Exploring a Python-based Semi-Automatic Approach for Coronary Artery Segmentation

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Abstract. The segmentation of coronary arteries from Computed Tomography (CT) images is vital for coronary artery diseases (CADs) diagnosis and treatment. Combining thresholding, region growing, and several entity properties, we have implemented an in-house semi-automated method using Python, circumventing commercial software dependence in hospitals. Our technique swiftly isolates coronary arteries in under 2 minutes, enhancing efficiency, accuracy, and reproducibility compared to manual MIMICS® segmentation. Moreover, it is able to detect coronary branches that surge upstream severe stenosis which is usually a major limitation due to lack of contrasted blood. In sum, our proposed method stands as a transformative stride toward the efficient and accurate segmentation of coronary arteries in the clinical landscape. Anchored in the marriage of computational prowess and clinical imperatives, it emerges as a potent beacon, poised to illuminate a path toward enhanced diagnostic insight and treatment efficacy.

Keywords: Coronary artery segmentation, Computational methods, Image processing, Python, Cardiovascular diseases.

1 Introduction

Cardiovascular diseases (CVDs) stand as a major global health challenge, accounting for a staggering 32% of all deaths in 2019, with 17.9 million lives succumbing to their impact [1]. Central to these illnesses are CADs, which disrupt the vital supply of oxygen and nutrients to the heart muscle through atherosclerotic plaque accumulation, ultimately culminating in stenosis and restricted blood flow [2]. CT images, provide a glance into coronary artery pathology, yet they fall short in interpreting the hemodynamics at play. As such, the dire need emerges for a method that approaches the elaborate geometry of coronary arteries, a pivotal requirement for driving hemodynamic simulations that have emerged as pivotal tools in the diagnosis and prevention of CADs.

Existing models in coronary artery detection predominantly rely on labor-intensive manual segmentation, troubled with inter-observer variability that hampers consistency and accuracy. These challenges highlight the pressing need for an approach that harmonizes precision with efficiency. The surge of deep learning has ushered in a new era, culminating in automated techniques that harness Convolutional Neural Networks (CNNs) for coronary artery segmentation [3]. While promising, these methods grapple with the extensive requirement of expanded training datasets, potentially impeding their broad application.

The cornerstone of this investigation, embedded in the dominion of biomechanical applications, is the pursuit of a semi-automatic approach that reconciles accurate coronary artery segmentation with streamlined effort. We draw inspiration from a groundbreaking methodology by Ma et al. [4], which offers a compelling prospect for efficient segmentation while gracing the boundaries of existing approaches. However, we pivot our gaze to a new frontier: CT imaging.

CT emerges as a non-invasive, high-resolution alternative to the invasive X-ray coronary angiography (ICA), bypassing uncommon yet grave complications [5]. In juxtaposition to the invasive nature of ICA, CT scans confer cost-effectiveness and widespread accessibility, a must in routine clinical practice [5]. As CT results in Digital Imaging and Communications in Medicine (DICOM) files, it provides an extensive library anatomical and pathological information. This panoply of data opens up unprecedented insights, pushing us towards the identification and quantification of stenosis.

Our goal, the development of a semi-automatic coronary artery segmentation method, is magnified by Python's power and focuses on a region-growing algorithm. This study, an evolution of prior research centered around CT cardiac imaging with Python and linear transformations [6], promises to alleviate the temporal and financial investments associated with manual segmentation while allowing the creation of an accurate model that does not rely on an extensive data set, such as the ones required for deep learning methods. Beyond fostering precision in CAD diagnosis and treatment, the resulting coronary artery geometry, wields significance in the future of hemodynamic simulations.
The culmination of this works relies on the validation of our methodology through meticulous comparison of hemodynamic results obtained computationally and invasively. For now this will only serve as a proof of concept but the aim is to test the validity on the full dataset of about 20 patients.

2 Methodology

The DICOM files of the coronary arteries used in this study were provided by the Cardiology Department of the Gaia/Espinho Hospital Centre (CHVNG/E). These image datasets serve as the foundation for the proposed coronary artery segmentation algorithm. The DICOM files contain comprehensive structural information pertaining to the heart, notably encompassing details of the coronary arteries. The patients gave informed consent; and the local institutional ethics committee authorized the present research.
The methodology of the proposed semi-automatic segmentation approach is delineated below, specifically for patient 1.

