Development of a Python Software for the Cardiovascular System Segmentation such as Arteries and Left Ventricle

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Abstract. Coronary artery disease (CAD) remains a leading cause of mortality. Accurate coronary arteries (CAs) and left ventricle (LV) segmentation from computed tomography (CT) scans is essential for effective diagnosis. This article presents semi-automatic methods for their segmentation, integrating user input with image processing techniques to achieve reliable results. Our CA segmentation method, validated against commercial software, demonstrated high accuracy. This approach employs bilateral smoothing, skeletonization, and region-growing algorithms. The LV segmentation method, though less developed, shows potential by combining cavity and myocardial segmentation phases. This process utilizes multiplanar reconstruction and boundary detection techniques. However, dynamic CT scans used for LV segmentation present additional challenges due to their lower image quality. Combining these two segmentation methods can provide comprehensive insights into CA functioning. This approach not only enhances diagnostic accuracy but also has the potential to improve patient outcomes. These semi-automatic methods balance precision and efficiency, with minimal user input, making them suitable for both clinical and research applications.

Keywords: Python Programming, Cardiovascular System, Segmentation.

1 Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally, accounting for approximately 17.9 million deaths annually, with coronary artery disease (CAD) as a major contributor. CAD results from the build-up of atherosclerotic plaques, reducing myocardial perfusion and leading to conditions like angina and myocardial infarctions, severely affecting the left ventricle's function. Advanced diagnostic tools are being developed to enhance the segmentation of cardiovascular structures, improving diagnostic accuracy and treatment outcomes.

Accurate segmentation is crucial for analyzing coronary behavior via Computed Tomography Angiography (CTA), a non-invasive alternative to coronary angiography, and for planning surgical interventions. Furthermore, the models retrieved after segmentation can be enlarged simulating hyperemia for further hemodynamic simulations. Similarly, segmenting the left ventricle in dynamic CT scans is vital for assessing cardiac health through measurements like ventricular volume and ejection fraction.

However, manual segmentation is time-consuming and suffers from variability, which can lead to significant diagnostic errors [1]. As such, there is a pressing need for more automated tools that enhance accuracy while reducing manual labor.

Most common advancements are in the realms of deep learning. These have propelled automated medical image segmentation, achieving results with high efficiency and reliability [2]; however, these require extensive data sets and high variability. In scenarios where such datasets are limited or exhibit low variance, these models risk developing biases or failing to achieve accurate results in cases that are very different then the norm of the training dataset.

To mitigate these risks, we are developing a Python-based semi-automatic algorithm that relies on existing open-source libraries, enhancing them with custom developments tailored to our specific needs, while relying on technician input to enhance classical image processing, ensuring adaptability to varied clinical conditions. We are testing this tool with patient data, with results that are very promising. We plan to release it as open-source software, encouraging a community-driven approach for continuous improvement and adaptation to clinical needs. The initial tests allows to believe this tool can be a robust and accurate software that can be used in hospital or for investigation purposes. The semi-automatic nature allows for user input and post processing tailoring of the segmentation.

2 Methodology and Results for Left Ventricle Segmentation

There is no fully automatic methodology that provides accurate results for segmenting the left ventricle in seconds, at a very fast level, without resorting to machine or deep learning [3] [4] and consequently using a very large database of patients in order to train the networks. Thus, the proposed methodology consists of a semi-automatic region growing segmentation method that starts from a point chosen by the user obtaining accurate and fast segmentation results without the need for an extremely large database.

The user interface of the application developed to segment the left ventricle has been designed to be clear and easy to use. The interface includes interactive visualization tools enhancing detailed examination of cardiac structures resulting in real-time interaction that immediately reflects changes, offering a reactive and engaging experience. These features not only simplify the assessment and segmentation of the left ventricle, but also improve the accuracy and efficiency of the diagnostic process.

2.1 Mitral Valve Detection and Mitral Plane

Accurate delineation of the mitral valve is critical because it identifies the atrioventricular bound- ary, which is required for exact left ventricle segmentation. Because of the quick capture of images, which results in lower quality, the mitral valve appears as a discontinuous structure, making direct segmentation difficult.

The initial step in mitral valve detection involves determining its approximate location based on user input. The user applies a threshold to enhance the image contrast, making it easier to identify the cardiac structures. Using this enhanced view, the user clicks on the suspected mitral valve zone, which serves as a seed point for further image processing. This seed point is crucial for subsequent flood fill operations, which iteratively examine and connect pixels with similar intensity values to form a contiguous region representing the mitral valve, auricle, and ventricle.

