towards quantification of tubular objects such as vessels.

Many methods for 3D skeletonization or centerline extraction of objects have been introduced in recent years which are mostly extensions of 2-D methods.

The most popular methods for skeletonization are distance transform-based methods [2,3,4,5], which tend to determine medial points by locating voxels, which lie farthest with respect to the boundary of the object on its cross section normal to the local major axis. In the work presented in [2] two distance maps were used to approximate the distance of object voxels from boundary voxels and a single reference point. Using recursive algorithms has made their skeletonization method time consuming. By using the algorithm in [3] the recursive steps are bypassed, yet it takes 10 hours on a Pentium III PC, 1000 MHz, to analyze a set of 256x256 confocal microscopic images with 20 frames. The boundary surface shrinking method based on distance transforms presented in [5] seems to be faster but the resulting graph contains medial surfaces.

Thinning methods are another category of skeletonization methods [6,7]. The idea is to apply morphological erosion operators to successively “peel off” the outer layer of the object until it is reduced to its skeleton. These methods are about 50% faster than the above methods but the extracted skeleton contains 2D surfaces for 3D objects and produces spurious branches and hence are not applicable for accurate quantification of branching vessels unless a coding stage is added to obtain a refined centerline. Apparently this will result in a significant increase in the processing time.

Another category of related works are path planning methods [8,9,10] which have application in virtual endoscopy and robotic path planning. The idea is to choose an initial path along the object which is then adjusted toward the central axis, connecting the two given points. A major drawback of these methods are that the start and end points of the paths must be defined by the user. This is a very tedious and almost impossible task when dealing with complex and branching structures.

In this paper, we present a novel method for fast and accurate extraction of centerlines of 3D elongated objects. This method can be effectively applied to the complex branching structures in vascular images. It extracts a thin, connected centerline of objects without requiring any user interaction or any prior knowledge of the object shape. In Section 2, our algorithm will be presented. Discussion along with the experimental results will be provided in Section 3 and conclusion remarks will be given in Section 4.

2. CENTER-LINE EXTRACTION

Our algorithm can be categorized as a path planning method in which the start point and the end points are automatically defined and then the paths are initialized and centralized. Our algorithm consists of the following steps:

1. Segmentation
2. Distance Transform Mapping (DT)
3. Automatic Selection of End Points
4. Paths Initialization
5. Paths Centering

2.1. Segmentation

After performing the required preprocessing tasks such as filtering and thresholding, a binary structure of interest is segmented by using a region-growing algorithm. The seed voxel for region growing is the first foreground voxel met in scanning the frames. A region of 26-connected voxels is then grown outward. The last voxel marked, is chosen as the Start Point (SP) and also as the reference for distance transform mapping.

When we select a voxel as the SP that most probably belongs to the centerline of the object, we perform the DT mapping to the right reference point and consequently, we obtain the real end points of our branching structure. This SP selection procedure leads to more accurate centerlines compared with choosing an arbitrary voxel on the first non-zero frame, used in [2].

2.2. Distance Transform Mapping

To increase the speed, our algorithm applies the DT mapping only to the surface of the segmented object. After the surface extraction, it computes the Chamfer DT with <3,4,5> metrics from the reference point, SP. The DT map is computed by assigning the SP voxel a distance of zero and iteratively assigning neighbor voxels using weighted metrics: 3 for face, 4 for edge and 5 for vertex neighbors. Chamfer <3,4,5> DT mapping has the following merits over the other well-known DT mappings:

1. The more the region grows, the greater value is assigned to the voxels. (This case is not satisfied in exact Euclidean DT).
2. It is a better approximation of EDT compared to the Chamfer DT with the weighted metric (1,2,3).
3. It is an integer-valued metric.

Figure 1 shows the Chamfer <3,4,5> DT map of a synthetic object.

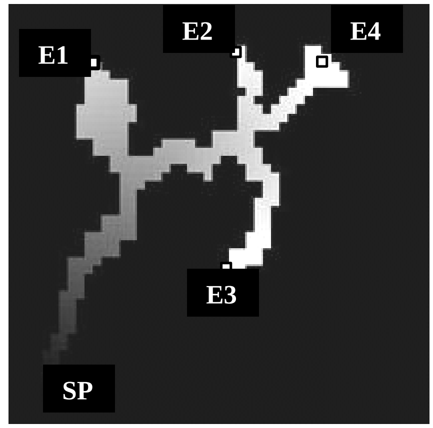


Fig. 1. Chamfer <3,4,5> DT map of a synthetic object. The obtained End Points have the local maximum DT value.

