COMPONENT-COMPOSITION BASED HEART ISOLATION FOR 3D VOLUME VISUALIZATION OF CORONARY ARTERIES

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ABSTRACT
Heart isolation (separating the heart from the neighboring tissues, e.g., lung, liver, and rib cage) is a prerequisite to generate a 3D volume visualization as an intuitive view for coronary disease diagnosis and treatment planning. Previously, we proposed a component-carving based heart isolation approach by removing unwanted background tissues (e.g., non-cardiac structures, left atrial appendage, and pulmonary veins/arteries) sequentially. However, the final mask usually has many small extra pieces due to the difficulty to model and segment all background tissues. In this paper, we propose a component-composition based approach, which starts from an empty mask and then adds in wanted components (coronary arteries, four chambers, and the aorta) segmented from the original image. The proposed method can generate a much cleaner mask than the component-carving approach since only the wanted structures are added and the segmentation of the heart chambers and the aorta is more robust and accurate due to their greater predictability.

Index Terms— Heart Isolation, Heart Segmentation, Coronary Artery Disease, Computed Tomography

1. INTRODUCTION
Coronary artery disease (CAD) is a leading cause of death in the developed countries. Computed tomography (CT) is a widely used non-invasive imaging modality for CAD diagnosis and treatment planning. In cardiac CT images, not only the heart but also surrounding structures are imaged and the latter block a direct view of the heart (Fig. 1a). Segmenting the whole heart from surrounding tissues (a.k.a. heart isolation) is a prerequisite to generate a 3D visualization of the heart. A few heart isolation methods have been proposed using atlas based methods [2, 3] (which are often time consuming) or inference from the segmented lungs [4, 5] (which only generate a rough segmentation of the heart). Previously, we developed an efficient component-carving based approach [1] to remove un-wanted background tissues sequentially, e.g., non-cardiac structures, pulmonary arteries (PA), pulmonary veins (PV), and the left atrial appendage (LAA). Coronary arteries can be clearly visualized after such a heart isolation, as shown in Fig. 1b. However, the resulting mask still contains many small pieces of un-wanted highly-contrasted structures (indicated by green arrows in Fig. 1b) for the following reasons. First, it is almost impossible to model and segment all background tissues. For example, cardiac fat, the vena cava, and the right atrial appendage are not segmented in our previous work [1], therefore they are often preserved in the final mask. Second, the LAA and PV are notoriously difficult to segment accurately due to their large anatomical variability. The segmentation errors may result in incomplete removal of them in the final mask. Third, the LAA, PA, and PV may touch the coronary arteries. To avoid cutting the coronaries (the most critical requirement), a conservative removing strategy was exploited resulting in an un-clean mask.

In this work, we propose an entirely different approach to the heart isolation problem. Instead of carving away highly variable un-wanted structures, we start from an empty image and add in wanted structures. These include coronary arteries, aorta, and four chambers (namely, the left ventricle (LV), right ventricle (RV), left atrium (LA), and right atrium (RA)). The proposed component-composition based approach has several advantages. First, the four chambers and aorta are more consistent in shape and appearance, therefore can be segmented more robustly and accurately than the variable LAA and PVs. Second, since only the wanted structures are added to the final image, the proposed approach can create a cleaner heart isolation mask without extra pieces of un-wanted structures as shown in Fig. 1c.

2. COMPONENT-COMPOSITION BASED HEART ISOLATION
Our approach automatically segments the components that are desired in the final visualization, and then generates a masked volume that only contains these components. In our case, it is necessary to segment the four cardiac chambers and the aorta, as well as the coronary and bypass arteries. We will describe how these components are segmented in the following.

Segmentation of Four Chambers and Aorta: We leverage our previous work on cardiac chamber [6] and aorta [7] segmentation based on marginal space learning (MSL), although other segmentation methods can also be used [8, 9].

M. Chen and H. Zhong contributed equally to this work.
Fig. 1. Heart isolation visualization. (a) The original CT scan. Note that bones and other structures block a direct view of the coronary arteries. (b) Result of component-carving based approach [1]. (c) Result of the proposed component-composition based approach, which generates a cleaner heart mask compared to (b).

