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Linear cost reconstruction of vascular trees from intensity volume angiograms

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ABSTRACT

This paper introduces a two-phase algorithm to extract a center-adjusted, one-voxel-thick line representation of cerebral vascular trees from volume angiograms coded in gray-scale intensity. The first stage extracts and arranges the vessel system in the form of a directed graph whose nodes correspond to the cross sections of the vessels and whose node connectivity encodes their adjacency. The manual input reduces to the selection of two thresholds and the designation of a single initial point. In a second stage, each node is replaced by a centered voxel. The locations of the extracted centerlines are insensitive to noise and to the thresholds used. The overall computational cost is linear, of the order of the size of the input image. An example is provided which demonstrates the result of the algorithm applied to actual data. While being developed to reconstruct a line representation of a vessel network, the proposed algorithm can also be used to estimate quantitative features in any 2-D and/or 3-D intensity images. This technique is sufficiently fast to process large 3-D images at interactive rates using commodity computers.

Keywords: Centerline Extraction, Intensity Volume Image, Voxel Coding, Directed Graph

1. INTRODUCTION

In variety of situations it is useful to reduce three dimensional voxel-encoded data sets to more compact representations. A particularly useful process is the extraction of the centerlines in a vascular tree acquired with modern medical imaging techniques. We describe an efficient algorithm which is applicable when the image is encoded as gray levels in each voxel. The method takes advantage of the excellent contrast achieved by modern imaging machines and that it is possible to assume that the underlying organ is imaged as a connected set of voxels.

The algorithm automatically extracts the vessel network connected to a user-selected reference point (RP) on the vessel and is such that its intensity has a value between two low and high thresholds. It then extracts a line representation of the segmented vascular tree. This produces a set of one-pixel-wide lines that go through the centers of the vessels, highlighting the topological features of the original image. Each point of these centerlines carries two labels, one to indicate its distance to the background and a second to encode topological information such as bifurcation points and merging points (loops can occur). The centerline representation reduces the storage requirements, increases data accessibility, and can be used to improve the display and the visualization of a vascular tree. For example, the centerline can be overlayed with data from other modalities (Sollenberger and Milgram, 1991; Puig, Tost and Navazo, 1997).

In Henri and Peters (1996a, 1996b) the reconstruction of vascular centerlines was performed from several 2-D projections of the vascular tree. Assumptions regarding consistency and connectivity constraints were used to bypass the correspondence problem. 2-D center-lines of the vessel network, which would be manually obtained during a preprocessing step, were required as inputs . Nystrom described a two-phase thinning algorithm to extract the centerlines from binary angiographic images of the vessel system , but which are rotation dependent

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and sensitive to noise (Nystrom, 1998). Krissian *et al.* (1999) reconstruct the tubular structure of vascular vessels by applying multi-scale analysis to raw unsegmented intensity images.

In related work (Yi and Hayward, 2002), the centerline representation of vessel network is derived from a binary volume image, which in turn is obtained by segmenting the intensity volume angiogram using an automatic flood-fill-in algorithm. The binary image is then skeletonized by employing a voxel coding approach originally proposed by Zhou and Toga (1999). However, we observed that with some modifications, the most time consuming processes — segmenting the object from its background and the boundary-seeded coding used to calculate the distance of each object voxel to a common RP — can be done in one step to both reduce the required number of scans over the original volume image and to remove the pre-processing requirement. The ultimate goal is to make of vascular centerline reconstruction an automatic, user-interactive process.

The rest of the paper is organized as follows: Section 2 defines the needed concepts. The details of the method are described in Section 3. Section 4 reports on the results of the method as applied to an actual volume data set. A brief discussion is provided in Section 5.

2. TERMINOLOGY

Three-dimensional cubic elements are usually called voxels. Each voxel has 26 neighbors divided into three types. The closest neighbors are those 6 that are joined by a face. They are called *face neighbors*. The 12 neighbors joined by an edge are referred to as the *edge neighbors*. The 8 neighbors joined by a vertex are called the *corner neighbors* (see Figure 1). Two voxels are said to be connected if they are either face, edge or corner neighbors. A *connected set of voxels* must satisfy the condition that given any two voxels within the set, there exists a sequence of connected voxel pairs to connect them.

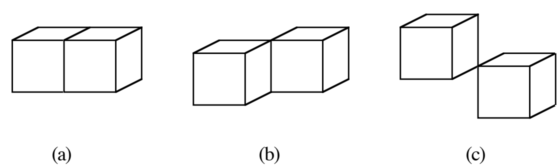

Figure 1. (**a**) 6 Face neighbors. (**b**) 12 edge neighbors. (**c**) 8 corner neighbors.

