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A Robust Deterministic-Based Automatic Vessel Centerline Extraction Algorithm in 3-D Binary Volumes

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***Abstract*—In this manuscript we propose a new fully automated approach for centerline extraction in vascular trees from a 3D medical binary volume that delivers smooth and robust results. A 3D binary volume which has been segmented is taken as an input data. Distance map is generated from the tridimensional Euclidian distance transform of the 3D binary volume data followed by the Hessian matrix computation for each target voxel based on the distance map. We utilized the distance transform because it indicates the distance between the point to the closest surface of the vessel. Analysis of Hessian matrix eigenvalues for each target voxel is used to extract the direction of the centerline. Since the proposed approach is totally automated, the user is not required to carry out any data preprocessing. The initial point from the centerpoint list is taken as the seed point through which the algorithm propagates to generate the centerline. We also tackled the complex issue of bifurcation where the vessel splits into multiple branches. We have demonstrated the performance of our algorithm on 6 different datasets of coronary artery, where the outcome was one voxel thick, connected centerline. Based on this centerline we can estimate the different geometrical parameters of the vessels, like radius, curvature, and length.**

***Index Terms*—centerline, Distance transform, Hessian matrix, Eigenvalues**

I. Introduction

The narrowing or obstruction of the arteries that supply blood to the heart muscle is referred to as coronary artery disease (CAD). It is the leading cause of death worldwide and in recent years its incidence has surged in countries with low and moderate incomes [1].

The visual examination of coronary angiograms is often ambiguous, which has resulted in the development of semi- and fully automated instruments that use computational image analysis techniques to evaluate coronary artery disease. The fundamental and most vital step in performing a precise coronary artery analysis is often determining the centerline of the vessel. In addition to attaining necessary geometrical parameters such as diameter, length, and volume of vessels, the extracted centerline is also used further in calculations to examine, reconstruct, and visualize the coronary arteries [2].

Approaches to centerline extraction can be generically classified into various categories. The most basic approach for forming the centerline is to depend on the expertise of a radiologist [3]. The radiologist is provided with a series of 2D cross sections. The "center" of each cross section is manually identified by the radiologist. Then these cross-sectional centers are merged to form a path. Unfortunately, this approach is quite time-consuming and deeply depend on the radiologist's knowledge and experience. Morphology-based methods acquire centerlines by thinning pre-segmented 3D vessel data [4]. Their output is usually 3D point sets devoid of vascular bifurcations and linear information. Moreover, these approaches are not specifically resistant to the complex vessel net. Distance transformation techniques are proposed based on the distance map, in this map, voxel value reflects the shortest distance between each voxel and the vascular edge. The centerlines can be extracted from the local maxima of the distance map. Though Distance transform methods are invariant to translation, scaling, and rotation and can find precise centerline positions for simple and particular vessels, but they frequently behave poorly in complex vessel shapes [5]. By learning attributes from labeled data, machine learning-based algorithms can get better solutions. When the training set is precise and substantial enough, only then can machine learning approaches produce better, and robust results. Dealing with small or limited datasets increases the risk of succumbing to overfitting. In the shortest path based approach, centerline is tracked back from the minimal path between the initially user defined start and end points [6], [7]. Although the benefit of this procedure is its low time complexity, the disadvantage is its inaccuracy because short pathways are primarily pursued. A Voronoi diagram-based centerline extraction method generates centerlines from binary or segmented vessel data using voronoi diagrams. Voronoi diagram-based method are employed in the medical imaging assessment toolkit, example in the VMTK extension in 3D slicer [8]. In the state of the art method [9] for centralized path generation VMTK extension in 3D slicer is used to extract the centerline, but for VMTK, it involves at least one initial seed and one target seed. Also, objects with irregular borders are more liable to have dense Voronoi diagrams, requiring extensive pruning of the medial surface to obtain a fine centerline which makes this method computationaly expesnive.