2.1 Preprocessing

Numerous essential preprocessing steps are executed to increase the quality of the input data, fortifying the foundation for the subsequent coronary artery segmentation algorithm.
The initial files often exhibit noticeable noise that necessitates reduction to facilitate an accurate segmentation process. This noise stems from various sources, such as image acquisition artifacts, patient movement, and electronic noise inherent to the medical imaging devices.
In response, noise reduction is required. This is indispensable to alleviate potential misrepresentations and inconsistencies that may impede the segmentation procedure. In addressing this concern, a bilateral filtering technique, harnessed from the OpenCV (cv2) library, is used. This choice is attributed to the filter’s unique ability to balance noise suppression and edge preservation. By assigning weightings to neighboring pixels based on both their spatial proximity and intensity similarity, the bilateral filter attenuates noise while safeguarding the edges. Preserving these edges is of great importance, as it ensures that the crucial morphological details of the arteries remain intact and unblurred. Fig. 1a shows a layer of the voxels in the retrieved array and Fig. 1b the same layer after the applied filter.

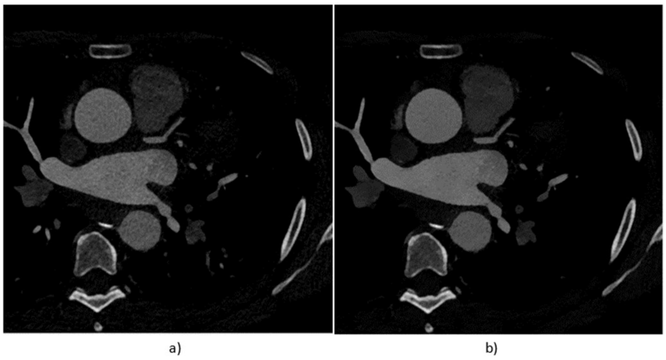

Figure 1. a) An array layer of the voxel intensities as they are retrieved from DICOM files; b) The same layer after Bilateral Filter is applied

Furthermore, the initial voxel values are transmuted into HU, a standardized metric employed in CT scans to measure radiodensity. This transformation correlates the information with the physical properties of the imaged tissues. Notably, the preprocessing sequence involves the identification of regions representing air, indicative of the lungs. A discriminative extraction of these regions aids in reducing the field of interest, boosting computational efficiency, and targeting the pertinent anatomical structures. Voxels bearing HU values that significantly deviate from the range characteristic of contrast-enhanced blood are effectively eliminated from consideration, further refining the region of interest (ROI). The synthesis of these preprocessing steps amalgamates into a refined image dataset wherein noise is attenuated, edges are preserved, and spurious voxel values are pruned. This serves as the cornerstone upon which subsequent segmentation efforts are founded, ultimately culminating in more accurate and clinically valuable coronary artery segmentations.

2.2 Seed Point Selection

The seed point selection phase is designed to empower clinicians with an intuitive and streamlined initiation process. The emphasis of this approach is on minimal user intervention, in conjunction with intelligent analysis to establish an optimal seed point. To commence this process, the user is tasked with a singular responsibility: selecting an initial seed point within the aorta artery. This mitigates user fatigue and streamlines the procedure.

Subsequently, an analysis of the area and circularity attributes within the aorta is performed. This assessment continues until a noticeable deviation in these attributes is detected. Such is a marker, signifying the transition where the coronary arteries surge attached to the aorta.

By identifying and segmenting these regions, the computational system intrinsically recognizes the preliminary layers that precede the coronary arteries' attachment. This area-circularity analysis allows for identification of the *de facto* initial seed point, meticulously chosen to minimize potential variance arising from user input variability. Hence, this can address the challenges associated with manual seed point selection. Variability attributed to user input is significantly mitigated, and the segmentation process is employed with a higher degree of consistency, contributing towards a robust and reliable coronary artery segmentation.

2.3 Aorta-Coronary Separation

In the intricate interplay between the aorta and coronary arteries, relying solely on HU values to distinguish them presents inherent challenges, particularly within the layers where their circulatory pathways overlap. This results in similar voxel intensities, given that both the aorta and coronary arteries convey blood infused with a contrast agent. The necessity for an approach to discern and segregate these entities accurately arises. Commencing at the layer identified as the coronary's inception, where it connects to the aorta, a meticulous analysis is initiated. Subsequent layers that necessitate separation are identified. This process dynamically unfolds, discerning the pivotal moment when these entities unequivocally disengage, represented in Fig. 2a.

Key characteristics underscore the efficacy of this separation strategy:

Relative Aspect Maintenance of the Aorta**:** The aorta's characteristic structural attributes are vigilantly preserved throughout the separation process, by tracking the morphological traits.

Identification of the Separated Vessel**:** The transition from the aorta-coronary conjunction to their individual pathways is ascertained, a marker for the subsequent separation algorithm.

