Pulmonary Arteries Segmentation and Feature Extraction through Slice Marching

Raphaël Sebbe, Bernard Gosselin, Emmanuel Coche, and Benoît Macq
Faculté Polytechnique de Mons, Laboratoire de Théorie des Circuits et Traitement du Signal
Bâtiment MULTITEL - Initialis, 1, Avenue Nicolas Copernic, 7000 Mons, Belgium
Phone: +32 (0)65 354742 Fax: +32 (0)65 354729
email: raphael.sebbe@tcts.fpms.ac.be

Abstract— **We propose a novel method, slice marching [1], for segmenting opacified vessels tree in 3D images (volume data), from multislice computed tomography (MSCT) scans. The method uses fast marching with freezing of boundaries to advance inside the vessel, slice per slice. Large scale features, such as vessel section and curvature, are evaluated for each slice. These features can then be used to influence the speed of propagation (in the sense of interface evolution theory), thus combining image data and anatomical properties for the segmentation task. As a by-product of the method, the extracted features can also be used for other purposes, for instance, vessels diagnosis.**

Keywords— **segmentation; pulmonary arteries; pulmonary embolism; fast marching; region growing; CT; vessels; emboli detection**

I. Introduction

A. Background

The recent progress achieved in X-ray CT (computed tomography) devices enables us to observe the human body and organs in a very precise manner, through submillimeter thick slices. This leads to a more accurate diagnostic at the price of increased work load for the radiologist. In that context, computer aided diagnosis (CAD) systems are needed.

Working on the design of tools for automatic emboli detection in pulmonary arteries, we have split the problem into two subproblems:

1. segment the pulmonary arteries (PA),
2. detect emboli by analysing the boundaries of the PA.

This paper focuses on the first topic.

The segmentation of pulmonary arteries is complex, mainly due to the fact that these anatomical structures have an elongated shape. Moreover, arteries present multiple contacts with pulmonary veins that could interfere with automatic delineation of arterial boundaries. Background noise, leading to irregular vessel surfaces, could also interfere with proper delineation of these anatomical landmarks.

B. Image Acquisition

A contrast medium is injected through the patient's vein. This is realized by the radiologist, which may tune injection parameters (rate, timings) for appropriate opacification of the PA. Then, PA interior appears as white (as well as a few other vessels) and the clot (embolus) as a darker, noisy spot. Figure 1 shows an example of an obvious pulmonary embolism.

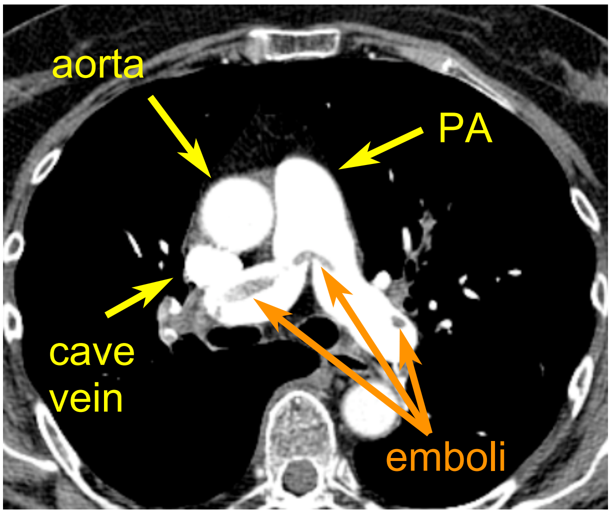

Fig. 1. One slice of CT volume. The clot appears as a dark spot inside the PA

C. State of the Art

Many methods have been presented for handling segmentation of elongated shapes. Kirbas et al. [10] did a classification of these methods according to the techniques that were used . Considering the kind of structures we are tracking and the type of modalities we use, region growing methods have shown a superior ability for the segmentation task.

Region growing methods, by definition, start from a

[1] named after its close relationship with fast marching and its ability to decompose vessels into slices

seed surface or point (either provided by the user or automatically generated by the machine) and make it grow until the entire structure is recovered.

Zahlten [1] has developed a wave propagation technique that reconstructs the bifurcation graph as it advances in the vessels. It consists in recursively marching through 3D neighbours of a seed voxel, taking into account image intensity (actually X-ray attenuation expressed as Hounsfield units) through thresholding. A bifurcation graph is established by looking at the connectivity of the wavefront. Bruijns [2] extended this method by considering a deeper wavefront (double waves) in order to minimize false bifurcation detection for irregular/noisy vessel surface. We note that this method has implementation burdens and although it makes the bifurcation process more accurate, it still presents bifurcation errors.