Due to the diversity of anatomical structures, 3D centerline extraction remains a challenging task. Some of the algorithms listed above such as in shortest path based and voronoi diagram based depend upon user for input parameters to extract the centerline and do not typically generate a one voxel thick, connected, and smooth centerline straightaway due to which they require further post-processing phases to improve the results, whereas machine learning based methods rely on a substantial dataset for training purposes. In this manuscript we propose a robust automatic method for centerline extraction, neither does it require any prior knowledge of the object's structure, nor does it depend on radiologist to engage in data preparation. The rest of this paper is structured as follows. Section II introduces the centerline extraction approach proposed including 3D Euclidean distance transform combined with the analysis of Hessian matrix. Evaluation of the proposed method is presented in Section III, and concluded with the conclusion in Section IV.

II. Algorithm

As an input to our algorithm, we use a binary 3D array of segmented imaging data. The proposed algorithm for centerline extraction is composed of following steps: Euclidean distance transform is applied to the binary mask, followed by extracting centerpoints and the direction of the centerline from the eigenvalues and eigenvectors of the Hessian matrix at each extracted centerpoint. The simplified version of the algorithm is described in Algorithm 1.

Algorithm 1 - Pseudo code of proposed centerline generation algorithm

Input: 3-D Binary mask B
Output: Smoothed centerline array L
Algorithm steps:
$D \leftarrow$ GenerateDistanceMap(B)
$S \leftarrow$ ApplyGaussianSmoothing(D)
$C \leftarrow$ ExtractCenterpoints(S)
$L \leftarrow$ Empty array
while C is not empty **do**
  $P \leftarrow$ RemoveFirstPoint(C)
  $D_P \leftarrow$ DistanceTransformValueAtPoint(S, P)
  $M \leftarrow$ ComputeHessianMatrix(S, P)
  $E \leftarrow$ ComputeEigenvalues(M)
  $V \leftarrow$ EigenvectorWithLowestMagnitude(E)
  $L_C \leftarrow$ Empty array
  $L_C \leftarrow$ FormCube(P, $2 \times D_P$)
  $I \leftarrow$ IndexOfMaxValueOnIntersectedSideOfCube(S, L_C, V)
  AddPointToCenterline(L, P)
  AddPointToCenterline(L, I)
  while new centerpoint can be extracted **do**
    $D_P \leftarrow$ DistanceTransformValueAtPoint(S, I)
    $M \leftarrow$ ComputeHessianMatrix(S, I)
    $E \leftarrow$ ComputeEigenvalues(M)
    $V \leftarrow$ EigenvectorWithLowestMagnitude(E)
    $L_C \leftarrow$ FormCube(I, $2 \times D_P$)
    $I \leftarrow$ IndexOfMaxValueOnIntersectedSideOfCube(S, L_C, V)
    AddPointToCenterline(L, I)
  end while
  RemovePointsFromCenterpoints(C, L)
end while
$L \leftarrow$ ApplySplineInterpolation(L)
Return: Smoothed centerline array L

A. Euclidean Distance Transform and Smoothening

According to [10] given a 3D binary mask of shape $a \times b \times n$, if a voxel (p, q, r) lies in the foreground, i.e., coronary artery, it is set to 1, otherwise set it equal to 0. According to (1) and (2) the Distance Transform computes the distance between all voxels equal to one and their closest voxels equal to zero.

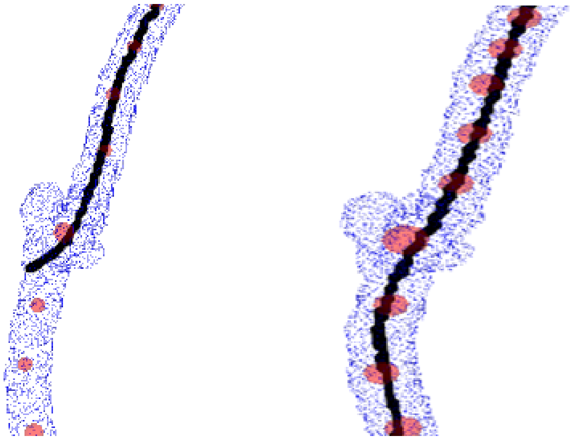
$$dt_{p,q,r} = \min_{(x,y,z) \in B_r} DT[(p,q,r),(x,y,z)] \tag{1}$$