After analyzing the sagittal section, the investigation moves on to the axial section, with the aim of identifying specific layers that encompass different regions of the mitral valve. The axial image is then processed to isolate possible areas of the mitral valve using the minimum and maximum Hounsfield unit (HU) values obtained from the sagittal segmentation and the region of interest (ROI) is narrowed to more precisely focus on the potential area of the mitral valve (Fig.1a). The thresholding and flood fill operations are then applied to create a binary image that is further refined using the remove-small-holes function caused by pixel-level variations, ensuring a cleaner and more accurate segmentation of the mitral valve. To improve the mitral valve's identification even further (Fig. 1b), the sagittal view repeats the axial view's procedures. This entails using comparable flood fill and thresholding methods to guarantee accuracy and consistency when recognizing the mitral valve in various imaging planes.

a) b)

Figure 1: a) ROI - Auricle + Ventricle; b) Mitral valve.

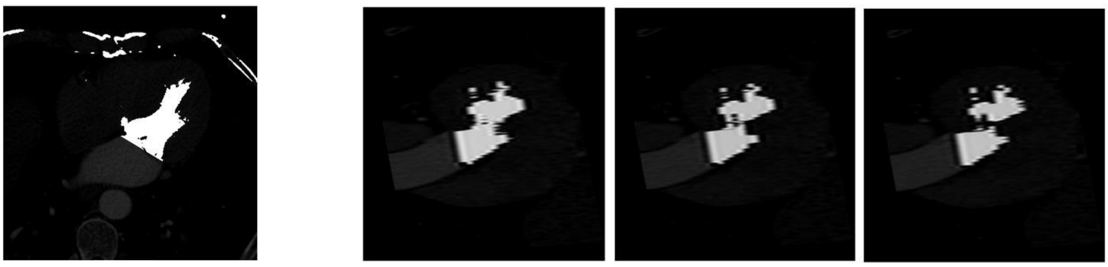
Once all the potential mitral valve points have been identified, these points are approximated to a plane that best fits their spatial distribution in the 3D volume. This process involves calculating the centroid of the mitral points and using eigenvalue decomposition to determine the normal vector to the most suitable plane. The importance of identifying this vector should be emphasized, as it is essential for accurately delineating the atrioventricular boundary, which is critical for subsequent segmentation of the left ventricle.

2.2 Segmentation

Cavity Segmentation

Segmentation can be divided into two main phases: cavity segmentation and myocardial segmentation. Using the axial view, a line is established that defines the intersection between the mitral plane and the layer where all y values below this plane are part of the left ventricle, making it possible to segment the ventricle in all layers. Despite some inconsistencies, this approach provides a preliminary segmentation of the left ventricular cavity (Fig. 2a). The accuracy of this first segmentation is then increased by applying multiplanar reconstruction (MPR), which provides images of the long and short axes of the ventricle, giving a more complete and realistic view of the ventricle.

A critical step to ensure accurate segmentation involves removing the aorta, which often contains contrast-enhanced blood, complicating differentiation from the ventricle. When analyzing images of the short axis of the ventricle, a transition point is identified where the aorta separates from the ventricle (Fig. 2b). This separation is essential to accurately isolate the left ventricular cavity. The process involves initializing an empty volume to store the aortic regions, iterating through each layer to identify and isolate these regions, and applying filling and binary dilation operations to ensure accurate segmentation.



a) b)

Figure 2: a) ROI segmented; b) Identification of the ventricle and aorta regions.

Myocardium Segmentation

Segmenting the myocardium is particularly challenging due to its similar density to adjacent tissues, such as the right ventricle. The process begins with the lower part of the ventricle, using the previously segmented cavity volume and applying bilateral filtering to reduce noise. By identifying the layers closest to the mitral plane and using different tolerance values, both the cavity and the myocardium are segmented (Fig. 3a). For the upper ventricle, segmentation extends to layers that overlap other entities, such as the aorta, using the previously segmented lower ventricle as a reference (Fig. 3b).

a) b)

Figure 3: a) Segmented Lower Ventricle; b) First myocardium segmentation achieved in axial view.

