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To cite this version:
Marie-Paule Garcia, Jérôme Velut, Dominique Boulmier, Christophe Leclerc, Mireille Garreau, et al.. Coronary Vein Extraction in MSCT Volumes Using Minimum Cost Path and Geometrical Moments. IEEE Journal of Biomedical and Health Informatics, Institute of Electrical and Electronics Engineers, 2013, pp.336 - 345. <10.1109/JBHI.2013.2245420>. <inserm-00874947>

HAL Id: inserm-00874947
https://www.hal.inserm.fr/inserm-00874947
Submitted on 21 Nov 2013

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Coronary Vein Extraction in MSCT Volumes using Minimum Cost Path and Geometrical Moments

M.-P. Garcia, J. Velut, D. Boulmier, C. Leclercq, M. Garreau, P. Haigron, C. Toumoulin

Abstract—This work deals with the extraction of patient-specific coronary venous anatomy in pre-operative Multi-Slice Computed Tomography (MSCT) volumes. A hybrid approach has been specifically designed for low-contrast vascular structure detection. It makes use of a minimum cost path technique with a Fast-Marching front propagation to extract the vessel centerline. A second procedure was applied to refine the position of the path and estimate the local radius along the vessel. This was achieved with an iterative multiscale algorithm based on geometrical moments. Parameter tuning was performed using a dedicated numerical phantom, then the algorithm was applied to extract the coronary venous system. Results are provided on three MSCT volume sequences acquired for patients selected for a Cardiac Resynchronisation Therapy (CRT) procedure. A visibility study was carried out by a medical expert who labelled venous segments on a set of eighteen volumes. A comparison with two other Fast-Marching techniques and a geometrical moment based tracking method is also reported.

Index Terms—Coronary veins, MSCT, 3D vascular extraction, Minimum cost path, Fast Marching, Geometrical moments

I. INTRODUCTION

Cardiac resynchronization therapy (CRT) is assessed as an efficient therapeutic approach for patients who suffer from severe heart failure, sinus rhythm and ventricular conduction delay [1]. The procedure consists in pacing simultaneously or with a small delay, both the right ventricle (RV) and the left ventricle (LV). Daubert et al. proposed a totally transvenous approach [2] using three pacing leads. Two are respectively positioned in the right atrium ($l_3$) and the RV ($l_2$) through the vena cava while the third one ($l_1$) is inserted through the coronary sinus into a venous branch that runs along the free wall of the left ventricle (see Fig. 1). The major issue is the placement of the LV lead. Indeed, the implantation of the pacing devices is currently 2D venous X-Ray coronarography guided and the implant success rate is limited to 85 – 92% [3].

The main reasons of failure are the difficulty of accessing the candidate veins, incorrect or suboptimal pacing site selection and possible electrode displacements, as well as the risk of dissecting the coronary sinus. Thus, an adequate planning is needed to improve and secure the implant procedure. Our work deals with the description of patient-specific coronary venous anatomy to define pre-operatively the target vein, plan the best path to reach it and confirm its accessibility.

The study is carried out using contrast-enhanced Mutli-Slice Computed Tomography (MSCT) data. This modality is considered as a reliable technique to depict the cardiac venous system [4]. Nevertheless, MSCT scans are tailored for optimal visualization of the coronary arteries. Indeed, the dye product passes first through the coronary arteries before being gathered by the coronary venous tree, which lead to suboptimal enhancement of the coronary veins, especially of second and third degree side branches having a small diameter. More generally, the dye product appears diluted when reaching the venous network, resulting in a weak contrast and variable appearance along the vessels with hypodense zones and blurred contours. Another difficulty relates to the close proximity of structures having similar contrast, i.e., cavities and coronary arteries. In addition, the venous anatomy tends to be highly variable from one patient to another [5], i.e., number of branches, location and length. Thus, a primary goal towards planning is to provide an efficient method for extracting coronary veins in MSCT volumes.