$$DT[(p,q,r),(x,y,z)] = \sqrt{(p-x)^2 + (q-y)^2 + (r-z)^2} \tag{2}$$

Where (p, q, r) and (x, y, z) are the input binary data voxel coordinates. Searching ball is denoted by B_r with a radius equal to r and starting value of r is 1. For example, if r = 1, a ball with a diameter of 2 and center at voxel (p, q, r) is formed. Voxels lying on the surface of the ball are checked. If a voxel equal to 0 is detected, searching is halted to compute the distance according to (2). For all the targeted voxels that belong to the coronary artery, their distances are obtained according to the 3D Euclidean distance transform. The 3D binary array will then be converted into a distance map in which the target-voxel value is greater than 0 and the non-target-voxel value is 0.

We utilize the distance transform for centerline extraction simply because it estimates the shortest distance between each voxel and the nearest object border, thereby facilitating the rapid identification of an object's skeleton or medial axis. After obtaining the distance map of shape $a \times b \times n$ from the binary array of shape $a \times b \times n$, it is convolved with the Gaussian kernel. There are couple of reasons why Gaussian filtering comes in handy in this situation:

- Smoothing: Abrupt changes in the case of irregular object boundary in the distance values along the centerline can be smoothened via Gaussian filtering as can be seen in Fig. 1a before applying Gaussian smoothing, the centerline exhibits discontinuity after sharp turn which does not represent the true path of the vessel and Fig. 1b shows that the centerline better represents the underlying structure of the vessel after applying Gaussian smoothing.
- Feature enhancement: Gaussian filtering improves the centerline's key characteristics by keeping the essential structural information while decreasing noise and small anomalies introduced during the data procurement or



(a) (b)

Fig. 1: (a) Extracted Vessel Centerline without Gaussian Smoothening and (b) with Gaussian Smoothening.

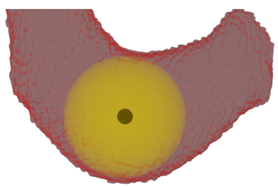


Fig. 2: Sphere formed around the centerpoint in Vascular Artery.

processing.

B. CenterPoints Extraction

The maximum value and its corresponding index (i, j, k) is identified in the distance transform array. This maximum value represents the greatest distance from the background, which indicates the potential centerpoint. The sphere is formed according to (3) with radius (r) equal to the value of the maximum distance transform and its center at the corresponding index (i, j, k) as shown in Fig. 2.

$$(i - x)^2 + (j - y)^2 + (k - z)^2 \leq r^2 \tag{3}$$

Where (x, y, z) refer to all the voxels that satisfy (3).

The coordinate (i, j, k) of Distance Transform max value are stored in the list. After this, the distance transform maximum value at (i, j, k) is set to 0, and all other voxels that satisfy equation (3) at the current centerpoint are set to 0 in the distance transform array. The procedure is repeated until distance transform max value reaches zero. Now, we have the list of all the centerpoints. Fig. 3 shows all the extracted centerpoints detected in the coronary artery.

C. Hessian Matrix

An n-dimensional image is analyzed often via the Taylor series expansion. Assuming that I denotes the n-dimensional image, and the expansion of point S in I in space is

$$I(S + \Delta S) \approx I(S) + \Delta S^T \nabla I(S) + \Delta S^T H(S) \Delta S \tag{4}$$

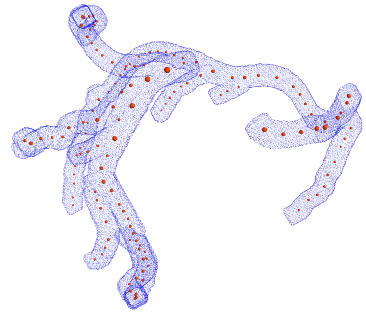


Fig. 3: Extracted Centerpoints (red) in the coronary artery (blue).