Masutani et al. [9] have developed a method that correctly handles branching and labelling of the arteries . They define the concept of *cluster*, which is a group of neighbouring voxels. This concept, although developed independently, is similar to our *slice* definition (section II-B).

Level set and fast marching methods, which are numerical schemes for solving interface evolution problems, have been developed by Sethian and successfully used for image segmentation [3]. They have been extended with *freezing* by Deschamps [6], to handle the peculiar case of elongated, tubular structures. We note that freezing is indeed required as, otherwise, under positive (non zero) propagation speed, the interface would go beyond vessel boundaries near the seed point by the time it reaches the end of the vessels.

In our method, we propose to use the concept of *slices of vessels*, which are groups of voxels close to each other in the sense of their computed fast marching solution. These slices can serve to compute anatomical features such as the vessel section, direction or curvature, which, in turn, can be used to influence the speed of the front. Analysing the connectivity of slices, we can reconstruct the hierarchical, branching structure of the vessels.

II. Principle

A. Interface Evolution Theory

We use a boundary value formulation of the problem of a propagating front(Sethian [3]): given an initial interface (curve in 2D, surface in 3D) and its speed of propagation along its normal (provided at every point), $F(\bar{X})$, we compute the solution of the Eikonal equation (1) at every voxel $\bar{X}$:

$$\left|\nabla T(\bar{X})\right| F(\bar{X}) = 1, \quad \text{with } T(\bar{X}) = 0 \text{ on the seed} \quad (1)$$

The solution $T(\bar{X})$ is the time when the front crosses the voxel $\bar{X}$. We note at this point that in the more general scheme defined by Sethian, the speed F may depend on interface characteristics (either local or global) as well as external properties (derived from the image). Sethian proposes two algorithms for solving that problem, the *fast marching* and the *level set* methods. Both methods correctly handle the shocks (discontinuity of the solution T) inherent to the solution of equation 1 in their numerical scheme. The fast marching method is computationally more efficient (about 1 iteration/voxel) than the level set but has the constraint that F should be strictly positive. The fast marching method recovers the entire domain by computing the solution $T(\bar{X})$ in order of increasing T, which makes it similar to region growing method in the way that it propagates from the seed.

B. Concept of Slice

If we suspend the computation of the solution when the arrival time $T(\bar{X})$ becomes higher than a given threshold T_{slice},

$$T(\bar{X}) > T_{slice} \quad \Rightarrow \quad \text{suspend} \quad (2)$$

and if we define our speed function $F(\bar{X})$ so that it is near unity inside the vessel, and noticing that time and distance are equivalent when speed is unity, we can tell that T_{slice} is the depth of the slice.

Next, by choosing a speed function $F(\bar{X})$ that is small enough outside the vessel, we can freeze the active front (denoted as *trial* in the *fast marching* algorithm [3]) by not considering voxels for which arrival time is bigger than a second threshold, T_{bound}:

$$T(\bar{X}_t) > T_{bound} \quad \Rightarrow \quad \text{remove } \bar{X}_t \text{ from trial set} \quad (3)$$

Note that another approach for freezing could be the one used by Deschamps et al. [6] where they compute the approximate solution for $F(\bar{X}) = 1$ along the usual one and compare both values to determine the stopping criterion.

We then iterate using a time threshold T_{slice} of the form:

$$T_{slice} = T_k = k\Delta T_{slice} \quad (4)$$

ΔT_{slice} being the depth of the slice, each time getting a new *slice*. We define a *slice* $\mathscr{S}$ as:

$$\mathscr{S}_k \triangleq \{\bar{X} \mid T_k <= T(\bar{X}) < T_{k+1}\} \quad (5)$$

where a temporal criterion is used to define spatial zones.