A lot of work has been devoted to the extraction of vascular networks, but a large majority concerns coronary arteries in Magnetic Resonance Imaging (MRI) and MSCT (see [6], [7], [8] for the main surveys). The methods can be categorized in different ways (the application [6], the mathematical framework [7] or the extraction scheme [8]) according to the issue to be highlighted. If we consider the extraction scheme, three main families are reported in the literature: region-growing-based approaches [9], active contour family [10], [11]...
and centerline extraction methods. The latter gathers direct centerline tracking [12], [13], model-based [14] and minimum cost path techniques [15], [16], [17], [18]. The performances of these methods vary according to multiple factors: the presence of severe pathologies (acute stenosis, large aneurysm), local complexity of vascular networks (complicated branching situations) and the surrounding tissue environment. A first standardized evaluation methodology and reference database has been set up, within the 2008 MICCAI challenge, to quantitatively evaluate the coronary artery centerline extraction algorithms [19]. This evaluation does not include coronary venous structures.

The method, which is described here, aims to take into account the presence of nearby contrasted artery vessels and strong contrast changes along the veins. It makes use of a two-stage process. A minimal path technique is first applied to extract vein centerlines [20]. A new cost function has been designed that combines the multiscale Frangi’s filter response with the direction of the front with respect to the vessel orientation in order to constrain its propagation direction and better handle contrast inhomogeneity and weakness inside the veins as the presence of nearby blood vessels. The extracted path does not always correspond to the vessel central axis. We applied then an iterative multiscale recentering process to shift it towards the central axis position and estimate the local radius along the vascular branch. This stage was carried out using geometrical moments under the hypothesis that the vessel can be locally modeled by a cylinder. Section II describes this algorithm. Parameter tuning was carried out on a numerical phantom. The set of experiments are described in Section III. Section IV finally provides some preliminary results on the coronary vein extraction with a qualitative evaluation and a comparison with three other methods dedicated to centerline extraction.

II. METHOD

This section introduces our vessel extraction algorithm designed for coronary veins into MSCT data sets.

A. Minimum Cost Path Computation

Minimum cost path techniques aim to find a curve from a source point \( P_0 \) to a final point \( P_f \) that minimizes an energy functional that is of the form:

\[
E(\gamma) = \int_\gamma \Lambda(\gamma(s))ds
\]

where \( \Lambda \) is an image-based measure and \( \gamma \) is the path joining the two points. The value \( \Lambda \) is given by a cost function that is defined to provide low values on the desired features (i.e. contour or centerline), the objective being to find a path along which the integral of \( \Lambda \) is minimal. The solution of this minimization problem goes through the computation of an energy map \( U(P) \) such as:

\[
U(P) = \inf_{P_0, P} \inf_{\gamma \in \gamma(P_0, P)} \int_\gamma \Lambda(\gamma(s))ds
\]

where \( \gamma(P_0, P) \) is the set of all possible paths going from a source point \( P_0 \) to a given point \( P \). To ensure that the map \( U(P) \) has got only one minimum, we assumed that \( \Lambda > 0 \).

Then the minimum cost path can be retrieved by applying a gradient descent algorithm on the map \( U \) from \( P_0 \) to \( P_f \).

1) Fast Marching Algorithm: The computation of the energy map \( U(P) \) is solved considering a Hamiltonian approach. We aim at computing the travel time \( U \) that satisfies the Eikonal equation:

\[
\| \nabla U \| = \Lambda
\]

The Fast Marching algorithm [11] is an efficient way to solve the previous equation. It consists in a front which starts its propagation from the point \( P_0 \) and progresses over the image towards areas presenting low costs. Each time the front passes over the point \( P_{x,y,z} \), its travel time \( U_{x,y,z} \) is computed corresponding to the cumulative travel cost of the minimum cost path from \( P_0 \) to \( P_{x,y,z} \). In our approach, to deal with low-contrast environment, we constrained the front progression towards a privileged direction. We want the front not to propagate beyond vessel boundaries. Therefore, the computation of the energy map \( U \) was restricted to a region assimilated to a narrow band around the front to fit the following constraints (see Fig. 2): (1) the direction of propagation was restricted into an area in the estimated local direction, (2) and into vessel regions, given by Frangi’s filter response [21], (3) a freezing distance was applied to freeze the points located at the tail of the propagating front and avoid the front flowing over the boundaries [22], [17]. In this implementation, the bifurcations of the coronary venous tree are not handled.

The algorithm is introduced in Table I and is referred as method (VM + OC) later on.