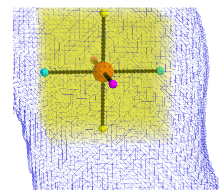


Fig. 4: Cube Around centerpoint (axes represented in black).

Where gradient vector of point S is represented by $\nabla I(S)$ and its Hessian matrix by $H(S)$, composed of its second derivatives. $H(S)$ is a real symmetric matrix in 3D volume data,

$$H(S) = \begin{bmatrix} H_{xx} & H_{xy} & H_{xz} \\ H_{yx} & H_{yy} & H_{yz} \\ H_{zx} & H_{zy} & H_{zz} \end{bmatrix}$$

By eigen analysis of the Hessian, three eigenvalues λ_1, λ_2 and λ_3 and their corresponding eigenvectors v_1, v_2, v_3 are computed. Subsequently arranging them with their absolute values as $|\lambda_3| \leq |\lambda_2| \leq |\lambda_1|$, where λ_3 denotes the eigenvalue along the direction of the vessel.

D. Centerline Construction

To start with the centerline formation, first point from the centerpoints list is considered as a seed point by the algorithm. A cube is formed around this seed point with the length (l) as stated in (5).

$$l = 2 \times DistanceTransform(C(i, j, k)) \tag{5}$$

where $C(i, j, k)$ are the coordinates of the seed point. Due to its simple geometrical shape with well-defined edges and corner, the cube is the optimum geometrical shape in this case. In addition, since the edges of the cube correspond to the cardinal directions, it makes the process of determining the vessel's centerline direction simpler. Fig. 4 shows the axes around the current seed point.

Next, Hessian matrix is computed at the current seed point and its eigen analysis provides us with the eigenvalues. Direction along the vessel is determined by the eigenvector

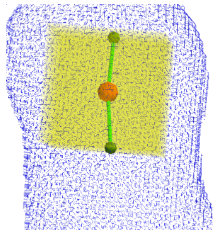


Fig. 5: Vessel direction (green lines) via Eigen analysis around the center point.

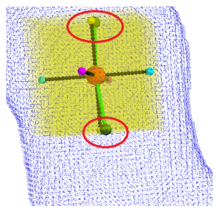


Fig. 6: Eigen direction (green line) interesting 2 faces of the cube (marked in red circle).

v corresponding to the eigenvalue of lowest magnitude as shown in Fig. 5 where direction along the vessel at particular centerpoint is represented in green.

Since a cube is bounded by 6 square faces, the corresponding face in which the eigen vectors intersect the cube, the coordinates of the distance transform maximum value are extracted from that particular face of the cube, as can be seen in Fig. 6 faces that are intersected by the eigenvector shown in green are marked in red circles. Consequently the centerline is allowed to grow from this seed point until it reaches the either end of the vessel as can be seen in Fig. 7.

All the points from the centerpoints list that lie on the centerline generated from the seed point are removed from the centerpoints list including the seed point. The algorithm repeats the process where the next first point from the centerpoints list is considered as a seed point and the centerline is grown from it. This procedure keeps going on until the centerpoints list becomes empty. This way we have catered to all the centerpoints which results in generating the centerline for the coronary artery dataset. To smoothen the centerlines, spline interpolation is further applied. Fig. 8 shows the smoothed centerlines extracted in the coronary artery.

