

# Centerline Extraction and 3D Reconstruction of Coronary Angiography Based on Attention 3D U-Net

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**Abstract:** Coronary artery disease ranks among the leading causes of death globally, and the three-dimensional morphology of atherosclerotic plaques is a critical factor in assessing their rupture risk. To achieve precise 3D modeling of coronary arteries and plaques, this paper proposes an automated reconstruction method integrating angiographic and OCT (Optical Coherence Tomography) images. First, an Attention 3D U-Net network is employed to segment vessels and extract centerlines from angiographic images; Subsequently, based on dual-view projections from the XOZ and YOZ planes, a smooth and continuous three-dimensional centerline is reconstructed through parametric curve fitting and nonlinear optimization techniques. Finally, using this centerline as a spatial reference, OCT cross-sectional sequences are aligned, and the Marching Cubes algorithm is employed to generate a three-dimensional model of the coronary artery, incorporating distinct plaque components. Experimental results demonstrate that this method effectively restores three-dimensional vascular structures from two-dimensional projections. The reconstructed models exhibit excellent geometric plausibility and continuity, accurately reflecting actual anatomical morphology. This study provides a reliable three-dimensional geometric foundation for precise quantitative analysis of coronary lesions and biomechanical assessment of plaque rupture risk.

**Keywords:** Deep Learning; 3D Reconstruction; Coronary Artery; Attention 3D U-Net; Marching Cubes Algorithm

## 1. Introduction

Cardiovascular diseases, particularly coronary

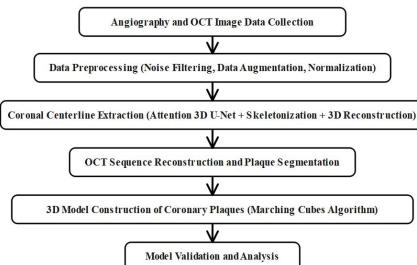
heart disease, rank among the chronic diseases with the highest incidence and mortality rates worldwide. The formation and progression of coronary atherosclerotic plaques constitute the primary pathological basis for the development of coronary heart disease. During plaque development, the gradual accumulation of lipids, calcium deposits, and fibrous tissue within the vascular endothelium leads to alterations in the structural and mechanical properties of the vessel wall. Research indicates that over half of acute coronary syndromes are caused by plaque rupture [1], making the early prediction of plaque rupture risk crucial for the prevention and treatment of coronary heart disease.

Currently, clinically used OCT and coronary angiography can clearly identify vascular morphology and plaque types, but their results are predominantly two-dimensional images [2], making it difficult to fully present the three-dimensional spatial characteristics of vessels and plaques. In recent years, image analysis technologies based on deep learning and 3D reconstruction have provided new approaches for precise modeling and risk assessment of coronary artery lesions.

To achieve the goal of accurately reconstructing three-dimensional models of coronary arteries from two-dimensional images, this study proposes a novel method that integrates angiographic and OCT data. This method is based on the Attention 3D U-Net model [3], which realizes automatic extraction of the vessel centerline and plaque regions. Building upon this foundation, it completes three-dimensional geometric modeling, providing a reliable geometric basis for the precise quantification and risk prediction of coronary artery lesions. The research process is shown in Figure 1.

## 2. Data Preprocessing and Vessel Centerline Extraction

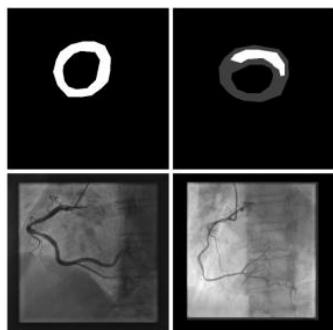
To construct a three-dimensional model of the coronary artery, it is necessary to first extract the centerline structure of the vessel from the imaging data. This section describes the dataset composition, preprocessing workflow, and centerline extraction method based on Attention 3D U-Net.



**Figure 1. Overall Research Process Flowchart**

## 2.1 Data Description

The data for this study was sourced from the “iFlytek AI Developer Competition—Coronary Artery and Plaque 3D Reconstruction” challenge and has been authorized for use. The data comprises two components: coronary angiography images and OCT cross-sectional images. The angiography images are stored in DICOM format, providing two-dimensional projection information of the vessels; OCT images are stored in NumPy array format, containing cross-sectional information of blood vessels and different types of plaques. Data is categorized and stored by case number, with each case containing complete angiographic images and OCT sequences, as illustrated in Figure 2.

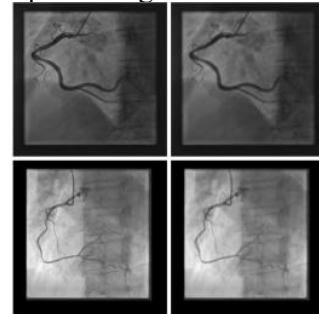


**Figure 2. Partial Coronary OCT and Angiographic Images**

## 2.2 Data Preprocessing

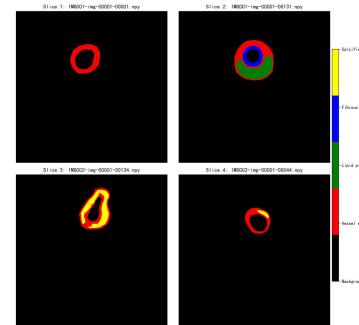
After reviewing the image data in the dataset, it was found that most of the original OCT images exhibit noise and brightness inconsistencies. These issues may negatively impact the results of subsequent experiments. To this end, this

study first employs Gaussian filtering [4] to smooth and denoise the images, suppressing noise while preserving vascular edge structures. The images were subsequently standardized in size and underwent grayscale normalization to ensure data consistency. The comparison before and after preprocessing is shown in Figure 3.



