Seeing the Invisible: On Aortic Valve Reconstruction in Non-Contrast CT

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Abstract. Accurate segmentation of the aortic valve (AV) in computed tomography (CT) scans is crucial for assessing AV disease severity and identifying patients who may benefit from interventional treatments, such as surgical and percutaneous procedures. Evaluation of AV calcium score on non-contrast CT scans emphasizes the importance of identifying AV from these scans. However, it is not a trivial task due to the extremely low visibility of AV in this type of medical images. In this paper, we propose a method for semi-automatic generation of Ground Truth (GT) data for this problem based on image registration. In a weakly-supervised learning process, we train neural network models capable of accurate segmentation of AV based exclusively on non-contrast CT scans. We also present a novel approach for the evaluation of segmentation accuracy, based on per-patient, rigid registration of masks segmented in contrast and non-contrast images. Evaluation on an open-source dataset demonstrates that our model can identify AV with a mean error of less than 1 mm, suggesting significant potential for clinical application. In particular, the model can be used to enhance end-to-end deep learning approaches for AV calcium scoring by offering substantial accuracy improvements and increasing the explainability. Furthermore, it contributes to lowering the rate of false positives in coronary artery calcium scoring through the meticulous exclusion of aortic root calcifications.

Keywords: Aortic valve · Non-contrast CT · Weakly-supervised learning · Image registration · Calcium scoring.

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1 Introduction

Computed tomography (CT) angiography serves as a fundamental diagnostic tool for evaluating aortic pathologies, including the aortic valve (AV) and aortic root. This imaging technique is crucial for assessing the severity of diseases and identifying patients who may benefit from interventional treatments, such as surgical and percutaneous procedures. High-quality delineation of the AV and aortic root on CT images is essential for effective treatment planning and ensuring optimal patient outcomes. By providing detailed images and accurate segmentation of these structures, CT facilitates the selection of patients requiring interventions and the choice of the most suitable treatment option [1, 18].

Non-contrast CTs could be used for straightforward identification of calcifications, but distinguishing between the aorta, coronary arteries, and surrounding tissues is challenging due to their similar radiological densities. This similarity complicates the clear visualization of vascular structures and heart chambers. Contrast CT imaging, by enhancing the contrast between these vessels and surrounding tissues, notably improves their visibility, albeit with less emphasis on calcifications, which are more prominently detected in non-contrast CT.

Beside of applications in identification of AV calcifications [7], the segmentation of the aorta is crucial for accurately computing the Agatston score, a key metric in assessing coronary artery disease. The ability to automatically identify the aorta's location, including the aortic root, is vital for calcium scoring approaches based on anatomical information [15, 17] as well as for attributing calcified plaques to specific coronary vessels. Moreover, recent studies [10] indicate the potential value of non-contrast AV segmentation in radiation therapy planning concerning regions close to the heart, e.g., in the case of breast or lung cancer, as the exposure to radiation of selected heart substructures can increase the risk of cardiotoxicity to a different extent. Nevertheless, existing machine learning (ML) models capable of non-contrast CT segmentation are limited to identifying the aorta's location outside the pericardium [14]. This study aims to fill this gap by evaluating the feasibility of using non-contrast CT scans and the nnU-Net framework [8] for comprehensive aorta segmentation.

2 Context and Contribution

In this section, the state of the art in AV segmentation is given. The section is split into two parts. First, we focus on the approaches targeting accurate AV segmentation for the tasks related to treatment planning, including both operative interventions, done typically based on contrast-enhanced CT, and alternative applications, e.g., in radiation therapy of organs close to the heart. The second part deals with the methods developed specifically for AV calcium scoring, where moderate AV segmentation quality is often accepted, and usually constitutes only an intermediate step of a larger framework. The section is concluded with a summary of the most important contributions of our work.

2.1 Related Work

Aortic Valve Segmentation Methods The literature on AV segmentation has predominantly targeted scans with contrast enhancement. In their 2020 study, Pak et al. [18] approached AV segmentation as a multi-class task, differentiating each leaflet as an individual category. Additionally, Aoyama et al. [1] elevated the approach by integrating landmark localization along with the prediction of a segmentation map. While the aforementioned studies have concentrated on tricuspid valves, the methodology was extended in [24] to incorporate multi-segmentation of bicuspid valves. Furthermore, Pak et al. [19] demonstrated that AV segmentation can be effectively addressed as a mesh prediction problem.