Fig. 2. Expanding the cardiac chamber and aorta meshes. (a) Using the original over-smoothed meshes, some parts may look like they were “shaved.” (b) After mesh expansion, more details on the left atrium and aorta surface are visible.

The outputs of the segmentation are 3D meshes. Directly converting such meshes into a voxel mask for visualization may have some problems. First, the meshes do not have resolution as high as the original CT scan and they are over-smoothed. The result is that fine details on the surface of the chambers and aorta may not be captured by the mesh. In visualization, such local discrepancy may cause visual artifacts (as shown in Fig. 2a). Second, only the endocardium is segmented for the RV, LA, and RA. Although the epicardium is also segmented for the LV, the coronary arteries are normally on top of the epicardium. It means usually the four chamber meshes are too small to include other required structures (fine details and coronary arteries) on the chamber surface.

To generate a nicer visualization, the meshes are expanded out-ward along the normal direction for each vertex to include more desired regions, especially coronaries. The growth range for each mesh vertex is determined differently from a data set containing manually annotated regions. The data set includes 116 CT coronary angiography scans. All were annotated for coronaries (which are considered as wanted regions) and 88 of them were annotated for unwanted regions, including LAA, PA, PV, sternum and diaphragm. The growth range is determined by maximizing the following functions:

\[
\arg \max_{\mathbf{f}} C(\mathbf{f}) = D(\mathbf{f}) - \lambda U(\mathbf{f})
\]

\[
s.t. \forall (i_1, i_2) \in E, |f(i_1) - f(i_2)| < f_T
\]

where \( f(i_k) \) is the growth range for mesh vertex with index \( i_k \); \( E \) is the set of connecting vertices; \( \mathbf{f} \) is the vector of \( \{f(i_1), f(i_2), \ldots, f(i_n)\} \) where \( n \) is the number of mesh vertices; \( D \) and \( U \) are the function measuring the number of annotated desired and undesired voxels that fall within the enclosed region of \( \mathbf{f} \), respectively. The cost function \( C \) favors \( D \) and has penalty on \( U \), with \( \lambda \) as a weight for \( U \). \( f_T \) is a threshold constraining the smoothness of the growth for adjacent mesh vertices.

At the connecting region of two chambers, for example the RV and RA, the vertices are shared by the meshes of both chambers. Those connecting parts will be moved outward along different directions, resulting in gaps in the enlarged meshes, as shown in Fig. 3a. To fix this, the averaged normals in both meshes are used for the shared vertices (shown in Fig. 3b).

Coronary Artery Segmentation: After expansion of the chamber meshes, most coronaries (especially the middle and distal segments) are already included in the mask. Sometimes, a small part of a coronary may be cut by the mask, e.g., a proximal segment, which is a bit far way from the cardiac chamber surface. The bypass arteries are usually out of the mask too due to their variable course and loose attachment to the surface of the heart. Therefore, in the next step, we perform explicit segmentation of the coronary and bypass arteries and add the segmentation results to the heart isolation.
To trace these arteries, the first step is to detect native ostia of the left and right coronary arteries, as well as any bypass ostia. We use a fully automatic machine learning algorithm to detect them [10]. The native coronary ostia are detected using MSL since they are anatomical structures with a consistent location relative to the aortic valve. Because the locations of bypass ostia have much more variation than native coronary ostia, we use a learned location distribution map to guide the bypass ostia detection. A mis-detection of a bypass ostium results in missing the whole bypass artery; therefore, the bypass ostia detection algorithm is tuned to have a high sensitivity. False positive detections are removed if a centerline tracing algorithm cannot confirm the presence of a vessel originating from the detected ostium.

After ostia detection, the coronary centerlines are traced. For robustness under severe stenoses, we use a hybrid algorithm [11] combining both a model-driven approach and a data-driven approach. A model-driven approach is exploited to trace the centerlines of the three major coronaries, namely, the left anterior descending artery (LAD), left circumflex artery (LCX), and right coronary artery (RCA). The segmented cardiac chambers are used to predict the initial path of the major coronary centerlines, which helps to cross severe stenoses. The initial centerline is then refined to fit the image data. Next, the bifurcations of side-branches on the extracted major centerlines are detected and at each bifurcation, a data-driven tracing [12] is initialized to extract the sub-tree of a side-branch. Similar to side-branch tracing, the bypass arteries are traced using a data-driven approach [12] starting from the detected bypass ostia.