Marker-Based Separation Algorithm**:** A selection of a separation algorithm, founded upon markers, is employed to partition the overlapping regions accurately. To this end, markers derived from the layers where the entities distinctly diverge are strategically utilized.

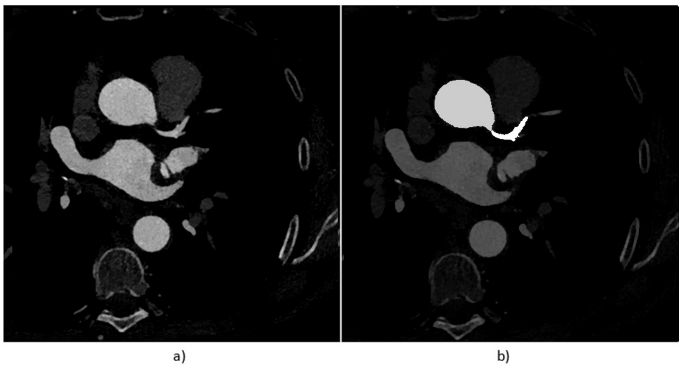

Figure 2. a) Layer identified as the first where aorta and coronary emerge separated; b) Separation of the entities via Watershed

The chosen algorithm leverages the concept of watershed segmentation, a renowned technique prevalent in image processing. In the context of image segmentation, watershed transforms leverage gradient information to segregate distinct regions by treating intensity values as elevations. The markers, strategically placed at the disengagement points of the aorta and coronary, serve as high points from which "water sheds" flow to delineate and separate areas. In essence, the watershed segmentation operates as an intelligent partitioning mechanism, distinguishing the aorta and coronary arteries while retaining anatomical coherence. Fig. 2b shows the final results of the separation method where the entities were previously connected.

2.4 Region Growing

The Region Growing phase is divided into two distinct yet interrelated aspects. By employing sophisticated algorithms, this phase progressively identifies and isolates the coronary vessels, mitigating the challenges of over and under-segmentation.

2.4.1 Side-by-Side Region Growing

At the beginning of this phase, the total voxel information array is copied into two identical versions. Each of these replicas serves as an independent canvas, in order to start parallel region growing processes.
Coronary Elimination and Aorta Segmentation**:** From one of the replicated arrays the coronary artery that had been previously separated from the aorta is eliminated. This preparatory step clears the path for a dedicated region growing, with the aorta's defined seed point serving as the epicenter. This algorithm dynamically expands from the seed, and smaller objects are not considered since they may be part of the coronary. The culmination of this process yields a binary mask that delineates the aorta.
Coronary Seed and Coronary Segmentation**:** On the counterpart array, the resultant binary mask is now removed. A new seed point is established for the coronary artery, in a same way as for the aorta but for the defined coronary entities in the watershed process. Starting on this seed point, an independent region growing algorithm starts. Similar to the aorta (and others) segmentation, the coronary is represented by a binary mask.
Iterative Behavior and Tolerance**:** To reduce the problems of over-segmentation and to embrace the nuances of diverse entities, successive iterations of this side-by-side region growing are systematically performed. Each iteration progressively identifies and isolates distinct anatomical structures, contributing to a refined and comprehensive segmentation outcome. The maximum tolerances employed for intensity comparisons are defined proportionally in relation to the initial seed's intensity.

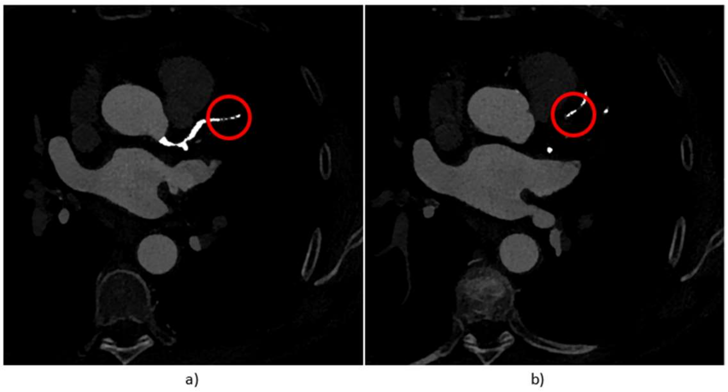

Figure 3. Identification of under-segmented areas in different layers a) and b)

The side-by-side region growing approach significantly refines the segmentation of the coronary arteries, however, a challenge arises in the form of under-segmentation. This phenomenon manifests as certain voxels, pivotal to the composition of the coronary artery mask, remain unsegmented during the initial region growing process, as represented in Figs. 3a and 3b. Notably, voxels bearing HU values lower than the anticipated range might elude segmentation during the initial pass or be removed during the aorta segmentation stage.

