Design of cerebrovascular phantoms using fuzzy distance transform based geodesic paths

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Abstract. Generation of digital phantoms specific to the patients' carotid vasculature is a complicated and challenging task because of its complex geometrical structure and interconnections. Such digital phantoms are extremely useful in quick analysis of the vascular geometry and modeling blood flows in the cerebrovasculature. All these analyses lead to effective diagnosis and detection/localization of the diseased arterial segment in the cerebrovasculature. In this work, we have proposed a semi-automatic geodesic path propagation algorithm based on fuzzy distance transform to generate digital cerebrovascular phantoms from the patients' CT angiogram (CTA) images. We have also custom-developed a 2-D/3-D user interface for accurate placement of user specified seeds on the input images. The proposed method effectively separates the artery/vein regions from the soft bones in the overlapping intensity regions using minimal human interaction. Qualitative results along with 3-D rendition of the cerebrovascular phantoms on four patients CTA images are presented here.

Keywords: Digital phantom design, carotid vasculature, fuzzy distance transformation, 3-D rendering, geodesic paths.

1 Introduction

Reconstruction of accurate digital phantoms of human cerebrovasculature is an active area of research in the field of medical image analysis. It helps researchers to explore the underlying hemodynamics which is one of the major factors in determining one's cerebrovascular health. In general, human cerebrovasculature refers to the vessel network circulating blood throughout the entire brain. Arteries and veins are the building blocks of this network. In this work, we are mainly interested in the carotid arteries which are supplying oxygenated and nutrient filled blood to the various parts of the cerebral system. Anatomical analysis of carotid arteries is the key to elucidate the blood flow patterns in the vasculature, determination of irregular dilation of vessel wall, detection of possible obstruction in the flow etc. To unveil the anatomy of carotid arteries properly, we should have the knowledge about the anatomy of *Circle of Willis*. This circular vasculature is formed by the left and right Internal Carotid

Arteries, Anterior and Posterior Cerebral Arteries (left and right), Anterior and Posterior communicating artery. The basilar and middle cerebral arteries are also part of this circle.

Generally, there are two ways to analyse the carotid arteries 1) using physical vascular phantom which is a replica of the original one 2) digital modelling of the vessel network using mathematical model. Both of them have individual advantages and disadvantages and researchers sometimes acquire both models to verify the experiments as in work [1-3]. In this paper we have focused only on construction of digital vascular phantoms using mathematical modelling from human cerebral CT angiogram (CTA) images. There are many existing works on generation of carotid vasculature [4][5][6]but all these methods need active human participation in the reconstruction process. In our work, user interaction with the system has been minimized by the notion of fuzzy distance transform (FDT) based geodesic path propagation approach[7].Please note that, the concept FDT has been widely used before in various vessel reconstruction algorithms [8][9][10].

Separation of vessel from bone and soft tissues is most critical in the cerebrovascular system, especially in the regions with high overlapping of vessels, bones and tissues. So, construction of accurate cerebrovascular phantoms in complex regions of human brains and capability to independently execute them has a multiple potential applications in the field of medical science. Moreover, Construction of phantoms from original CTA image helps to detect diseased vascular segments or disorders.

In the subsequent discussions, first we introduce the theory and notations used in the mathematical simulation of the digital phantoms of cerebrovasculature, followed by the methodology of our proposed algorithm and experimental results.

2 Theory and Methods

A three dimensional cubic grid is expressed by $\{Z^3 | Z \text{ is the set of positive integers }\}$. A point on the grid, often referred to as a voxel, is a member of Z^3 and is denoted by a triplet of integer coordinates. Each voxel has 26 adjacent voxels, i.e. two voxels $P = (x_1, x_2, x_3)$ and $Q = (y_1, y_2, y_3) \in Z^3$ are adjacent if and only if

$$\{\max(|x_i - y_i|) \leq 1 \mid 1 \leq i \leq 3\},$$

where $|\cdot|$ means the absolute value. Two adjacent points in a cubic grid are often referred to as neighbours of each other. 26 neighbours of a voxel P omitting itself is symbolized as $N^*(P)$.

CTA is a 3-D grey-scale image where each voxel is represented as 8 bit character or 16 bit unsigned short value. Numeric value of a voxel implies the intensity of the voxel. Artery, veins and soft tissues occupy small intensity value, where bones take high intensity values. We will denote artery and veins together as vessels. Intensity of vessels and soft tissues are highly overlapping. In this paper, we are mainly interested in reconstruction of arterial tree of human cerebrovasculature.

It has been observed that in general intensity of vessels lie between 130-450 Hu (Hounsfield unit) [13],but there is almost zero overlapping around the middle point of this intensity scale. Hence voxels within this intensity range are considered as object voxel and rest of the intensity regions are taken as background.