In the context of non-contrast CT, Jin et al. [10] conducted segmentation of the AV alongside eight additional cardiac structures, including heart chambers, valves, and the coronary artery. However, the precise demarcation of the AV segmentation is ambiguous, leading to suboptimal segmentation outcomes.

Aortic Valve Segmentation for Calcium Scoring An important application motivating the development of the methods proposed here is the evaluation of AV calcification, which enables the assessment of aortic stenosis severity in cases where Doppler echocardiography, the primary diagnostic tool, yields inconclusive results [20]. Despite the growing significance of AV calcium scoring in practice, the traditional, manual segmentation of AV calcifications [6, 20] continues to present limitations [22]. One of the main groups of methods addressing the challenge of automatic AV calcium scoring consists of approaches using aorta segmentation techniques to find corresponding calcifications. This group can be divided into atlas-based methods using image registration [11, 12] and region growth approaches [5]. In one of the early studies [9], a multi-atlas-based method for quantifying aortic calcifications in low-dose non-contrast chest CT was proposed. The segmentation of the aorta involved registering multiple non-contrast images with manually segmented aortas (atlases), aligning them with an input non-contrast scan using the Elastix technique [12], and merging the resulting masks. In another method [13], the circular cross-sections of the aorta were automatically identified using the Hough transform on axial slices from a non-contrast chest CT scan, and the segmentation was refined through a 3D level set method. Torío et al. [23] proposed a similar method, enhanced by mathematical morphology techniques. While the methods outlined above exhibit promise and offer strong explanatory capabilities by leveraging anatomical information about the aorta for calcification identification, they grapple with suboptimal segmentation quality of the aortic root, hardly visible in non-contrast CT. Consequently, the segmentation provides a rough estimate of the AV location, necessitating ML-based or heuristic post-processing steps to eliminate false positives.

2.2 Contribution

Non-contrast CT imaging offers limited details for accurately delineating the aortic root due to the radiological density of the aorta, coronary vessels, and heart

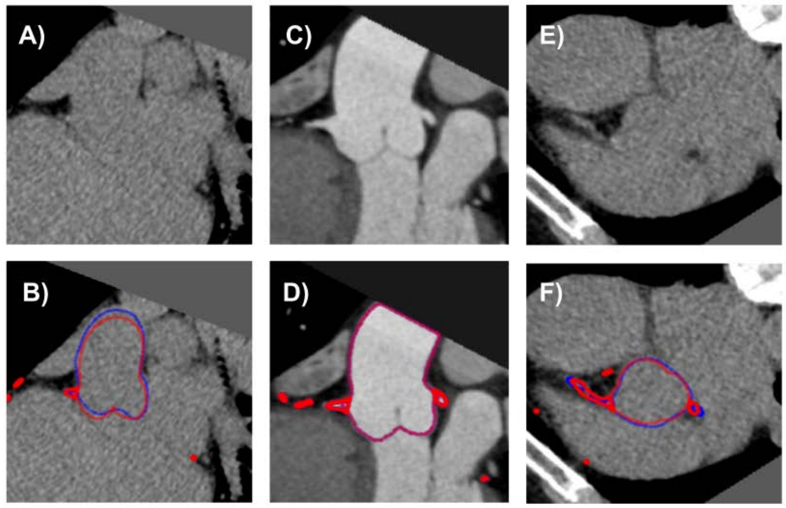

Fig. 1. Contrast-enhanced cardiac CT images reveal the clear delineation of the aortic root and valve (C), juxtaposed against the indistinct outlines in non-contrast images (A and E). The segmentation masks are shown in red, depicting the transformed segmentation from contrast CT (D), aligned to the non-contrast series in (B) and (F) using the Iterative Closest Point (ICP) method [2]. The blue masks in (B) and (F) highlight the aortic root segmentation as predicted by our ML model, which operates exclusively on non-contrast CT data, demonstrating high accuracy in shape extrapolation.

chambers being discernible only when adjacent to fatty tissue or air. While the aortic root is partially visible due to surrounding pericardial fat (Fig. 1), the delineation between the aorta and surrounding tissues can vary significantly, with clear boundaries in some areas and complete blending in others. This study explores the feasibility and accuracy of developing robust models for segmenting the aortic root in non-contrast images. We devise a scalable approach for constructing ML segmentation models of the aortic root and establish a method for assessing their accuracy. The final model, requiring only a non-contrast image, is capable of rendering the aortic root and extrapolating details of the AV with a mean precision equal to 0.8mm, which is the detection limit for this imaging modality. Our contributions comprises two key components: firstly, we construct the aorta model in non-contrast images using registered GT from high-precision contrast images combined with a subsequent weak supervision process. Secondly, we introduce an evaluation tool to gauge the precision of AV identification based on the Iterative Closest Point (ICP) algorithm [2].