2.4.2 Progressive Tolerance Region Growing

Progressive Tolerance Region Growing is the strategy employed. This will extend beyond the constraints of a fixed tolerance, adapting the segmentation process to encapsulate areas that may have been initially omitted.
***Divided Mask Analysis and ROI*:** The method requires the separation of the initial mask into distinct branches. Each branch is meticulously inspected, and an analysis of the segmented area is performed. The delineation of a more refined ROI can then be performed. This concentrated region becomes the epicenter for successive iterations of the region growing algorithm, engendering a gradual expansion of the tolerance and coronary artery mask.
***Refinement and Intelligent Stopping Criteria*:** These iterative cycles consecutively reinforce the algorithm, embracing the variability of HU values across diverse anatomical possibilities. Guiding the progression are stopping conditions, intimately tied to the total segmented area and the contour fidelity of the evolving mask. The cumulative area and contour comparison, via Hausdorff distance, assure accurate segmentation.
The inclusion of this step represents a dynamic stride towards enhanced accuracy and a meticulous depiction of the vessels. Balancing tolerance, iterative refinement, and stopping criteria create a workaround for the segmentation maintaining accuracy. Figures 4a and 4b show the same layers that were under-segmented above, now with accurate results.

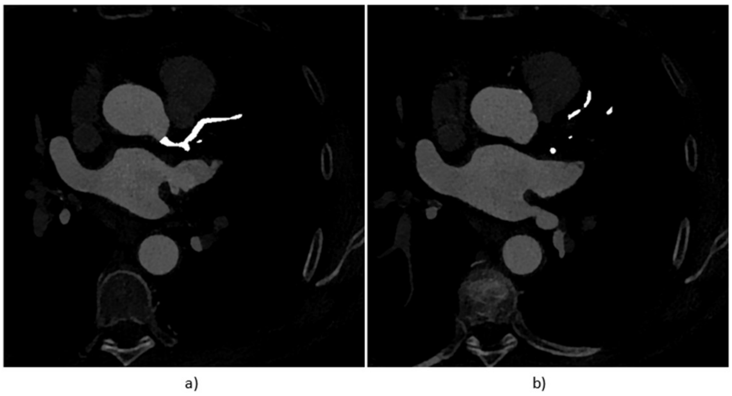

Figure 4. Previous layers a) and b) now with fully segmented left coronary arteries

2.5 Postprocessing

Throughout the stages of our methodology, our primary focus remains, as it was predicated, on mitigating miss segmentation challenges. However, occasional instances of over-segmentation can persist. To address this, a succinct postprocessing step is introduced. This step, characterized by its efficiency, specifically targets noise entities that materialize as seemingly isolated from the genuine coronary mask. By concentrating solely on this discontinuity aspect, our postprocessing eliminates noise, ensuring an accurate segmentation outcome.

2.6 3D Model Reconstruction

The process culminates in 3D model reconstruction, facilitated by the robust marching cubes algorithm, a pillar of computational geometry.
Marching Cubes Algorithm: This algorithm adeptly converts the binary coronary mask into a tangible three-dimensional structure. By partitioning data into smaller cubes and interpolating vertices along cube edges, it crafts a seamless mesh that mirrors the coronary artery network's intricate geometry.
Vertex Extraction and Mesh Generation: Utilizing the binary coronary mask, vertices are extracted to form the foundation of our mesh. This process translates voxel data into spatial coordinates, using the spacing and thickness provided in the DICOM files, yielding a detailed and accurate three-dimensional representation.
Layered Construction and Smooth Taubin: Layer-by-layer the mesh construction captures the essence of coronary anatomy, culminating in a visual 3D model however, with a very rough surface. To enhance surface quality, the Taubin smoothing algorithm is applied. Balancing smoothness with low volume loss, it refines the mesh for a proper visual outcome and possible utilization in hemodynamic analysis.

3 Results and Discussion

The proposed methodology's efficacy is evaluated through an examination of diverse datasets, with results of two patients, as a proof of concept (Fig. 5 for patient 1 and Fig 6. For patient2). Note that the final results of the commercial software’s model is presented after the branches have been trimmed for future hemodynamic simulations, a step that may be included in next versions.The obtained outcomes are compared with 3D models generated by MIMICS® software and subjected to 3D optimization via 3MATIC® software. These latter and manual methodology had been validated in previous research [7] by comparing computed FFR values obtained through hemodynamic analysis with invasive measurements in the hospital, demonstrating minimal errors.