To further refine the segmentation, boundary detection techniques are used, particularly in regions with over-segmentation problems. With reference to the right side of the ventricle, the segmentation mask is adjusted, gaps are filled, and continuity is ensured through morphological procedures and linear regression. At this stage, the cavity is included in the mask and small, irrelevant regions are eliminated, retaining only the largest connected area, ensuring that the entire structure is accurately represented (Fig. 4a). To obtain a fluid and accurate representation of the myocardium, an iterative procedure is used that involves binary closure, elimination of small holes, and dilation. Even so, the highest level of accuracy and completeness can be achieved by taking additional steps that include using an editing tool to manually change the segmentation when necessary, followed by an improved segmentation algorithm (Fig. 4b).

a) b)

Figure 4: a) Myocardium segmentation after boundary detection; b) Myocardium and cavity after segmentation improvement.

3 Methodology and Results for Coronary Artery Segmentation

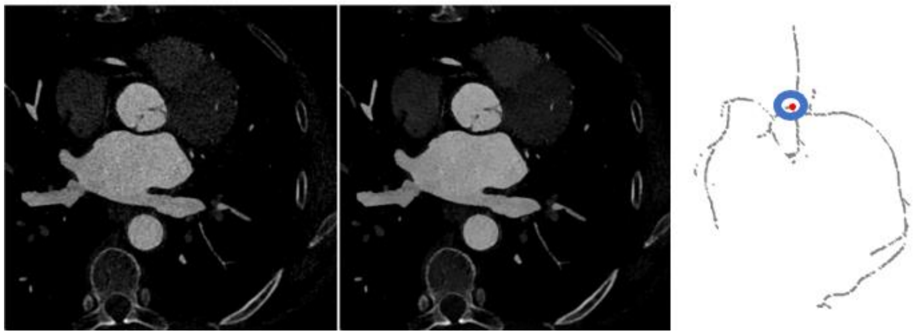
Coronary artery segmentation from computed tomography (CT) scans is a critical process in cardiac imaging, aiding in the diagnosis and treatment of coronary artery diseases.

As for left ventricle research, recent advancements in coronary artery segmentation have mainly focused on deep learning methods [5]. However, these techniques require extensive databases for training of the models and can suffer from initialization problems, impacting their reliability and efficiency. In this section, we outline a novel semi-automatic approach that integrates user input with advanced image processing techniques to reliably produce accurate and robust segmentation results.

3.1 Preprocessing, user defined seed point and initial aorta segmentation

The initial step in our approach involves the preprocessing of CT images to increase the signal to noise, ensuring clearer and more precise segmentation. Bilateral filtering is employed for this purpose due to its ability to maintain the integrity of edges between different anatomical structures. This is required specifically on smaller area vessels so that they don't get misinterpreted as noise. Still, for the branch ends the initial images might also be used. The

images prior and after the smoothing process are show in Fig. 5a and 5b, respectively.
The segmentation algorithm initiates with a user-defined seed point for the aorta. From this seed point, the section of the aorta not connected to the coronary is segmented. Cross section area and circularity can be analyzed. Further the rest of the aorta is obtained and robustly separated from the left ventricle via an iterative process of increments in value for thresholding methods. This first segmentation contains the aorta and a small part of the coronary trees with low detail and poor segmentation. A robust skeletonization algorithm is then applied [6]. Skeletonization simplifies the vascular structures into a skeletal form, enabling the identification of the first bifurcation point which represents the branching from the separated aorta to the coronary arteries. The bifurcation point facilitates the division of the skeleton and will be a foundation for further steps of this process. A schematic representation of the first bifurcation point identification is shown in Fig. 5c.



a) b) c)

Figure 5: a) Initial layer from the CT scan; b) Same layer after smoothing filter; c) Skeletonization of the first segmented model with first bifurcation identification.

3.2 Coronary arteries separation and definition of seed points

The next phase involves a detailed analysis of the model's section in the bifurcation point that was previously found. Using the tangent to the skeleton at the bifurcation point, the model can be cut to find the cross section area and corresponding radius of the aorta. These values are used to create a cutting entity that will remove the aorta surrounding the bifurcation point, accurately separating the coronary arteries from other anatomical entities.
The remains of the skeleton after the cutting entity is applied are analyzed, here the skeleton that is already known to be simply disconnected aorta are not accounted for. The points that are closer to the initial bifurcation point are stored, and based on their relative position to this bifurcation, the left and right coronary seeds are defined. It is important to note that more than two entities (LCA and RCA) can be present since some of the remaining skeleton may represent lower parts of the aorta that were not cut. The algorithm anticipates this situation and properly defines the coronary arteries, ensuring accurate segmentation despite potential complexities.
Following the separation, the user can specifically select which coronary artery will undergo detailed segmentation. This interactive step ensures that the segmentation process is tailored to the individual needs of a given patient or the specific requirements of the ongoing research. During this step, there is also the option to correct any misidentifications of the actual coronary seeds through user input. Although this tool addresses complexities that might arise (explained before), it was not necessary for the patients tested in the current research.