The scalability of our method is demonstrated by its ability to be nearly automated for processing a potentially unlimited dataset without significantly impeding human tasks. Initially, our process relies on the conventional method of registration between contrast and non-contrast images. Subsequently, the intervention of a human annotator is necessitated, yet this involvement is confined to the straightforward tasks of approving or dismissing the outcomes of the registration. Typically, this stage demands approximately 1 minute per scan for an annotator with experience. Furthermore, the technique for evaluation operates entirely autonomously, eliminating the need for manual intervention.

3 Methods

Figure 2 presents the main steps of the framework introduced in this paper. Firstly, we perform image-based registration of the contrast and non-contrast scans, and use an ML model to segment aortic roots. Subsequently, manual evaluation is performed to generate GT for training. The approach is concluded by the segmentation accuracy evaluation. Below, we describe these steps in detail.

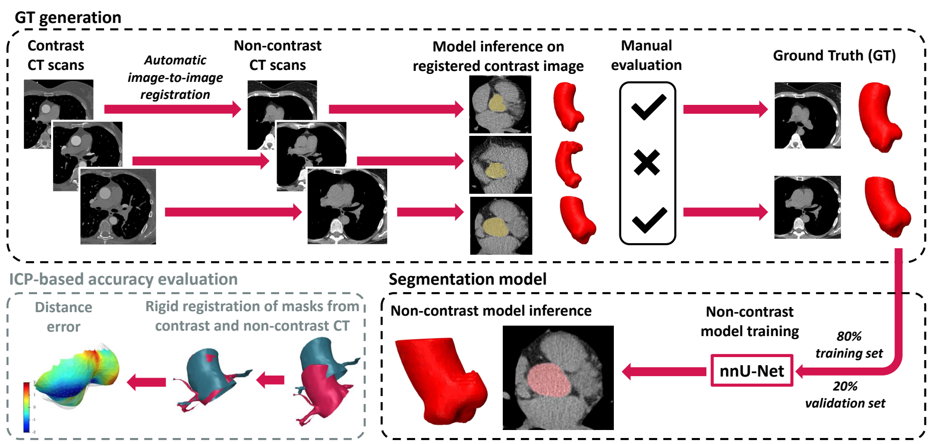

Fig. 2. Main steps of the framework for training and evaluation of the aortic root segmentation neural network based on non-contrast CT scans.

Aortic Root Segmentation in Contrast CT First of all, in order to generate input masks used in subsequent image registration steps, we segment aortic roots in contrast-enhanced CT scans. Due to the good visibility of the aorta including the aortic root in this modality, both manual delineation based on standard procedures and automatic segmentation using state-of-the-art deep learning models are possible. In this work, we use a high-resolution ML model trained based on proprietary in-house data and the standard nnU-Net [8] framework with default settings, however, any of the openly available deep learning models could be used here, as well. On an in-house test set consisting of 26 cases, segmented manually by two medical imaging experts with over three years of experience, the model yields a mean Dice score of 0.98, which is at the same level as the interrater variability. A subset of 19 GT segmentations with the corresponding inferences of our ML model, for the scans from the open-source orCaScore dataset [25], is made available online [3].

Aortic Root Segmentation in Non-contrast CT based on Image Registration In the next step, we perform image registration of 268 contrast CT scans to their non-contrast counterparts, based on a standard Greedy framework [26, 11] with default settings. The ML model described in the previous section is used to segment aortic roots in the contrast scans transformed to the reference frame of the corresponding non-contrast images.