2.3. Automatic End Points Selection

As the surface of the object has already been coded, we can use the computed DT map to define the voxels having the maximum DT value. Each voxel on the surface is examined and is compared to its neighbor voxels to define if it has the maximum code or not. In order to avoid spurious end points, we define a neighboring window in which the selected end point must have the local maximum DT value.

2.4. Paths Initialization

Having the end points and the start point, the initial paths can be generated starting from each end point to the start point. The first path or the main branch is constructed connecting the end point with the max DT value and the selected SP by monotonically decreasing in distance. For any point in the distance map, the set of all neighbors with lesser distance values can be determined and this yields several possibilities for traversing the distance map: Steepest decent (choose the minimum neighbor in the set), median decent (choose the median neighbor in the set) and shallowest decent (choose the maximum neighbor in the set). We used the shallowest decent for path construction since it has more centralized behavior across 2D components of medial axis [8].

For the rest of the end points, if any, paths are constructed starting from each end point and terminating when a voxel on the previous paths is reached.

2.5. Path Centering

In order to centralize the paths that were initially constrained to lie on the surface of the object, we used the approach proposed by Paik et al [8] with making some modifications to apply it to our application.

The idea is that the surface of the structure of interest, is iteratively removed until the structure has been thinned to the point at which only the centralized path remains.

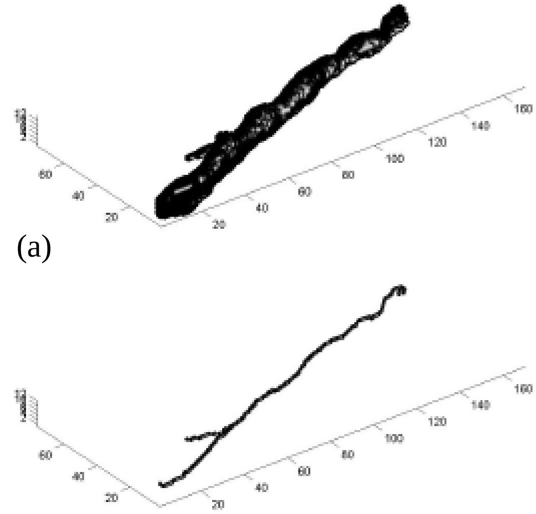
The first step in each iteration of thinning is the parallel removal of all surface voxels from the structure of interest.The next step is to compute a Chamfer distance map for the union of all voxels on the newly exposed surface of the structure and those voxels in the current path.The final step in each iteration of thinning is to determine a new voxel path through the distance map. At any point in traversing the distance map, following voxels along the new surface is preferred to those along the old path so that the new path will follow the eroding surface wherever possible. The new path traverses voxels of the old path only where the old path is the only connection between disconnected components of the surface [8]. The path centering algorithm in pseudo codes is as follows:

<u>Paths Centering Algorithm:</u>

```
Paths := Initial Paths;
NewObject := Object - Surface;
While   (NewObject is not empty) do
    Surface := identify_surface;
    Vsurface:= Surface + Paths;
    Make_Chamfer_DT_map (Vsurface, SP);
        For i=1 to Number of End Points do:
            Path :=Paths[i];
            V :=EndPoints[i];
            Next Path := V;
            While (V != (SP or A_Voxel_on_PrevPaths))
                If exists (Shallowest_neighbor(Surface,V))
                   V_next= Shallowest_neighbor(Surface,V)
                Else
                   V_next= Shallowest_neighbor(Paths,V)
                End
                V:= V_next;
                NextPath:=NextPath+V;
            End
            Paths[i] :=NextPath;
        End
    NewObject := NewObject - Surface;
End
```

Table I. Computation time for each step for extraction the centerline of the 10,402-voxels vessel shown in Fig. 2.