2) Cost function definition: The front propagation is guided by the following cost function which considers the reciprocal of the normalized vessels measure \( F_{x,y,z} \) weighted by

![Fig. 2. The restricted and oriented front propagation and its combination with the Freezing procedure in 2D space. The front is only allowed to propagate into a restricted area defined by the angular value \( r \). The angle \( \theta \) is the angle between the direction of the normal to the front \( n \) at position \((x, y, z)\) (red or green arrow) and the local orientation \( \Gamma \) (black arrow).](image)
and:

\[ F_{x,y,z} = \begin{cases} 0, & \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ \left(1 - e^{\frac{-R^2}{2\sigma^2}}\right) e^{\frac{-R^2}{2\sigma^2}} \left(1 - e^{\frac{-S^2}{2\sigma^2}}\right) & \text{otherwise} \end{cases} \]

with \( F_{x,y,z,\sigma} \) at a scale \( \sigma \) given by:

\[ F_{x,y,z} = \max_{\sigma_{\min} \leq \sigma \leq \sigma_{\max}} F(x, y, z, \sigma) \]

\[ with \rho = \sin(\theta) \]

\( F_{x,y,z} \) corresponds to the optimal response given by the vesselness function \( F(x, y, z, \sigma) \) at the scale \( \sigma \) that copes with the vessel radius:

\[ F_{x,y,z} = \frac{1}{\sigma_{\min}} \cdot \rho^2 \quad \text{if } \theta < \pi \text{ and } F_{x,y,z} > s \]

\[ C, \] \quad \text{otherwise} \]

Orientation information \( \rho \):

\[ \lambda_{x,y,z} = \left\{ \begin{array}{ll} \frac{1}{\sigma_{\min}} \cdot \rho^2 & \text{if } \theta < \pi \text{ and } F_{x,y,z} > s \\ C, & \text{otherwise} \end{array} \right. \]

\[ with \rho = \sin(\theta) \]

Interactive Initialization: The user points a seed point \( P_0 \) and a final point \( P_F \) in the branch of interest and gives the initial propagation direction \( \vec{v} \).

Fast Marching Front Propagation:

1. **Initialization:**
   - Tag the point \( P_0 \) as **Alive** and set \( U(P_0) := 0 \);
   - Tag **Far**, all other points \( P \) and set \( U(P) := \infty \).
   - Tag **Trial**, each neighbour \( P_{x,y,z} \) of the point \( P_0 \) for which the direction of the normal to the front is close to the initial propagation direction \( \vec{v} \) and set \( U(P_{x,y,z}) := 1/F_{x,y,z} \).

2. While \( P_F \) is not reached and the **Trial** set is not empty:
   - Find \( P_{\text{min}} \), the **Trial** point with the lowest \( U \)-value;
   - Tag \( P_{\text{min}} \) as **Alive**;
   - For each neighbour point \( P_{x,y,z} \) of \( P_{\text{min}} \), tagged as **Far**: Compute the cost \( \lambda_{x,y,z} \) (4); Compute \( U(P_{x,y,z}) \) by solving the Eikonal equation (3); \( P_{x,y,z} \) is a **Far** point: Add it to the **Trial** set; \( P_{x,y,z} \) is a **Trial** point: Update \( U(P_{x,y,z}) \) if the new value is smaller.
   - Freeze **Trial** points whose distance to the front ‘head’ is greater than the freezing distance \( d \) (Freezing process).

Path Extraction: Compute a path from \( P_0 \) to \( P_F \) by gradient descent on the travel time map \( U \).

### Algorithm Minimum Cost Path Computation

**Notations:**
- **Alive** Set: Nodes reached by the front whose \( U \)-value will not be changed;
- **Trial** Set: Nodes having at least one Alive neighbour and their \( U \)-value already estimated;
- **Far** Set: Nodes whose \( U \)-value has never been computed;
- \( F_{x,y,z} \) is the vesselness measure of the point \( P_{x,y,z} \).

**Fast Marching Front Propagation:**

1. **Initialization:**
   - Tag the point \( P_0 \) as **Alive** and set \( U(P_0) := 0 \);
   - Tag **Far**, all other points \( P \) and set \( U(P) := \infty \);
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   - Freeze **Trial** points whose distance to the front ‘head’ is greater than the freezing distance \( d \) (Freezing process).

**Path Extraction:** Compute a path from \( P_0 \) to \( P_F \) by gradient descent on the travel time map \( U \).

**TABLE I**

**Minimum Cost Path Computation Using a Fast-Marching Front Propagation.**

4) **Path extraction:** Once the final point \( P_F \) is reached by the front, the path from \( P_0 \) to \( P_F \) is computed using the travel time map \( U \). A gradient descent is applied on the map \( U \) from the point \( P_F \). Each new point \( P_i \) of the path is the one amongst the neighbours of the point \( P_{i-1} \) presenting the smallest difference between \( U_i \) and \( U_{i-1} \).