E. Bifurcations

Bifurcation is the branching of a vessel in a vessel network which can be divided further into multiple branches. Most vessel tracking algorithms strive with this feature because the eigenvalues cannot represent every distinctive bifurcation. Here is how bifurcation is tackled in our approach. A skeleton array is created corresponding to the shape of the binary mask. Initially, all values inside the skeleton are set equal to 0. When we start plotting the centerline from the initial seed point from the centerpoints list, it grows from the seedpoint outwards until it reaches the end of the vessel as can be seen in Fig. 7. We then extract the coordinates of the extracted centerline and

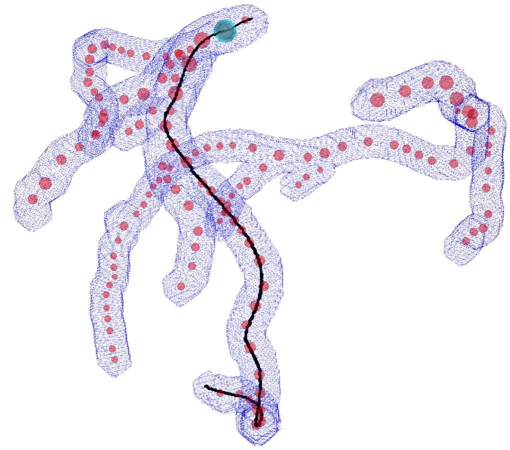


Fig. 7: Centerline construction (in black) from seedpoint (cyan color).

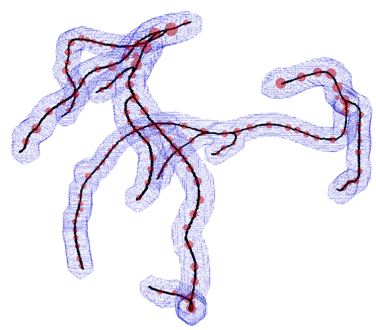


Fig. 8: Complete centerline (black) in Coronary Artery.

the corresponding coordinates in the skeleton array are set to 1. So for the next iteration with a new seed point from the centerpoints list, centerline grows outwards from this; if in the skeleton array while growing outwards from the seed point, value 1 is detected, the centerline growth is stopped, if not, then new coordinates in the skeleton array are set to 1. Fig. 9 shows the comparison between without bifurcation detection (left) and with bifurcation detection (right). It can be noticed that without bifurcation detection, the centerline is plotted over the previously detected centerline, resulting in centerline which is not one voxel thick.

III. Results

To assess the performance of the proposed method, an open access coronary artery dataset composed of 512 x 512 x 275 voxels proposed by [11] is used. We tested our algorithm on 6 datasets of coronary artery. We presented the automatic method where the user has to only select the gaussian scale. Fig. 10 shows six exemplary images of coronary arteries for which centerlines were extracted using the proposed method. It can be seen that the centerline passes through the extracted centerpoints. The whole algorithm was implemented in

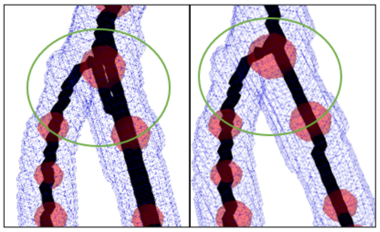


Fig. 9: Comparison between without bifurcation detection (left) and with bifurcation detection (right).

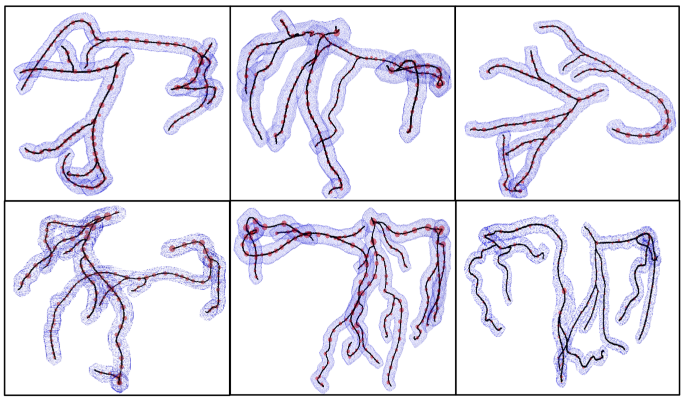


Fig. 10: Centerline extraction on 6 Datasets of Coronary Artery.