3.3 Coronary Segmentation and Refinement

Initially, the segmented coronary artery is not accurately delineated since it is only meant to be an initial representation to get the coronary seed. To address this, the entities of similar HU value are removed from consideration in a copy of the smoothed volume and a first region growing process is employed for the retrieval of the coronary tree.
With the coronary tree and the entities of similar HU value on different masks a side-by-side region growing method is applied. By iteratively increasing tolerance levels, the algorithm progressively refines the segmentation, ensuring that non-relevant entities are excluded. In each iteration, the entities that are not to be considered are

removed from the volume used for region growing (so for example, for the coronary artery all the other entities found in “the other side” of the process are removed)

After this step most of the coronary tree is segmented but there is a lot of under-segmentation (Fig. 6a). So, a region of interest (ROI) is defined to apply higher tolerances and precisely delineate the coronary artery edges. This focused approach ensures that the critical areas are accurately segmented. Here, only on each ROI the tolerance is increased on each iteration and the resulting coronary section is analyzed via comparison with surrounding layers and area increases on each iteration (Fig. 6b).

After all this steps only high stenosis areas (>95%) pose significant challenges due to their narrow lumen. The algorithm searches for continuation branches that may be omitted in earlier segmentation layers. When a continuation is detected, the entire branch is segmented initially with a hole in the volume. Stenosed section is handled within a small ROI with high tolerance, ensuring that even severely narrowed sections are accurately captured.

An example of a left coronary tree 3D model is shown in Fig. 6c.

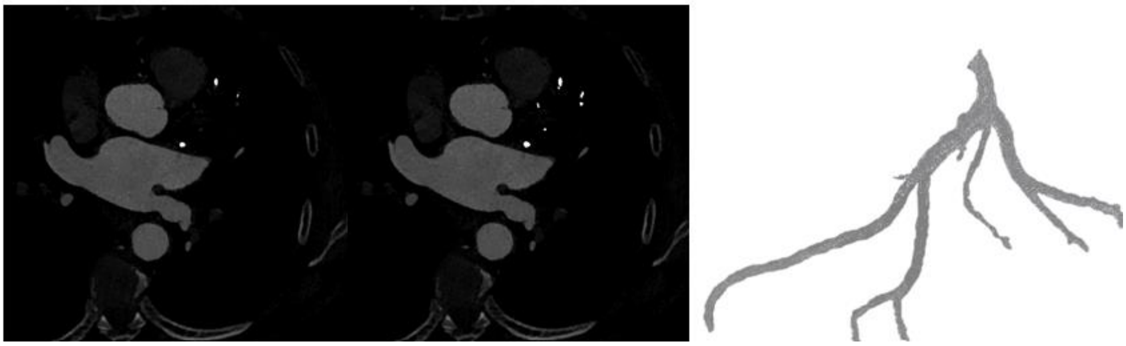


Figure 6: a) Segmented left coronary artery with undersegmentation; b) Same layer with final segmentation; c) Example of left coronary tree 3D model.

4 Conclusions

In this article, we presented semi-automatic methods for the segmentation of both coronary arteries and the left ventricle from CT scans. The results from the coronary artery segmentation are particularly promising when compared with commercial software. There is accuracy and reliability of our method, which effectively combines user input with advanced image processing techniques such as bilateral filtering, skeletonization, and region-growing algorithms.

The semi-automatic approach for coronary artery segmentation proves to be both rapid and effective, requiring minimal user input while providing high accuracy. This makes it an ideal tool for clinical and research settings where precise segmentation is crucial. Moreover, the ability to tailor the segmentation process to individual patient anatomy and specific research needs enhances its utility and relevance.

Similarly, the semi-automatic segmentation method for the left ventricle also shows potential, though it requires further refinement and validation. By combining cavity and myocardial segmentation phases, and employing techniques such as multiplanar reconstruction and boundary detection, the approach lays a solid foundation for accurate left ventricle segmentation.

The promising results obtained from the coronary artery segmentation method also suggest several avenues for future research and development. Combining the semi-automatic approach with deep learning methods can enhance the accuracy and robustness of segmentation. Deep learning models can benefit from the precise initialization provided by the semi-automatic method, leading to improved results.

Conducting studies on larger patient datasets will be crucial for validating the robustness and generalizability of the proposed methods. This will also help in identifying potential areas for improvement and fine-tuning the algorithms.

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