Voxels contained in a volume image can either be *background voxels* or *object voxel*. A boundary voxel has at least one background voxel as its face neighbor. Two codes are assigned to each object voxel: the boundary-seeded (BS) code and the single-seeded (SS) code. The BS *code* indicates the distance of an object voxel to its nearest boundary, whereas the SS *code* corresponds to the in-object distance between the object voxel and the user-selected RP.

The SS codes are used to convert the building element of objects embedded in a volume image from a voxel to a *cluster*, which is a connected set of voxels with the same SS code. Two clusters, A and B, are *neighbors* if there exists one voxel in A that is connected to a voxel in B. A *branching cluster* (BC) has at least two neighbor clusters with a SS code that is larger by one. Conversely, a *merging cluster* (MC) has at least two neighbor clusters with a SS code smaller by one unit. A *local maximum* (LMC) cluster contains a local maximum of SS code. These concepts are illustrated in Figure 2.

3. METHOD

A volume angiogram is first graphically displayed using, for example, the maximum intensity projection (MIP) technique whereby the intensity of a pixel on the screen results from the maximum value encountered by the corresponding ray. The user then selects any point on the vessel system as the reference point (RP). Prominent ones, however, such as those with high intensity are preferably selected. The user selects the low and high thresholds to extract the vessel system from the background, that is, the set of voxels whose intensity lie between the selected thresholds. Modern high contrast machines commonly, yield low intensity values for background tissues. Other tissues such as scalp voxels have a bright intensity.

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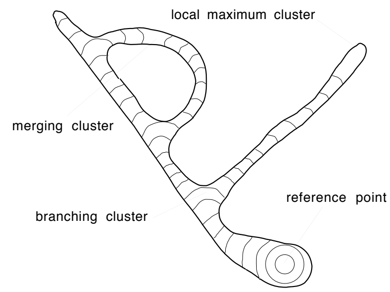

Figure 2. A 2-D illustration of the concept of clusters.

3.1. Vessel System Retrieval

The vessel system is then reconstructed layer by layer by a forward propagation process. Point RP is first extracted, its SS code labeled "0" and assigned to be a background voxel with zero intensity value. The cluster with a zero SS code contains only one element: RP. Then, those face neighbors of the RP whose intensities fall within the thresholds are selected to be the first surrounding layer of RP and assigned an SS code of "1" and assigned to be background voxels. If this layer is connected, it constitutes one cluster. Otherwise, it is separated into two or more clusters, and the RP is called a branching cluster.

Each surrounding layer of RP leads to the next until the farthest element from RP is added. All the voxels in the n_{th} layer receive n as their SS code, reflecting their 6-neighbor distance to RP (Borgefors, 1984). Each layer is divided into one or more clusters as determined by the connectivity of its voxels. Eventually, the clusters approximate the cross sections of the vessels.

The extracted vessel system is converted into a directed graph with clusters as nodes. Node connectivity expresses the adjacency of the clusters, producing a cluster graph which starts at RP and spreads within the object as the SS code increases, until it meets either the ends of the vessel branches, or the merging clusters if the vessel system contains loops (see Figure 3) (Zhou and Toga, 1999). All voxels that connect to the RP and have intensity values fall within the high and low thresholds are collected into the cluster graph.

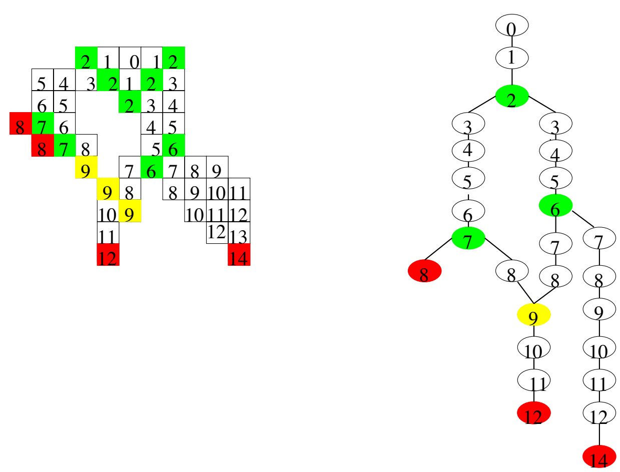

Figure 3. A planar shape with SS codes (left) is converted into a directed graph (right). The red color indicates local maximum clusters, green color indicates branching clusters and yellow, the merging cluster.