The distance transform (DT) is an algorithm generally applied to binary images. The output of this algorithm is same as the input image except that the values of each foreground points of the image are changed to the distance to the nearest background from that point. Over the years several distance transformation algorithm have been developed both in 2-D and 3-D[14][15].If $P = (x_1, x_2, x_3)$ is a point in a 3D image, then DT value of that point will be,

$$DT(P) = \begin{cases} DT(Q_i) + d_k, & DT(Q_i) + d_k < DT(P) \\ DT(P), & otherwise \end{cases} \quad (1)$$

where,Q_i is the neighbour of P,$i = 1,2, \ldots\ldots,26$. $d_{k=1,2,3}$is the approximate Euclidean distance from three different kinds of neighbour. Distance transform performs very well in case of binary images .But in case of digital phantom generation distinction between vessel intensity and other objects intensity is crucial which cannot be done in DT image. Hence fuzzy distance transform is more suitable. In this work, we have used triangular fuzzy membership function to convert a DT image into a FDT image[16].

$$FDT(P) = DT(P) * \mu(P) \quad (2.a)$$

$$\mu(P) = \begin{cases} \dfrac{I - I_A}{I_M - I_A}, & I_A \leq I \leq I_M \\ \dfrac{I_B - I}{I_B - I_M}, & I_M < I \leq I_B \end{cases} \quad (2.b)$$

where, I denotes the gray scale value of voxel P. I_A,I_B denotes the max and min grey-scale intensity respectively.$I_M$is the median of $I_A$and I_B.

$$I_M = \frac{I_A + I_B}{2} \quad (2.c)$$

We represent whole image as an undirected graph $G = (V, E)$ where $V$is the vertex set denoted by$\{ P \mid \text{P is a voxel in the 3D image} \}$, E is the set of edges denoted by $E = \{(P_1, P_2) | \text{P}_1 \text{ and } \text{P}_2 \text{ are adjacent} \}$.

Methodology used here is to find the centre point of the presumed artery between input seed points and draw spheres in these points with radius equal to the FDT value of that point. We may define a sphere $S(P, r)$ with centre$P$ having coordinates (x_c, y_c, z_c) and radius r is the locus of all points (x, y, z) in z^3 such that,

$$(x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2 = r^2 \quad (3).$$

A point$Q$ is called local maxima if,

$$\{Q \mid Q \epsilon Z^3, FDT\ (Q) = max\big(FDT\ (Q_i)\big),$$
$$1 \leq i \leq 26, all\ Q_i's\ have\ same\ eucledian\ distance\ to\ P, \} \quad (4)$$

So a point may have several local maxima points in its neighbourhood or it may not have any local maxima point in its neighbourhood. Geodesic path is defined as minimum cost shortest path between two points in two or three dimensional space. Dijkstra's shortest path algorithm[17]has been used for geodesic path propagation with modification so that shortest path will always pass through the nearest local maxima point if it exists, otherwise it will pass through the maximum FDT value point in its neighbourhood. To force the geodesic path between two seed points to pass through nearest local maxima points or maximum FDT value point, edge weight between any point and corresponding nearest local maxima point or maximum FDT value point should be minimum. Here we introduce a cost function β that computes edge weights between two adjacent voxel $\mathrm{P} = (\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3)$ and $\mathrm{Q} = (\mathrm{y}_1, \mathrm{y}_2, \mathrm{y}_3) \in \mathrm{Z}^3$ as follows:

$$\beta(P, Q) = \left(\frac{2}{\left(DT\ (P) + \ DT\ (Q)\right)}\right) \times DIST\ (P, Q). \qquad (5)$$

where, $DIST\ (P, Q) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2}. \quad (6)$

Dijkstra's algorithm is a greedy method where from current point algorithm chooses a neighbour connected through least cost edge for next iteration. In the proposed method due to cost function β it will always select the nearest local maxima point or maximum FDT value point in the neighbourhood of the current point. After termination of this algorithm will return connected centre points of the presumed artery. If we draw sphere taking these points as centre and radius equal to the FDT values of the point, we will get the desired digital phantom.

As the proposed method is a semi-automatic algorithm hence user may not get accurate result at first hence trial and error method should be used to generate accurate phantoms. In this method user can modify the generated phantom by giving extra seed points.

We can summarize the whole method in following steps. In first step Original CT image is taken as input and converted into FDT image. In next step start and end input seed points are taken from user and geodesic path is found between those two points. Next sphere is drawn at each point on the geodesic path with radius equal to the FDT value of that point. If generated phantom needs further modification user can give more seed points and followed same steps described before. Fig 1 shows steps of the algorithm.