Features for these slices can be computed, such as the center of gravity $\bar{C}_k$ (6), as represented on figure 2, the section S_k (7), inter-slice direction D_k (6) and curvature κ_k (7) . These features can be re-injected in the process

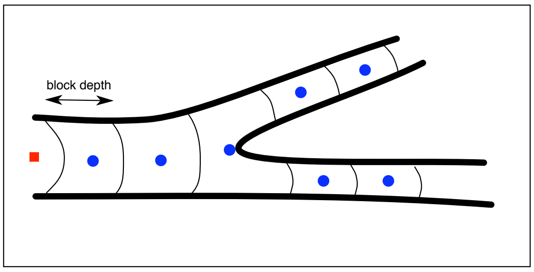

Fig. 2. The concept of *slices*. Seed voxel is represented as a red square, and successive centers of gravity as blue disks

through the speed function $F(\bar{X})$. This can be used for accelerating voxel traversal on the outside of a turning vessel to keep the front perpendicular to the vessel, for instance, in a way similar to the approach of Zahlten et al. [1].

$$\bar{C}_k = \frac{1}{N_k} \sum_{\bar{X}_i \in \mathscr{S}_k} \bar{X}_i \qquad \bar{D}_k = \bar{C}_{k+1} - \bar{C}_k \tag{6}$$

$$S_k = \frac{N_k}{T_{k+1} - T_k} \qquad \kappa_k = \left|\bar{D}_k - \bar{D}_{k-1}\right| \tag{7}$$

N_k is the number of voxels belonging to $\mathscr{S}_k$.

C. Speed Function F

The speed function, as said before, should be near one inside the vessel, and near zero outside. Moreover, in the *fast marching* method, the propagation speed is required to be strictly positive. Considering an input voxel density $I(\bar{X})$ between 0 and 1, we provide the corresponding speed by

$$F = \epsilon \qquad \text{if} \quad I(\bar{X}) < I_{th} \tag{8}$$

$$= I(\bar{X}) \qquad \text{otherwise} \tag{9}$$

The threshold I_{th} can be determined by analysing the density histogram and picking a value just below the opacified vessel peak. We note that the threshold I_{th} may be modified as we advance in the vessel to accomodate changes in opacification intensity.

We can further modulate the speed by considering slice-derived parameters (as noted at the end of section II-B).

D. Bifurcation Detection

As we iterate for recovering the entire arterial tree, we keep a hierarchical structure of the vessels. Voxels of slices of the same generation (same k) are checked for their mutual connectivity (connected component analysis). Unconnected groups of voxels define as many slices.

E. Handling Touching Vessels

Touching vessels are vessels that have contacts between them in the image (no intensity fall when moving from 1 vessel to its neighbour). They are of course physically separate but acquisition noise and reconstruction artifacts tend to merge them. This is illustrated on figure 3.

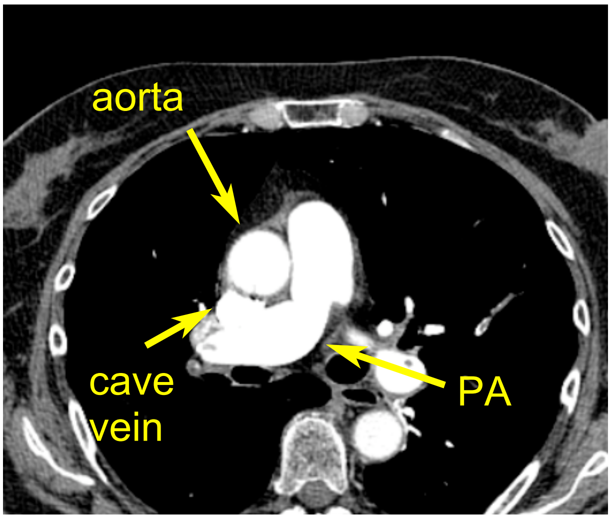

Fig. 3. Touching vessels: PA touch both the cave vein and the aorta

Region growing methods are obviously not aware of that and will simply take over the neighbouring vessels. To overcome that problem, we perform an opening (mathematical morphology). Once applied to the slice, we find the connected component that is in contact to the previous slice and mark other voxels as unaffected.

The opening is performed per slice. Alternatively, one could consider applying it to the entire image. The reason for doing it *per slice* is that we can vary the size of the structuring element according to the vessel section estimate. Indeed, using a constant size for the structuring element (kernel) is not acceptable as it would erase small vessels completely (large kernel size) or would have no effect on large vessels (small kernel size), as the PA structure is effectively of multi-scale nature.

We note that this method is successful for small contacts between vessels but fails otherwise. An extension for solving that problem is mentioned in section V.

F. Comparison with Masutani et al.

We note here the main differences between our method and Masutani et al. segmentation method [7][8][9]:

- the speed of propagation can be used to tune slice shapes (which may then lead to better features estimates),
- the solution of equation 1 is continuous, leading to continuous slice depth. Masutani's only considers discreet

slice depth (based on dilation).

The effect of the second point has not been investigated yet, but it is our belief that it may improve segmentation of small ramifications of the PA, as we use smaller slice depth.