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3.2. Binary Volume Image

A binary volume image is obtained from the directed graph representation of the vessel system. Its size is $N_{\text{binary\_volume}} = (i_{\max} - i_{\min} + 1) \times (j_{\max} - j_{\min} + 1) \times (k_{\max} - k_{\min} + 1)$, where $i_{\min}$ and $i_{\max}$ correspond to the minimum and maximum indices in the x direction of the voxels contained in the directed graph, $j_{\min}$ and $j_{\max}$ and $k_{\min}$ and $k_{\max}$ are those corresponding to the y and z directions. Each voxel in the binary image is initialized to zero, a background label. Then the entries that correspond to the voxels contained in the directed graph are modified to receive the label "1".

3.3. BS Codes

The BS codes of object voxels are derived from the segmented volume image in a manner similar to the traditional distance transformation (Borgefors, 1984). First, a BS map, equal in size to the binary volume image, is initialized so that each object voxel has an infinite distance and each background voxel, a zero distance. A forward mask is then swept over the volume, starting at the upper left corner of the first front slice, moving from left to right, from the top to the bottom, and from the front to the back (Figure 4). This scan yields the minimum distance of an object voxel to the boundaries in 3 directions: the left, the top and the front. Next, this distance is adjusted by considering the boundaries to the right, the bottom and the back sides. This involves moving a backward mask (Figure 4) starting from the bottom-right voxel of the last back slice in a way opposite to the movement of the forward mask (Borgefors, 1984).

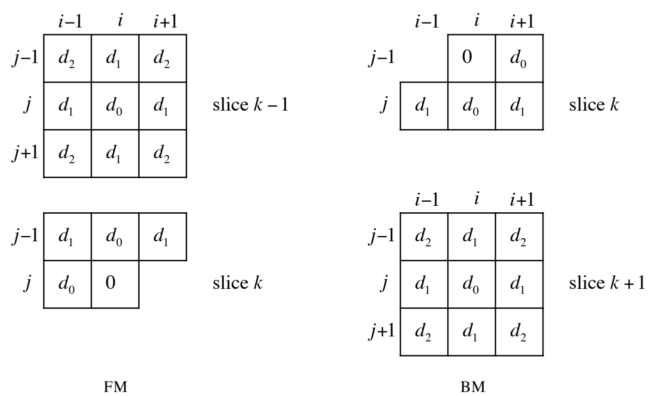

Figure 4. Forward mask: FM. Here $d = (d_0, d_1, d_2) = (3, 4, 5)$. For each mask entry, $\text{FM}_{[i',j',k']}$, the value d_i indicates the local distance to the 0 voxel, i.e., $\text{FM}_{[i,j,k]}$. Backward mask: BM.

3.4. Extraction of the Centerlines

The cluster graph can be shortened by removing as much as possible clusters while still keep the connectivity of the resulting vessel system. We use one path that starts at RP and ends at the largest SS coded local maximum cluster c_1 to illustrate the shortening procedure. Starting from c_1, a cluster is removable if it stands between c_1 and the cluster c_2 to which the smallest SS coded 26-connected neighbour of the center of the cluster c_1 belongs and if it is neither a merging cluster nor a branching cluster. At each node, at most 2 neighbouring nodes can be removed in order to keep the connectivity. This process iterates until no more clusters can be removed from the path and a shortest cluster graph is thus obtained. Figure 5 illustrates such an example of shortening procedure in 2-D.

The centerline of the vessel network can be obtained by replacing each cluster in the shortened cluster graph by a voxel that is farthest from the boundary, i.e., has a biggest BS code. Hence, one voxel-thick center adjusted line representation of the vessel system is obtained. The replacement of center voxel for the cluster may resulting in gaps. However, as the centeredness is guaranteed for both ends of the gap, so the gaps can be filled in by a linear interpolation. It is also possible to generate a shortest path that connects the two ends of the gap with one of them as the new RP (Zhou and Toga, 1999).

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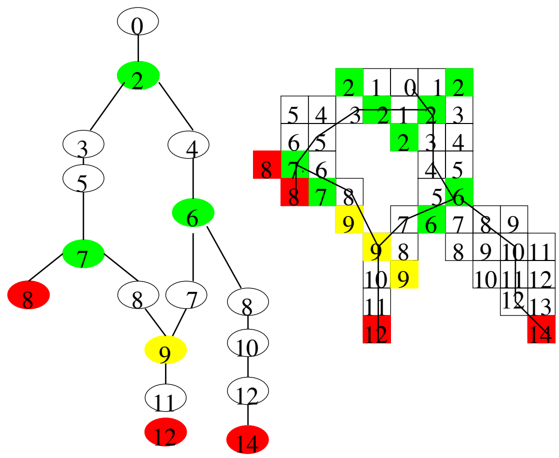