**B. Path Centering and Radius Estimation**

This second procedure aims at refining the path extracted at the previous stage (see II-A) and estimating the local radius at each centred position (see Fig. 3 for an overview of the approach). Local vessel features can be estimated analytically from geometrical moments computed in a spherical window centered on the vessel central axis and that fit the vessel radius. To achieve this goal, we use an iterative multiscale algorithm [24] which alternatively moves the sphere towards its center of gravity, estimates the vessel radius \( r \) and adjust the size of the sphere \( R \) until convergence of the sphere radius to the vessel size. The center of gravity and the local vessel radius was estimated using the first order moments (analytical expressions can be found in [24]).

This algorithm is described in Table II. The extracted path from \( P_0 \) to \( P_F \) consists of successive neighbouring points of the image. The path is subsampled to avoid the spherical window (in the iterative multiscale algorithm) converging towards identical positions for several neighbouring points.
For each point of the subsampled path $P_i$, given an initial spherical window size $R_i^0$ and a priori estimation of the mean local vessel and background intensities, $I_{v,i-1}$ and $I_{b,i-1}$ respectively, geometrical moments allow estimating the local center $P_i^0$ and radius $r_i$ (see Fig. 3). For the first position $P_0$, the user has to specify the initial size of the spherical window $R_0^0$, $I_{v0}$ and $I_{b0}$. Then, for any point $P_i$, the initial size of the spherical window $R_i^0$ is set with respect to the previous local radius $r_{i-1}$, $I_v$ and $I_b$ are estimated using an expectation maximization (EM) algorithm. A histogram computed on an extended region (including the vessel and the background) around the point $P_{i-1}$ is modeled by two Gaussians. The background intensity $I_b$ (respectively the vessel intensity $I_v$) is considered as the mean of the Gaussian corresponding to the lowest intensities (respectively the highest).

**III. Parameter Tuning**

Several parameters of the algorithm must be tuned: the vesselness filter parameters ($\alpha$, $\beta$ and $\gamma$) and the thresholds controlling the orientation constraint of the front ($\mu$, $r$ and the *Freezing* distance $d$). Experiments were performed on synthetic data to study the influence of these parameters. The following tests were executed on a 1.6 GHz Xeon PC, 2 GB RAM. The algorithms were implemented in C++.

**A. Numerical Phantom Description**

An isotropic synthetic data set of size $110 \times 90 \times 90$ voxels has been designed from the VTK library which represents a part of the coronary venous tree with typical nearby structures such as cardiac cavities and coronary arteries. The contrast features of coronary veins in data sets are simulated to have the same density distribution as in real data. From here on we will refer to this data set as ‘phantom’. Fig. 4 depicts a surface representation of the phantom. For geometry simplicity, the coronary venous tree model is based on coronary vein centerlines extracted from real data (Coronary Sinus (CS), Great Cardiac Vein (GCV), Antero Lateral Vein (ALV)). This model that includes a bifurcation, consists of a tortuous tubular structure of length similar to real veins (72, 8 mm). The main vessel radius varies from 6 to 1 voxels ($1voxel \approx 0.4mm$), and the second branch from the bifurcation has a constant radius of 1 voxel. Furthermore, a spherical structure represents a nearby cardiac cavity and cylinders of constant radius (4 voxels) represent crossing coronary artery segments (typical coronary radius varies from 1 to 4, 5 mm).

A curvilinear reconstruction along the main vessel axis is shown in Fig. 5(a) to visualize the intensity grey value distribution. As regards the densities laying inside the tube, difficulties due to the dye product have been considered. A succession of hypo-, hyper- and iso-dense areas was set in the range $[100 - 300]$ Hounsfield Units (HU). The sphere and cylinders density was set to 250 HU. As regards background density, since coronary veins are directly in contact with the adipose epicardic tissue, the value was set to -80 HU (mean density of adipose epicardic tissue on Hounsfield scale). The sphere and cylinders density was set to 250 HU. As regards background density, since coronary veins are directly in contact with the adipose epicardic tissue, the value was set to -80 HU (mean density of adipose epicardic tissue on Hounsfield scale).