III. Implementation

Our implementation of the method was realized in C and visualization with VTK/C++, requiring only a standard PC with appropriate visualization hardware. Taking into account that vessels are present in less than 5% of the volume data, we managed to design programming structures that allocate memory resources only where needed by the method (figure 4). Large amounts of memory are saved, making it possible to tackle even bigger data sets on PC-class workstations, as typically used in many radiology departments.

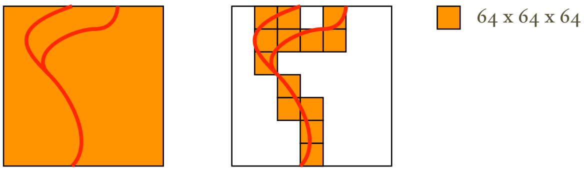

Fig. 4. Allocating segmentation structures only where needed

IV. Experimental details

We have tested this method on images obtained from MSCT in patients addressed for suspicion of pulmonary embolism (PE) (clot within a pulmonary artery). This last generation of CT (MX 8000, IDT, Philips, Cleveland, OH) is able to acquire 38 images per second and generate more than 400 images. CT examinations were performed using the following parameters: 16 X 0.75 mm slice thickness, 0.6 mm interval of reconstruction, 120 Kv, 150 mAs, pitch of 0.95, matrix size: 512 x 512, 12 bits per voxel. 100 mL of non ionic contrast medium was injected through an antecubital vein at a rate of 4 mL/sec with variable delay in order to opacify the pulmonary arteries. Figure 5 shows a 2D slice of the resulting segmentation (3D) through colour information superposed to the original image data. Successive slices are drawn in green, separated from each other by yellow lines. Frozen voxels (vessel boundary) are painted in blue.

No mathematical morphology opening is made on figure 6, contrary to figure 5. We can see that the region flows inside the aorta through its contact with the PA. Because the contact is only a few voxels in size, it is avoided by opening. However, it still fails at the cave vein/aorta contact.

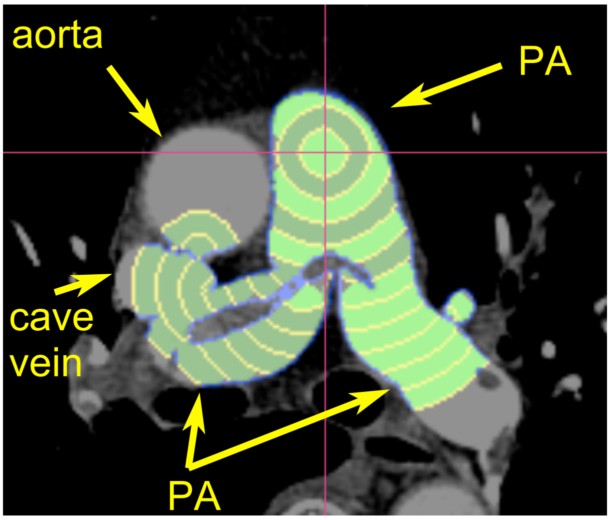

Fig. 5. Result of the segmentation process, vessel boundary appears in blue, slice boundaries in yellow.

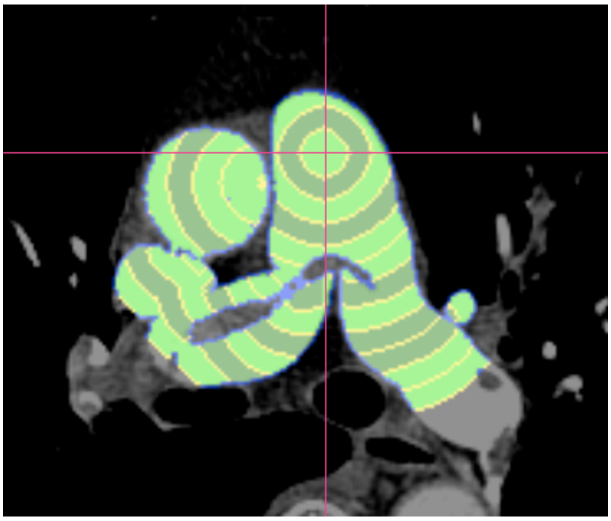

Fig. 6. Same parameters, but mathematical morphology is not performed

V. Discussion

This method shows encouraging results. It is less sensitive to irregular vessel boundaries than wavefront-based methods because more voxels participate in the bifurcation detection process. Moreover, it provides useful anatomical information as a by-product such as the section of vessels, their curvature, etc. that can be used by the physician for diagnosis purpose.