Python. Our platform is a common PC with 11th Gen Intel® Core™ i7, 2.3GHz.

IV. Discussion

Vessel Centerline extraction improves blood vessel visibility in medical images, making it simpler for healthcare providers to examine vessel anatomy and health. Based on centerline, vessel plane and geometry can be computed, this helps in vascular disease diagnosis and therapy since accurate measurements are vital for identifying conditions like stenosis, aneurysms and identify abnormalities, such as occlusions or narrowing of vessels. The centerline is essential in interventional radiology and practices such as angiography for directing catheters and medical apparatus through the circulatory system. It assists doctors in navigating and performing less invasive therapies.

The quality of centerline extraction is strongly associated with segmentation outcomes. A more precise segmentation increases the likelihood of a robust and consistent centerline extraction, reinforcing the importance of high-quality segmentation for optimal results. As this approach is dependent on segmentation, assessing artery pathology such as plaque or calcification from a binary perspective may pose challenges.

Method utilized in [9] to automatically generate vessel endpoints, often leads to inaccurate endpoints generated which means this can further lead to false centerline generation as can be noticed in Fig. 11. Therefore manual assistance is required to readjust the vessel endpoints, this is not the case with the approach presented in this paper as algorithm generates the centerpoints based on the distance transform.

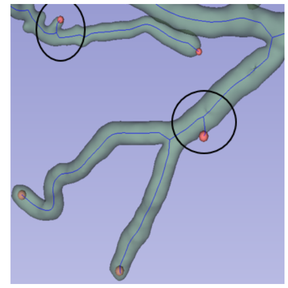


Fig. 11: Centerlines generated due to inaccurate automatically generated endpoints represented within circles.

Fig. 12: Centerlines generated around Plaque or Calcification represented within the circle.

In case of plaque or calcification, centerline extraction method mentioned in [9] tries to extract centerlines around it which is not the true representative of the vessel centerline shown in the Fig. 12.

Deep learning, particularly U-Net and its variants, has found widespread application in medical imaging for segmentation related tasks in recent years. Dorobanţiu et al. [12] utilized a 3D U-Net architecture to precisely segment the coronary artery centerline, detecting whether or not each voxel constituted a centerline point. In [13] implemented a local vessel filter based on a binary classification network, which effectively extracted centerlines by determining whether the center point of the current patch resided on the centerline. Nonetheless, the extraction of coronary artery structures is fraught with difficulties. Initially, the full CTA images are partitioned into smaller patches for training, which includes a significant amount of non-vascular information. Consequently, this procedure is tedious and time-consuming. Furthermore, these techniques demand complex post-processing procedures to address concerns such as vessel discontinuities in the collected data while maintaining the integrity of the coronary centerline.

Distance transform-based centerline extraction methods are adaptable to various imaging modalities, including MRI, CT, ultrasound, and angiography. Unlike the state-of-the-art method, the approach presented in this paper boasts a distinct advantage: it consistently generates centerpoints precisely at the center. This is achieved by leveraging the distance transform, effectively eradicating any potential for spurious centerline branches. This flexibility allows for the analysis of vessels in different clinical contexts. The concept of centerline extraction presented in this paper is not restricted to blood vessels alone and can be incorporated to various anatomical structures in medical imaging, such as colon and can be potentially used for virtual procedures e.g. virtual colonoscopy or virtual bronchoscopy.

V. Conclusion

This work presents an automatic robust centerline extraction approach based on Distance Transform and Hessian matrix with the objective of extracting the centerline of coronary artery with high precision. Compared to the state-of-the-art centerline computations, seed points are automatically generated, eliminating the dependency on humans thereby minimizing the chances of error. We then show that robust, smooth, and accurate results are obtained in the coronary artery through our implementation, as the proposed algorithm finds the ends of the coronary artery entirely automatically and always computes a provably connected centerlines as it passes through the centerpoints. For future work we plan to extend our algorithm to work with non-segmented data, and utilize the same approach for centerline extraction in the peripheral arteries.

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