With the centerlines traced, the exact voxel mask of the coronary and bypass arteries are generated by region growing. The growing is limited by a maximum size of the arteries learned as prior knowledge to prevent from growing into unwanted structures such as the LAA, PA, and PV.

### Table 1. Evaluation on coronaries and unwanted regions.

<table>
<thead>
<tr>
<th>Method</th>
<th>Carving</th>
<th>Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coronary</td>
<td>98.0% ± 4.0%</td>
<td>97.4% ± 3.5%</td>
</tr>
<tr>
<td>Sternal</td>
<td>12.1 ± 105.3 mm³</td>
<td>3.6 ± 22.2 mm³</td>
</tr>
<tr>
<td>Diaphragm</td>
<td>10.9 ± 7.2 cm³</td>
<td>4.3 ± 3.0 cm³</td>
</tr>
<tr>
<td>LAA, PA, PV</td>
<td>0.20 ± 0.36 cm³</td>
<td>0.05 ± 0.15 cm³</td>
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</tbody>
</table>

### 3. EXPERIMENTS

A critical issue in heart isolation for coronary disease diagnosis is that the visualization of the coronary tree should not be blocked by unwanted regions. In this experiment, we quantitatively evaluate the coronary and unwanted region voxels being preserved in the mask using both the component-carving approach [1] and the proposed component-composition approach. For this purpose, we collected 116 CT coronary angiography datasets acquired from Siemens Somatom Sensation and Definition scanners, including 56 low KV scans. A volume may contain 154 to 591 slices, while the size of each slice is 512×512 pixels. The resolution inside a slice is isotropic and varies from 0.24 mm to 0.45 mm for different volumes. The slice thickness varies from 0.30 mm to 0.80 mm for different volumes.

Table 1 shows the mean and standard variation of inclusion of coronaries and unwanted regions. The component composition approach reduces each type of unwanted regions by at least a half, with almost identical coronary coverage. Visual inspection on unseen data also reveals that the proposed approach produces a much cleaner mask (Figs. 1b and c).

The main purpose of heart isolation is for 3D volume analysis and visualization.
Fig. 5. More component-composition based heart isolation results.

visualization, which is hard to quantitatively evaluate. It is relatively easier to perform subjective comparison of different algorithms by visual inspection of the 3D visualization. In Fig. 4, we provide a few examples of heart isolation results using the proposed method (bottom row) and compare with the component-carving approach (top row). The component-carving approach fails to generate a clean mark (as indicated by white arrows in Fig. 4), especially in the area above the aortic valve. In many cases, the PA is not removed completely from the volume using the component-carving approach mainly due to the conservative removal strategy to preserve coronary and bypass arteries around the PA. While in the component-composition based results, the mask above the aortic valve is clean: no small pieces remain. In addition, since it only adds components that are needed, the vena cava and right atrial appendage are automatically “removed.” While in order to accomplish this in the component-carving approach, explicit segmentation of these un-wanted structures would be required, which is likely to require two additional detectors. Some more examples of component-composition based heart isolation results are shown in Fig. 5. All the results show that the proposed method can generate a much cleaner heart isolation mask than the component-carving based approach.

4. CONCLUSION

In this work, we proposed a composition-composition based approach by only adding wanted structures in the heart isolation mask. Its quality depends on the segmentation accuracy of the included components: the four cardiac chambers, aorta, coronary and bypass arteries. The four chambers and aorta are more stable than background tissues (e.g., the LAA and PV), therefore they can be segmented more accurately. By adding the segmented coronary and bypass arteries to the heart isolation mask, the risk of cutting an artery is mitigated. Quantitative evaluation on a cardiac CT database verifies that the proposed method has a risk of cutting coronary arteries as low as the component-carving approach while generating a much cleaner mask.

5. REFERENCES