Still, problems remain. Segmentation fails when acquisition resolution/noise tends to merge adjacent but physically separate vessels. Our approach for handling touching vessels, as expressed in section II-E, is definitely not sufficient. It seems difficult to handle that problem without a priori information, as the ”touching” area can actually be bigger than the section of the vessels.

A medical solution is not practical to solve this problem. Indeed, varying the timing and the rate of contrast medium injection to opacify the PA alone is not practically reproducible. We are therefore investigating the use of an a priori anatomical model, such as vessels skeleton expressed as parametric 3D curves, that could be co-registered to the image space as we advance into the vessels slice per slice. Kitasaka et al. [4] use a B-Spline model for that purpose. Such a model would permit rebuilding the missing vessel boundaries (figure 7).

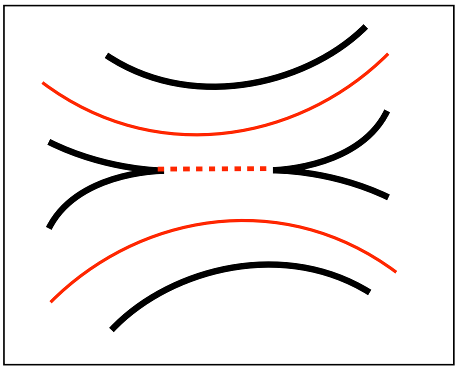

Fig. 7. Co-registrating the anatomical model (red) with the image to rebuild missing vessel boundaries (dotted red)

Another future work is to study the influence of the slice depth, considering that the method has to deal with vessels of various sizes (vessel section decreases as you move farther from the heart).

Acknowledgements

The fast marching algorithm used in this method has been collaboratively developed by Raphaël Sebbe, FPMs/TCTS[2] and Eduardo Romero, UCL/TELE[3].

This project is supported by the Région wallonne, Belgium, and the European Social Funds.

References

[1] C. Zahlten, H. Juergens, and H.-O. Peitgen. Reconstruction of branching blood vessels from ct-data. *Proceedings of the Eurographics Workshop on Visualization in Scientific Computing, Rostock*, pages 41–52, June 1994.

[2] J. Bruijns. Fully-automatic branch labelling of voxel vessel structures. *Proceedings of VMV 2001, Stuttgart*, Nov. 2001.

[3] J. A. Sethian. *Level Set Methods and Fast Marching Methods*. Cambridge University Press, 1999.

[4] Takayuki Kitasaka, Kensaku Mori, Jun ichi Hasegawa, Jun ichiro Toriwaki, and Kazuhiro Katada. Automatic extraction of aorta and pulmonary artery in mediastinum from 3d chest x-ray ct images without contrast medium. *Proceedings of SPIE*, 4684:1496–1507, 2002.

[5] Olivier Cuisenaire. *Distance Transformations: Fast Algorithms and Applications to Medical Image Processing*. PhD thesis, Université catholique de Louvain, October 1999.

[6] T. Deschamps and L. D. Cohen. Fast extraction of tubular and tree 3d surfaces with front propagation methods. In *16th IEEE International Conference on Pattern Recognition (ICPR'02)*, Quebec, Canada, Aug. 2002.

[7] Y. Masutani, T. Schiemann, and K. H. Hoehne. Vascular shape segmentation and structure extraction using a shape-based region-growing. *Proceedings of MICCAI'98*, pages 1242–1249, 1998.

[8] Y. Masutani, H. MacMahon, and K. Doi. Computer-assisted detection of pulmonary embolism. *Proceedings of SPIE (Medical Imaging 2000)*, 3979:944–950, 2000.

[9] Y. Masutani, H. MacMahon, and K. Doi. Computerized detection of pulmonary embolism in spiral ct angiography based on volumetric image analysis. *IEEE Transactions on Medical Imaging*, 21(12):1517– 1523, December 2002.

[10] C. Kirbas and F. K. H. Quek. A review of vessel extraction techniques. Technical report, VISLab, Wright State University, Dayton, Ohio, Nov. 2002.

[11] M. Sonka and J. M. Fitzpatrick, editors. *Handbook of Medical Imaging*. SPIE Press, 2000.

[2] Faculté Polytechnique de Mons, Laboratoire de Théorie des Circuits et Traitement du Signal

[3] Université catholique de Louvain, Communications and Remote Sensing Laboratory