**ALGORITHM Path Centering and Radius Estimation**

Notations:
- $R_i^k$ is the spherical window size centered on the point $P_i$ at the iteration $k$ of the iterative multiscale procedure;
- $r_i$, $I_{v,i}$, $I_{b,i}$ are respectively the vessel radius, the mean vessel intensity and the mean background intensity at the point $P_i$.

**Interactive Initialization:**
- Set the values $R_0^0$, $I_{v0}$ and $I_{b0}$;
- Subsample the path from $P_0$ to $P_F$.

**Iterative Multiscale Procedure:**
- for each point $P_i$ of the subsampled path:
  - Set $k = 0$;
  - Center the spherical window of radius $R_i^0$ on the point $P_i$;
  - do:
    - $k := k + 1$;
    - Move the center of the spherical window towards its center of gravity (use the centered geometric moments $\mu_{1,0,0}, \mu_{0,1,0}, \mu_{0,0,1}$) [24];
    - Compute the radius $r_i := f(R_i^k, I_{v,i-1}, I_{b,i-1}, \mu_{0,0,0})$ [24];
    - Adjust the spherical window size $R_i^k := f(r_i)$;
  - $P'_i$ is the corrected position on the central axis, corresponding to the spherical window center;
  - $R_{i+1}^k = f(r_i)$;
  - Estimate $I_{v,i}$ and $I_{b,i}$ using an Expectation Maximization algorithm.

**TABLE II**

<table>
<thead>
<tr>
<th>Path Centering and Radius Estimation using Geometrical Moments.</th>
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</thead>
<tbody>
<tr>
<td>$I_{v,i}$ and $I_{b,i}$ are available for testing. Fig. 5 depicts the intensity distribution for the six configurations.</td>
</tr>
</tbody>
</table>
with varying values of \( \sigma \) of the phantom (the parameter \( \sigma \) has a strong impact on it. Furthermore, the background noise suppression term \( \sigma \) whereas the background noise. A spherical structure representing a cardiac cavity and cylinders of constant radius (4 voxels) representing crossing coronary artery segments.

Fig. 4. Surface rendering of the synthetic data set under three different views (a)-(c): A tortuous tubular structure with a bifurcation representing a part of the coronary venous tree and exhibiting a radius varying from 1 to 6 voxels, a spherical structure representing a cardiac cavity and cylinders of constant radius (4 voxels) representing crossing coronary artery segments.

\( \sigma = 40 \) \( \sigma = 50 \)

Fig. 5. Curvilinear reconstruction along the main vessel axis of the model for the six configurations of the numerical phantom with \( \sigma_{\text{noise}} \) varying from 0 to 50: Succession of hypo-, hyper- and iso-dense areas in the range [100–300] Hounsfield Units (HU).

B. Vessellness Filter Parameters

Frangi’s filter parameters are \( \alpha \), \( \beta \) and \( \gamma \). Olabarriaga et al. [25] evaluated the previous parameters effect on coronary arteries axis enhancement from CT. They demonstrated the quasi insensitivity of the parameters \( \alpha \) and \( \beta \) on filter response, whereas the background noise suppression term \( \gamma \) has a strong impact on it. Furthermore, \( \gamma \) relies on the grey-value distribution present in the image [21]. We set \( \alpha \) and \( \beta \) both to 0.5 as in Frangi’s work [21] and performed series of test on the parameter \( \gamma \).

We applied the vessellness filter for a fixed scale \( \sigma = 4 \), with varying values of \( \gamma \), on each of the six configurations of the phantom (\( \sigma_{\text{noise}} = [0, 10, 20, 30, 40, 50] \)). In order to only study the influence of the parameter \( \gamma \), the tubular structure radius was set to a constant value similar to \( \sigma \) (4 voxels). Fig. 6 displays the mean vessellness measure (along the vessel) at different distances to center [0–5 voxels] for \( \gamma = [0.1, 1, 50, 100, 200, 300, 400] \) and for \( \sigma_{\text{noise}} = 50 \). Similar curves were obtained for the other values of \( \sigma_{\text{noise}} \), e.g., for \( \gamma = 50 \) at position 0, the mean vesselness measure varies from 0.451 to 0.456. Indeed, the different noisy data are based on the same noise-free data and the contrast with the background along the vessel trajectory is similar. Thus, we can say that the Frangi’s filter is very successful in removing the background noise.