Semi-Supervised Deep Learning Technique To assure sufficient quality of the automatic GT generation process, we employ a fast, manual evaluation step by a medical imaging expert by assessing the agreement of the segmentation with the non-contrast scan at consecutive axial slices. Since, as mentioned before, anatomical structures such as the aortic valve are not visible in the non-contrast scan, the evaluation is based mainly on the ascending aorta and the proximal parts of coronary arteries. At this stage, only a binary decision is made to reject samples not meeting the quality criteria. An evaluation by a medical imaging expert with over four years of experience led to a dataset consisting of 143 pairs of aortic root masks and the corresponding non-contrast CT scans. It formed a dataset which contained CT scans acquired in two clinical centers from two European countries and covered a range of scanner manufacturers: GE (7 scans), Philips (4), Siemens (129), and Toshiba (3). It was split into training and validation subsets containing 114 and 29 scans, respectively. In this study, we did not perform any kind of data stratification but we have evaluated the final result against a publicly available orCaScore dataset. The standard nnU-Net framework [8] was used to train an ML segmentation model. We used the previously selected 29-element validation set only for potential over-fitting monitoring.

Iterative Closest Point (ICP) Method for Accuracy Estimation Qualitative inspections of geometries created by the aorta model in non-contrast images suggest that it not only reproduces in detail the aortic root but also extrapolates the shape and position of the AV. GT is unavailable in this case; however, we have detailed segmentations of the aortic roots in contrast series. This suggests comparing the segmentations based on contrast series with ML inferences in non-contrast images. One might naively use image registration, but, as has been previously stated, this method might introduce significant errors and is unreliable. We have, however, observed that the ostia of coronary vessels and surrounding parts of the aortic root are visible in both contrast and non-contrast images. This observation suggests using characteristic points as landmarks to obtain a local transformation from contrast to non-contrast images. Manual marking of landmarks is feasible but not a scalable solution, so we propose an algorithm based on Interactive Closest Points (ICP) [2]. We proceed as follows:

1. We take segmentations of coronary vessels and the aortic root in both contrast and non-contrast images in the form of surface meshes. The masks

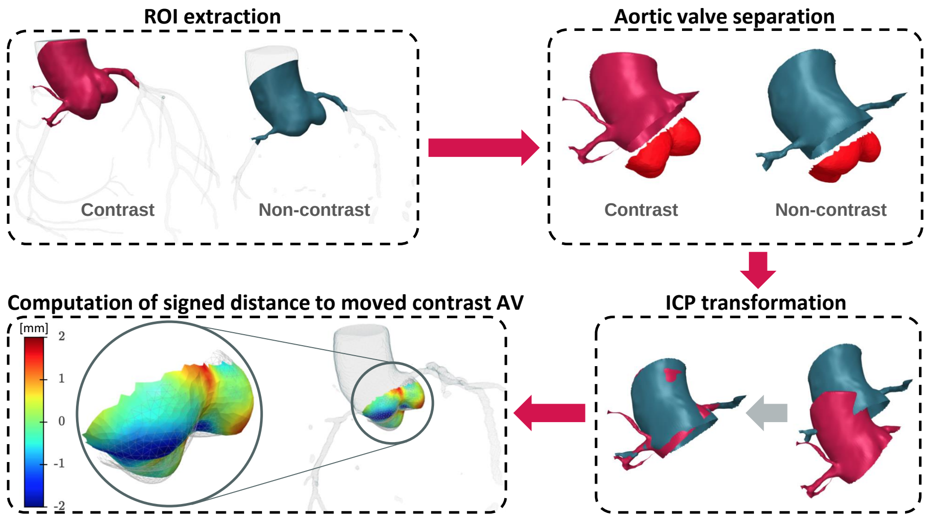

Fig. 3. The procedure of evaluation of aortic valve accuracy.

of coronary vessels in contrast and non-contrast CT are obtained based on neural networks trained using the nnU-Net framework [8], according to the methods described in [16] and [4], respectively.

2. We find the position of the ostia and a direction along the aortic root. It defines a system of coordinates for further processing.
3. We keep only parts within 55 mm from the mean ostia position in both cases.
4. We separate the AV mesh (lower part) and ostia with a fragment of the aortic root (upper part).
5. We use a modified variant of the ICP algorithm to find a local rigid transformation between the upper part only[5].
6. Using the transformation, we move AV only from the contrast to the non-contrast coordinate system.
7. We compute the distance using `vtkImplicitPolyDataDistance` from VTK library [21], for all vertices of AV transformed from contrast image to non-contrast ML model mesh. For each AV we calculate the mean of these distances and use it as measure of non-contrast ML model accuracy.