Processing Step	Computation time (sec.)
Segmentation	3.28
DT Mapping	5.18
End Points Selection	6.12
Paths Initialization	0.24
Paths Centering	42.4
Total	75.55



(a)

(b)

Fig. 2. a) A simple 10,402-voxels vessel b) The extracted centerline.

3. RESULTS AND DISCUSSION

Figure 2 illustrates the extracted centerline for a simple vessel with 10,402 voxels and Table I shows the computation time for perfoming each step of our algorithm for this vessel.

Our algorithm has been implemented in Matlab and was run on a Pentium III PC, 1000 MHz CPU, and 256Meg RAM. It has been tested on real Confocal Microscopy (CM) images of rat brains. 3D CM images are high-resolution pictures with superior quality and fine precision. The CM imaging allows one to collect a uniform series of optical sections through the material at steps of 0.6µm, which is the limit of resolution of a light microscope in Z-depth [12].

The sections we used were analyzed with a Bio-Rad MRC 1024 (argon and rypton) laser scanning confocal imaging system mounted onto a Zeiss microscope (Bio-Rad; Cambridge, MA). Image size was 260.6 x 260.6 ?m in X and Y directions and 1 ?m increment in the z-axis.

Complete processing of a 256x256x33 CM vascular images takes 58.12 minutes and as it can be observed in Figure3, the extracted centerlines are thin, connected and accurately centered.

Compared with a proposed DT method in [11], it is much faster and has no disconnectivity in the branch joints. Contrary to path planning methods [4,5,6], the process is totally automated and needs no user intraction to select some points on the vessels.

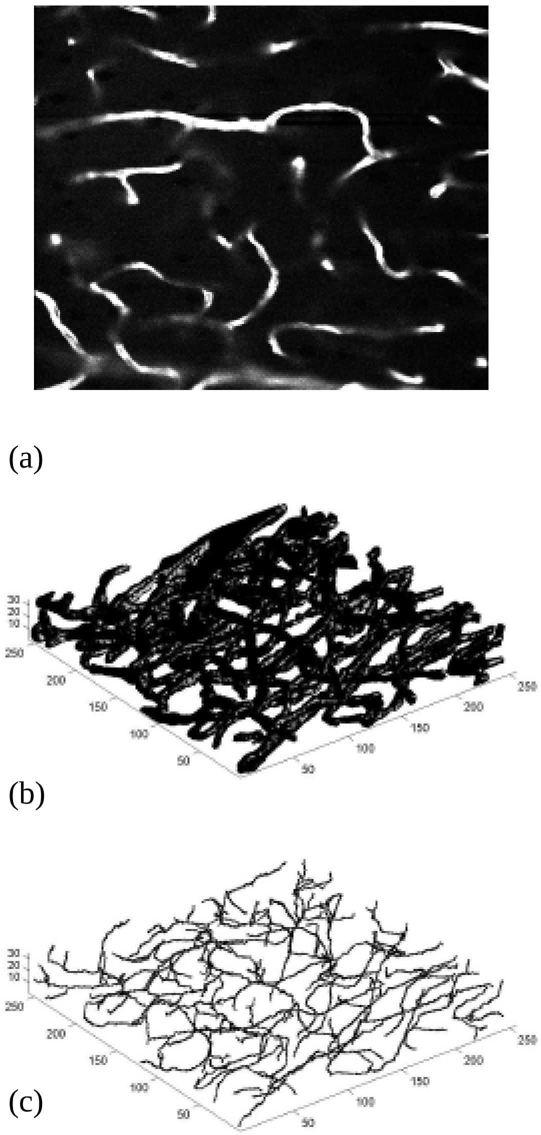


Fig. 3. a) A 2D CM frame, b) 3D visualization of 256x256x33 CM images, c) The extracted centerlines

4. CONCLUSION

We have presented a novel method for accurate and rapid extraction of centerlines of elongated objects. The proposed method is based on the distance transform concept and path planning approach. It generates thin, connected centerlines of objects without requiring any user interaction or any prior knowledge of the object shape. This automated method has been applied to the complex branching structures of vascular images of a rat brain provided by the novel confocal microscopy technology. The experimental results illustrate the efficiency of our method in extracting 3D centerlines of complex structures such as those in microvascular images.

5. ACKNOWLEDGMENT

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