We are looking for values of \( \gamma \) which yield high response close to axis (position 0) and an important slope between axis and contours (position 4). This is the case for \( \gamma \in [0.1–50] \) (plots superimposed in the figure). We finally chose \( \alpha = 0.5 \), \( \beta = 0.5 \) and \( \gamma = 50 \) for the following part.

C. Orientation Constraint Parameters

The second experiment consists in studying the influence of the parameters controlling the orientation constraint of the Fast-Marching front propagation i.e., \( \mu \), \( r \) and the Freezing distance \( d \). We applied our minimum cost path algorithm with the Fast-Marching front propagation (see II-A) to evaluate the impact of each parameter on our six configurations of the phantom (noise and noise free configurations). We made the parameter \( \mu \) vary within the interval [0.5–0.9] with a step of 0.1, \( r \) within [65–90] degrees with a step of 5 and the Freezing distance \( d \) within [6–12] with a step of 2. For each combination of these parameters, an Overlap score OV was computed to evaluate the extraction ability of the algorithm. This metric measures a point-to-point correspondence between the phantom centerline (ground truth) and the extracted centerline and provides a score between 0 and 1 (more details about the OV metric computation can be found in [19]). More the extracted centerline follows the phantom centerline, closer to 1 the score is. High OV scores (0.76–0.90) were obtained for combinations of \( \mu \), \( r \) and \( d \) respectively lying in the range
[0.7 – 0.75], [80 – 90] and [6 – 12]. The Freezing distance $d$ was not found to be a sensitive parameter. Indeed, the cost function guides the front propagation whereas the Freezing procedure aims at blocking the propagation at the front tail beyond a given distance. So based on these results, we chose $\mu = 0.75$ et $r = 80$ degrees and for the freezing distance, we applied a value close to the vessel radius.

IV. EVALUATION AND RESULTS ON VENOUS DATA SETS

A. MSCT DATA Description

Experiments have been carried out on three MSCT sequences of patients candidates to CRT. Imaging was performed with a General Electric LightSpeed VCT 64-slice Scanner. The same protocol was used for all the acquisitions, that is a contrast agent injection in the coronary tree and a prolonged scan delay compared to coronary imaging in cardiac MSCT. Each sequence included 20 volumes reconstructed from slices acquired every 5% of the R-R interval from the cardiac cycle. There are approximately 200 slices per volume, with $512 \times 512$ pixels per slice. The resolution is about $0.4 \times 0.4 mm^2$ per pixel. Since the interslice space is higher than the pixel size, a preliminary interpolation was performed to make the data sets isotropic.

B. Coronary Vein Visibility

As explained in the introduction, scanning protocols are tailored for optimal visualization of the coronary arteries. As a consequence, the coronary venous system exhibits a weak contrast is barely contrasted, vascular branches are located within a noisy multi-object environment and their appearance varies along the tree and over time. In addition, artifacts are present in some volumes due to reconstruction problems. They can be either caused by an irregular heart rate or by too fast motions of structures related to the rotation speed of the acquisition system. These artifacts mainly occur in early systolic and end-diastolic phases, and can affect 50% of the volumes of the sequence. Motion artifacts induce blurring effects and a splitting or duplication of vessels, making their extraction difficult, even impossible, in some cases.

Thus, we asked a medical expert (who is an interventional cardiologist) to qualify the venous branches for each volume of the considered sequences, according to their quality in terms of contrast or visibility and provide for each, their name and their location. He was able to only classify vessels in volumes ranging from 45% to 85% of the R-R interval from the cardiac cycle which approximately corresponds to the diastolic phase (its duration varies from patient to patient). He labelled thus the coronary venous branches on eighteen volumes as well as poorly contrasted in other volumes. The Coronary Sinus (CS) more often exhibits homogeneous high density with strong edges such as in Fig. 7(a) and 7(b). In case of good visibility (Fig. 7(c) and 7(d)) and medium visibility (Fig. 7(e) and 7(f)), the contrast filling is inhomogeneous with hypodense zones, attachment of nearby structures and blurred contours. Finally, in Fig. 7(c) and 7(d) we can observe low visible vessels with similar density to that of adjacent tissues.