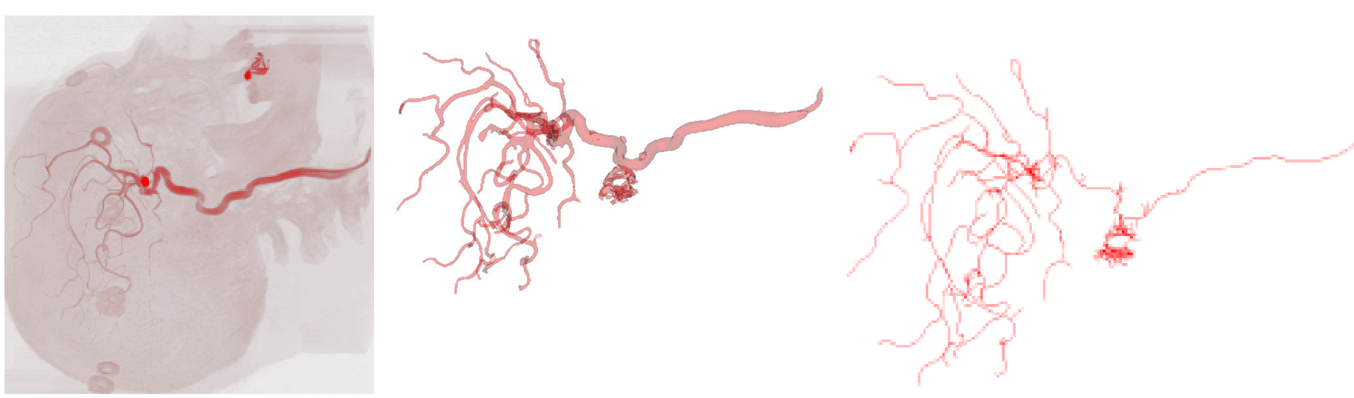
Figure 5. From the shortened directed graph (left) to the network of centerlines that superimpose on the planar shape. The conversion used is the same as in Figure 3.

The resulting centerlines can be arranged as a network of linked lists - one list per vessel branch/path. Each point on the centerlines is referred to by two integers (p, l), where p is the path/branch identifier and l is the point index within that branch.

4. RESULTS

4.1. An Example

The method described in Section 3 was first evaluated with synthesized image (not shown) and then applied to a real 3-D computed rotational angiography (CRA) image of size $360 \times 330 \times 420$, with a grid size of $0.54mm \times 0.54mm \times 0.54mm$. Figure 6a is its MIP display, Figure 6b is the surface rendering of the extracted vessel network, and Figure 6c reveals the centerline representation of the vessel system, which requires only 0.1% of the storage size occupied by the original volume image.



(a) (b) (c)

Figure 6. (a) MIP display (b) surface rendering and (c) the centerline drawing of a volume angiogram.

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4.2. Sensitivity to Boundary Noises and Thresholds

Reducing the low threshold and/or increasing the high threshold will result in some background tissues or bones being falsely extracted as part of the vessel system and thereby increases the thickness and length of the vessels. Boundary noise has a similar effect. They will not seriously affect the location of the centerline of the vessel network because clusters – not voxels – are used as the basic building elements. This has an integration effect.

4.3. Computational Complexity

To isolate the vessel system from the background tissues and bones, simultaneously obtain the SS code field and distribute the layers surrounding the RP into clusters requires one scan of all object background voxels that are the face neighbors of the boundary voxels. This leaves the other background voxels untouched. The corresponding computation cost of these operations is linear, in the order of the number of object voxels N_{object}, which is much smaller than N_{binary_volume}, which in turn is much smaller than the size of the original volume image. Two scans over the segmented binary image are needed to obtain the BS code field of the object. The cost of encoding the BS field is linear, in the order of N_{binary_volume}. The cost to convert the directed graph into line representation is also linear, in the order of N_{object}.

5. DISCUSSION

This paper describes an efficient method to extract a one-voxel-thick line representation of a vascular vessel system from the raw intensity data of volume angiograms. The line representation is center adjusted, hence, is a center-line representation of the vessel network. It is complete because all object voxels are contained in the directed graph representation. The information loss is kept to a minimum. This was verified by reconstructing the original vessel system from the line representation and from the BS code of each of its voxels. The topological information contained in the line representation increases accessibility and make a number of further processing steps possible (such as length). Our on-going research is concerned with the use of this representation to help a user navigate in the image using specialized graphic and haptics methods.

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