The congruence between our semi-automatic segmentation approach and the manual segmentation executed through MIMICS® software underscores the validity of our method. Importantly, the geometric model yielded by our semi-automatic methodology exhibits enhanced smoothness when compared to its counterpart. Notably, the segmentation process, encompassing essential steps such as preprocessing, separation between the aorta and coronary and coronary detection, concludes within a mere 70 seconds. This efficiency sharply contrasts with the laborious and time-consuming nature of manual segmentation, often spanning several hours for precision. In addition to expedited results, the proposed semi-automatic method ushers in improved accuracy and reproducibility, by mitigating the potential for human error.

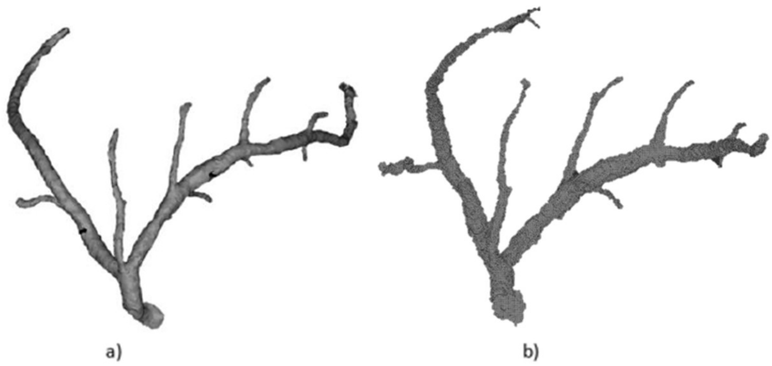

Figure 5. 3D model obtained via a) Manually via Mimics® and b) Semi-Automatic In-House method

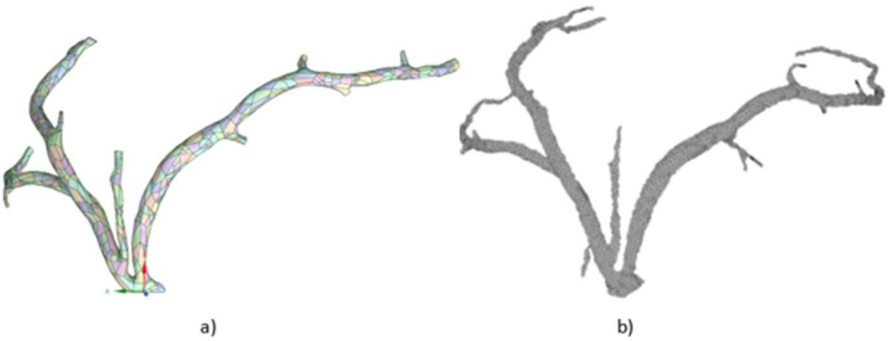

Figure 6. 3D model obtained via a) Manually via Mimics® and b) Semi-Automatic In-House method software of patient 2

4 Conclusions

In this research, we have achieved a significant milestone by formulating an In-House Semi-Automatic approach for coronary artery segmentation from CT-derived DICOM files. Through thresholding, region growing, and other techniques, our methodology isolates coronary arteries from their anatomical surroundings. The expeditious

generation of a meticulously defined mesh for the left coronary artery in short processing time attests to the remarkable efficiency and promise encapsulated within our proposed approach.
Crucially, our method's robustness and credibility are underscored through a rigorous comparison with models generated by the established MIMICS© software. This elucidates the method's validity and ability to capture coronary artery structures.
Unveiling a spectrum of advantages over manual segmentation, our method translates into tangible enhancements. It not only shortens processing time but also imparts enhanced smoothness, precision, and reproducibility to the resulting geometries. These virtues collectively resonate as powerful enablers. Impressively, our approach achieves these gains without a towering demand for voluminous datasets, setting it apart from fully automated segmentation techniques.
As we check into the horizon of future investigations, our focus converges on refining the segmentation process for thinner branch ends, a stride that promises to further amplify the accuracy and fidelity of our methodology. As mentioned, the preparation of the models for future hemodynamic simulations is also an aim of the project. Moreover, we are actively developing a dedicated strategy to identify vessel attachments in instances of severe stenosis. Our pursuit extends to methodological advancement as well, as we endeavor to implement a mechanism to superimpose our in-house models with MIMICS© counterparts. This innovation will empower us to quantify the precision of our segmentation by assessing volume errors. This validation method will rely on a quantitative and qualitative comparison of both methods using the results obtained for the total dataset provided.

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