The Coronary Sinus (CS) is generally highly visible. The Middle Cardiac Vein (MCV) may be well visible in some volumes as well as poorly contrasted in other volumes. The Posterior (PV) and Postero-Lateral (PLV) Veins more often exhibit medium or low visibility, with a few cases of good visibility. The Great Vein (GV) is mainly visible in most cases. Finally, the Antero (AV) and Antero-Lateral (ALV) Veins tend to be poorly visible. Those degrees of visibility are also correlated with vessel caliber (measures of the CS and its

<table>
<thead>
<tr>
<th>Vessel Visibility</th>
<th>++</th>
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<tbody>
<tr>
<td>Coronary Sinus (CS)</td>
<td>11</td>
<td>11</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>Middle Cardiac Vein (MCV)</td>
<td>7</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Posterior or Postero-Lateral Vein (PV/PLV)</td>
<td>2</td>
<td>4</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Great Cardiac Vein (GCV)</td>
<td>/</td>
<td>2</td>
<td>11</td>
<td>5</td>
</tr>
<tr>
<td>Antero or Antero-Lateral Vein (AV/ALV)</td>
<td>/</td>
<td>2</td>
<td>7</td>
<td>10</td>
</tr>
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TABLE III

PHYSICIAN EXPERTISE: CLASSIFICATION OF 114 CORONARY VEINS ACCORDING TO THEIR NAME AND VISIBILITY INTO THE EIGHTEEN MSCT VOLUMES. THESE VOLUMES ARE THOSE WHICH ARE NOT POLLUTED WITH MOTION ARTIFACTS OVER THE SET OF THE THREE SEQUENCES. EACH COLUMN DISPLAYS THE NUMBER OF SEGMENTS IN EACH CATEGORY (FROM HIGH TO LOW VISIBILITY)
tributaries can be found in [5]). Indeed, the CS exhibits a big diameter along its trajectory, and becomes smaller to form the Great Vein. Thinner calibers are observed for the Antero and Antero-Lateral Veins.

C. Extraction Results

In order to stimulate the left ventricle, the target vein is ideally located on the lateral wall. If any ALV cannot be reached by the cardiologist, the second choice of implantation is a PV or the MCV and the GV at last. In the context of interventional planning, it is of interest to visualize in 3D space the possible implantation paths (see Fig. 8), but also to observe accurately the extracted branches with their caliber information and the nearby structures on curvilinear reconstructions (see Fig. 9).

We applied thus the algorithm on the real data sets, using the parameters designed in section III: $\alpha = 0.5$, $\beta = 0.5$, $\gamma = 50$ for Frangi’s filter and $\mu = 0.75$, $r = 80$ degrees and the freezing distance $d = 12$ for the Fast-Marching front propagation. Frangi’s filter was applied at different scales in order to cope with vessels of different calibers. Since the coronary venous tree exhibits highly different diameters, we made the scales vary from 1 to 4. Limiting the highest scale to 4, prevented the filter from yielding false positive response beyond contours, which is essential in low-contrast environment.

Extraction results obtained on two patient data sets are shown in Fig. 8 (identified as cases Patient 1 and Patient 2). From user-defined points, the algorithm extracts first the coronary sinus and the great cardiac vein in its continuity. Then, each contributing branch is extracted in turn, which yields immediately a tree shape with bifurcation positions. For Patient 1, the whole coronary venous tree has been extracted from four initialization points, into three consecutive volumes (50% and 55%): the optimal path from CS to ALV and an alternative path through the MCV (see Fig. 8(a)). During the CRT procedure, the LV lead has been implanted in the distal part of the MCV. For Patient 2, the whole coronary venous tree has been extracted from four initialization points, into three consecutive volumes (50%, 55% and 60%): the optimal path from CS to ALV and an alternative path through the MCV (see Fig. 8(b)). During the CRT procedure, the LV lead has been implanted in the distal part of the ALV.

We can observe on the curvilinear reconstructions (Fig. 9), the method ability to accurately extract tubular structures of different calibers (1.0 to 9.3 mm) and structures presenting contrast difficulties. In Fig. 9(a) and 9(c), we can observe vessel segment whose densities overlap with those of nearby structures (circled in red on the image). In Fig. 9(e), the CS exhibits an abrupt change in diameter due to an area very thin and poorly contrasted (circled in red on the image).