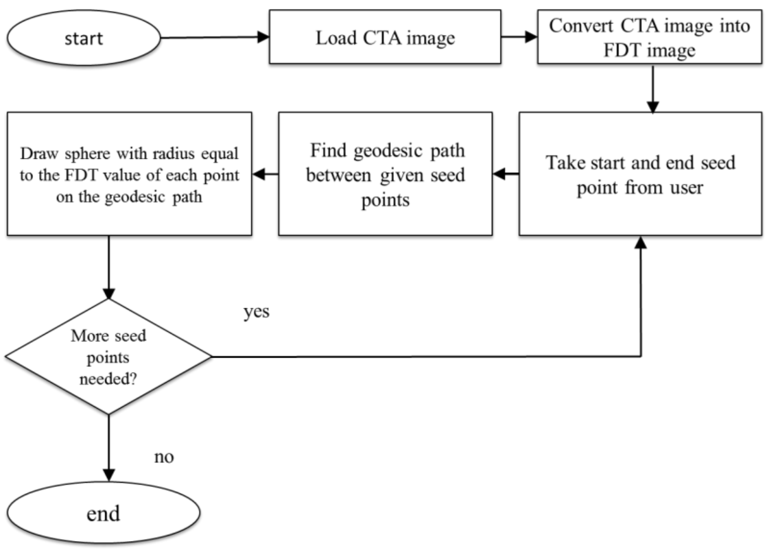

Fig.1.Modular representation of the algorithm used to generate phantoms.

3 Experimental Methods and Results

To facilitate the experimental methods an integrated custom designed 2D/3D graphical user interface was developed in our laboratory allowing axial, coronal and sagittal view of segmented data. Facilities of selecting and editing different seed points are supported within the graphical user interface.

Using developed GUI we have taken seed points as input and visualized generated digital phantoms in axial, coronal, sagittal and 3D views. In Fig 2, 3D view of different phases of generation of a digital phantom from CTA image is shown.

In the first phase we have generated segments 1, 2 and 3. In the next phase segments 4,5 and 6 are generated followed by segments 7 and 8. These 8 segments form a significant portion of *Circle of Willis*. Similarly other segments are generated to construct the complete digital phantom shown in image (d) In Fig3.we have shown 3D view of four digital phantoms constructed from four different CTA images. Blue colored portion in Fig. 3(a) shows aneurysm present in the cerebrovasculature.

Generated phantoms are overlaid with original CTA image to analyse the accuracy of the phantom. Fig. 4 shows the overlay of the digital phantom over original CTA image.

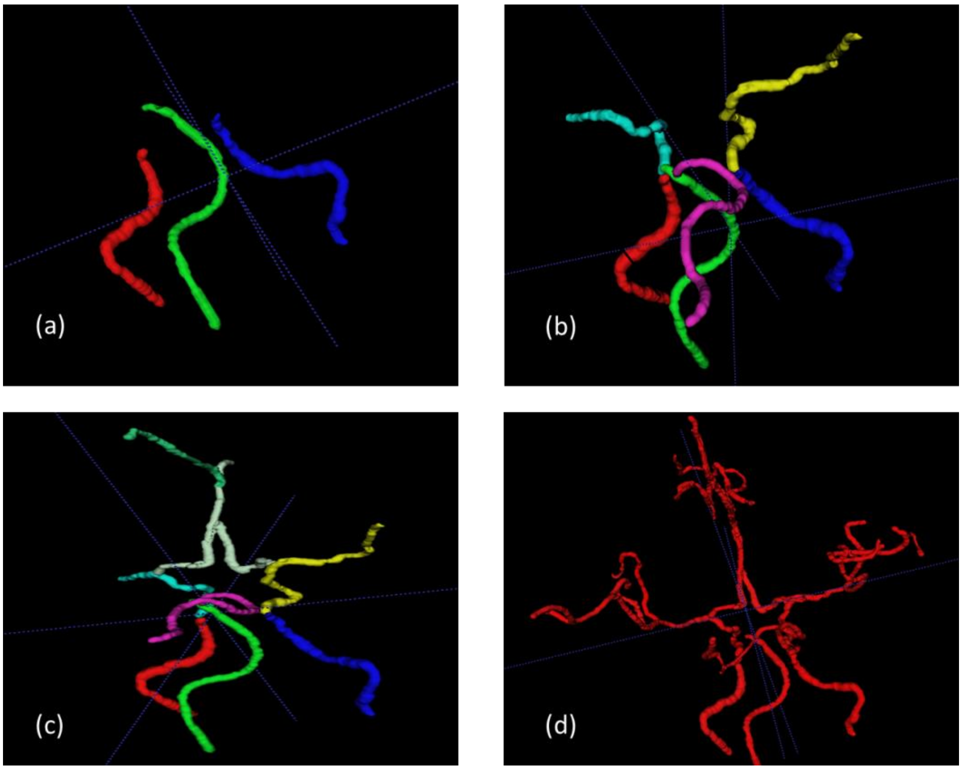

Fig. 2(a-d).Four phases of construction of phantom from a CTA image.