In this work, we assumed that a local rigid transformation is a good approximation, which is fulfilled if heart images in contrast and non-contrast are approximately in the same phase—this condition is met for our data. The full source code for this method is available in a public repository [3].

[5] Our variant of ICP acknowledges the subtle anatomical discrepancies between size of the ROI in contrast and non-contrast segmentations. By iteratively applying the ICP and excluding points beyond a certain distance, we refined alignment accuracy.

4 Analysis of Results and Conclusion

Our model demonstrates the capability to generate accurate segmentations of the aortic root from non-contrast cardiac CT scans. Utilizing the orCaScore dataset, which comprises 70 pairs of contrast and non-contrast gated CT scans, we have evaluated our model's performance. For both contrast and non-contrast images, segmentations were obtained and subsequently converted into surface meshes. An ICP-based alignment procedure was employed to align the aortic root from contrast images to the non-contrast coordinate system. This allowed us to quantify the distance between the reconstructed aortic valve based on non-contrast data and the aligned in ICP procedure shape derived from precise contrast images.

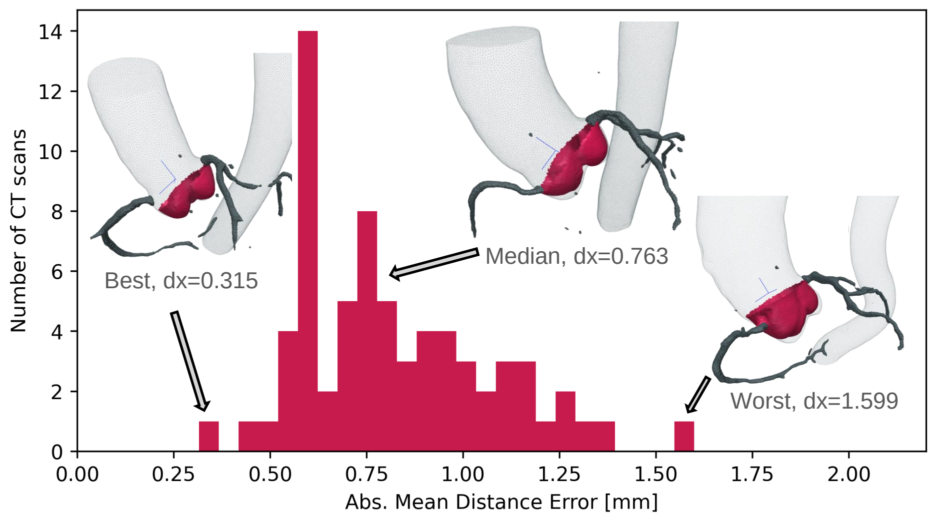

Fig. 4. The Quantitative Performance Evaluation of the nnU-Net deep learning model of aortic root over the orCaScore benchmark (challenge) dataset. This histogram illustrates the distribution of absolute mean distance errors in segmenting the aortic valve with the nnU-Net model. Evaluated on a set of 70 non-contrast CT scans from the publicly accessible orCaScore challenge dataset, the figure delineates the best (with dx=0.315mm), median (dx=0.763mm), and worst (dx=1.599mm) segmentation results. The semi-transparent gray mesh represents the aorta model, while the violet segmentation corresponds to the ICP-fitted ground truth derived from the contrast-enhanced CT scans. Finally, the histogram quantifies the model's performance across the orCaScore dataset, capturing the variability in segmentation accuracy.

As depicted in Fig. 4, the mean accuracy achieved was 0.82 mm ±0.24 mm. Remarkably, even the least accurate case fell within an acceptable error margin of 1.6mm, underscoring the model's utility for various clinical applications. It is noteworthy that the spatial resolution of non-contrast scans is approximately

1.5mm, which further substantiates the robustness of our results. Of note, the distribution of the absolute mean distance errors indeed indicate that there is a small number of outlying low-quality predictions, with the majority of test orCaScore scans showing high-quality operation of our approach.

Limitations and Challenges In our study, we excluded anomalies such as bicuspid prosthetic aortic valves and the presence of coronary artery stents. However, because our process is inherently data-driven, it is straightforward to include a significant representation of these cases in both the training and testing datasets. The methodology we adopted is flexible, allowing for modifications to develop machine learning models based on non-contrast data when ground truth is available from corresponding contrast-enhanced series. The future challenge lies in extending this work to derive clinically relevant information from high-resolution non-contrast series for patients who cannot receive contrast agents.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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