D. Qualitative Evaluation

We compared our minimum cost path algorithm (VM + OC) with a tracking technique developed by [24]. Moreover for our algorithm, we considered as a comparison, three different cost functions to build the travel time map: (1) the intensity information that makes the assumption that vessels are brighter than surrounded structures (method I - was applied in [15] to extract the trachea, brain vessels and an aorta), (2) the hessian-based vesselness measure (method VM - was applied in [26] to extract coronary arteries) in order to discriminate tubular structures from blob- or plate-like structures, (3) the combination of the multiscale Frangi’s filter response with the direction of the front with respect to the vessel orientation (our method VM + OC).

For method I, the cost function was defined as follows [15]:

$$\Lambda(x, y, z) = |I_{\text{mean}} - I_{x,y,z}|^2$$

(7)

where $I_{\text{mean}}$ is the mean lumen intensity of the vessels of interest and $I_{x,y,z}$ the intensity at position $(x, y, z)$.

The second one (method VM) was given by [26]:

$$\Lambda(x, y, z) = \begin{cases} \frac{1}{F_{x,y,z}} & \text{if } F_{x,y,z} > s \\ C, & \text{otherwise} \end{cases}$$

(8)

where $F_{x,y,z}$ is the Frangi’s vesselness measure at position $(x, y, z)$ and $C$ is the cost given at non-vessel positions (threshold $s$). $C$ and $s$ have similar values to those used in method (VM + OC). The three methods (VM + OC), (VM) and (I) are applied with the identical Freezing procedure (distance $d$ set to 12 voxels) and the same Frangi’s filter parameters ($\alpha = 0.5$, $\beta = 0.5$ and $\gamma = 50$).

The tracking algorithm (referred as method Mom) relies on a local modelling of the vessel by a cylinder in a 3D homogeneous space. The main advantage of this method is to provide analytical expressions based on 3D geometrical moments for the computation of the local cylinder parameters (location of the center of gravity, local orientation and diameter). The initialization step is performed interactively by pointing the vascular branch of interest. The tracking is then performed by shifting a spherical window according to the estimated orientation and the exploration is carried out in the two opposite directions. Nevertheless, the orientation estimated at a given position does not guarantee an accurate
The percentage of successful extracted path is given in Table IV. An extraction error means that the algorithm did not reach the final point of the branch. The method (I) based on intensity information fails in the proximal part of each branch (result are not reported in Table IV). The contrast inhomogeneities in the vessel lumen lead the front towards wrong directions. The method Mom exhibits a quite good score for images of good visibility. This score quickly decreases with the image corruption. This is due to the fact that the multiscale recentering process makes the center of the spherical window move towards brightest structures. As the contrast inside the veins is often weaker than its close environment (cardiac cavities, myocardium, arteries), the tracking algorithm tends to jump into these neighbouring structures. The methods based on a vesselness measure (VM and VM + OC) appear globally more successful. Indeed, we can notice the very high and similar scores for veins of high and good visibility for the methods (VM + OC) and (VM). Finally, the introduction of the orientation constraint in the cost function (VM + OC) allow to obtain the best results for veins of medium and low visibility.

V. CONCLUSION

An algorithm was proposed to deal with coronary vein extraction in MSCT volumes. Difficulties are related to the complexity of the scene that includes different structures such as the myocardium, the cavities and the coronary venous and arterial trees, which are very close to each other and have a similar contrast. Moreover, due to the MSCT scan protocol, the venous tree is not well contrasted and its appearance can be highly variable. One more difficulty comes from the cardiac beat that introduces in some volumes (especially those associated with the systolic and early-diastole phases) motion artifacts that blur the structures, making the extraction of the veins in these volumes impossible. As regards the minimum cost path method, we proposed a specific cost function, which allows to constrain a front propagation in the local vessel orientation. Parameter setting was performed on simulated data to find the optimal values based on different criteria. The qualitative analysis based on the vascular visibility and the comparison to three other methods shows a good efficiency of the algorithm in a low-contrast environment with a fairly good accuracy in the venous branch extraction. In the context of CRT, the method allows to describe the patient-specific coronary venous tree with the optimal implantation path as well as alternative ones. The proposed approach could be used pre-operatively to actually plan the catheterization procedure by mapping the possible 3D access paths. It could contribute to optimize the CRT procedure. Further work is needed to confirm the method robustness on more patient cases. In future projects, those results could be used as input data for catheterism simulation system and registered with intra-operative data for interventional assistance.
REFERENCES