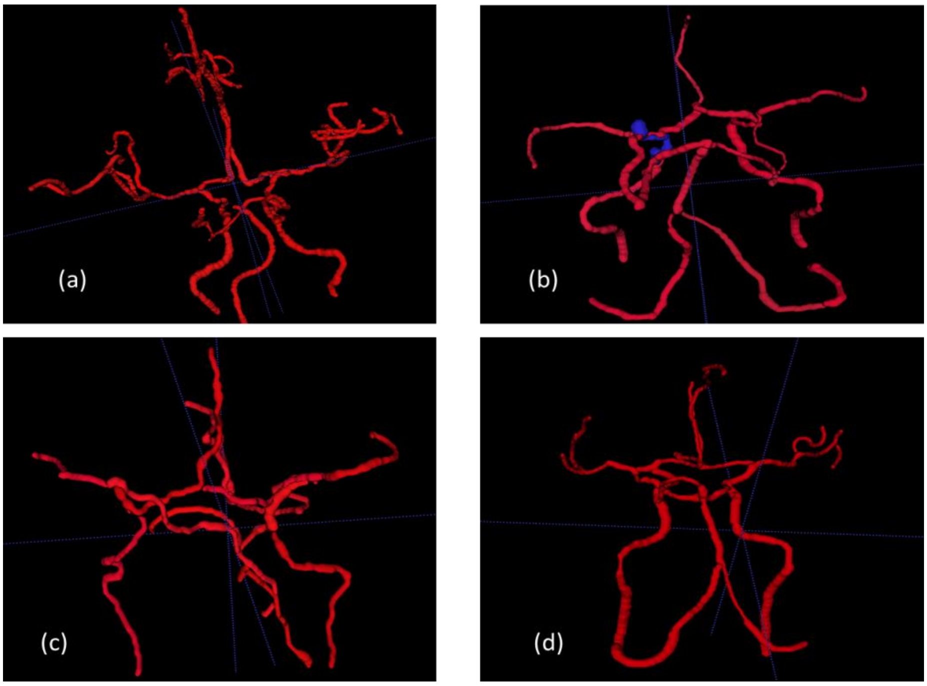

Fig. 3(a-d).Digital phantoms generated around *circle of Willis* from 4 different CTA images.

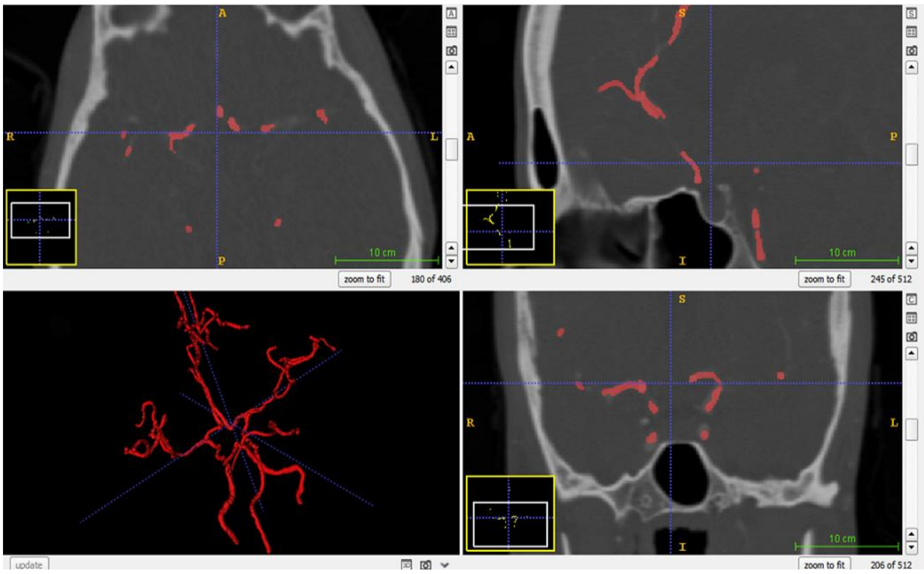

Fig.4. A segmented phantom image is shown with respect to the original CTA image in axial, coronal, sagittal and 3-D views.

4 Conclusion.

In this present work, we have shown an application of fuzzy distance transformation based geodesic path propagation approach to generate accurate phantoms from human CTA images. Local maxima points and distance transformation is used to find the radius of the arterial tube. The proposed process is semi-automatic and the user can modify the generated digital phantom structures to make it more accurate. We argue that the proposed algorithm is both efficient and precise. Digital phantoms generated through this algorithm can be helpful in studying the arterial bends, bifurcated regions, joins and possible modelling of digital fluid flows in human cerebrovasculature. We have used the ITK-SNAP[18]open-source software to overlay generated phantom structures over original CTA images. In future we may attempt to use the generated digital phantoms for homodynamic analysis in human cerebrovasculature.

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