**Figure 3. Gaussian Filter**

The OCT images used are pre-labeled with algorithmically generated tags, where pixel values 0–4 correspond to background, vascular contours, lipid plaques, fibrous plaques, and calcified plaques, respectively. This labeled data serves as the foundation for model training and 3D reconstruction. Label examples are shown in Figure 4.



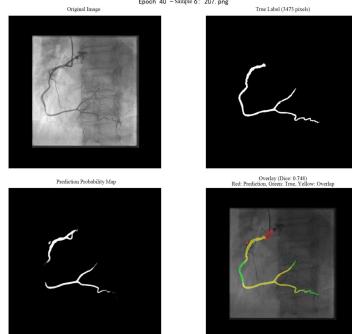
**Figure 4. Label Display**

## 2.3 Model Implementation (Attention 3D U-Net)

Building upon data preprocessing, this study employs the Attention 3D U-Net model to extract vascular centerlines from angiographic images. U-Net is a classic architecture for medical image segmentation, whose encoder-decoder structure effectively captures multi-scale features [5]. However, the traditional U-Net is susceptible to background interference in complex vascular structures. Therefore, this paper introduces an attention gating module into the skip connection, enhancing the model's focus on vascular regions through the attention mechanism while suppressing irrelevant information, thereby improving segmentation

accuracy.

The model training uses angiographic images as input and outputs a binary mask of blood vessels. Performing skeletonization on the segmentation results yields a set of centerline points. During training, 3D convolutional kernels are employed to leverage spatial contextual information, and data augmentation techniques such as random rotation, translation, and brightness perturbation are applied to enhance model robustness [6]. After iterative training, the model's segmentation performance stabilized, and the centerline extraction results are presented in Figure 5, laying the foundation for subsequent 3D reconstruction.



**Figure 5. Central Baseline Extraction Results**

### 3. 3D Coronary Artery Reconstruction and Assessment

#### 3.1 3D Centerline Reconstruction Based on Dual Views

Since angiographic images provide orthogonal projections of vessels in the XOZ and YOZ planes, the true three-dimensional positional information can be reconstructed through the registration relationship between the two projections [7]. After obtaining the baseline segmentation results of coronary angiography images, this study employed a parametric curve fitting method to construct the three-dimensional centerline structure of the coronary arteries [8]. Based on the orthogonal projection information from the XOZ and YOZ planes, the following three-dimensional spatial curve parameterization model was established.

$$x(t) = a \cdot t + b \cdot \sin(c \cdot t) \quad (1)$$

$$y(t) = d \cdot t + e \cdot \cos(f \cdot t) \quad (2)$$

$$z(t) = g \cdot t + h \cdot \sin(i \cdot t) \quad (3)$$

Among these,  $t$  is the normalized curve parameter, while  $a, b, c, d, e, f, g, h$ , and  $i$  are the parameters to be optimized.

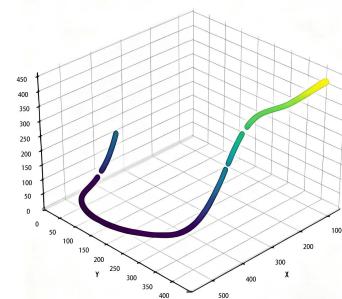
The reconstruction process begins with preprocessing the two-dimensional centerlines in the two projection images, including smoothing, filtering, and parametric alignment. By registering the  $x(z)$  provided by the XOZ projection and the  $y(z)$  provided by the YOZ projection along the shared depth axis  $z$ , a 3D point cloud  $P(z) = (x(z), y(z), z)$  can be established.

By optimizing the nine parameters using nonlinear least squares, the fitted curve achieves the best possible fit with the observed data. The optimized parametric model not only generated continuous and smooth three-dimensional curves but also demonstrated its ability to capture complex vascular geometries. This method enables the accurate reconstruction of three-dimensional centerlines using orthogonal projection information, even with single-angle angiographic input, thereby laying a solid foundation for subsequent vascular geometry analysis and volumetric modeling.

#### 3.2 3D Centerline Reconstruction Results

Based on the dual-view geometric reconstruction method mentioned in Section 2.1 of this study, we successfully generated a three-dimensional centerline of the coronary artery using projection curves from the XOZ and YOZ planes. The reconstruction results are shown in Figure 6.

3D Volume Reconstruction



**Figure 6. 3D Centerline Reconstruction Results**

As shown in Figure 6, the reconstruction results of the three-dimensional center baseline can be clearly visualized. From a geometric perspective, the reconstructed centerline exhibits excellent smoothness and continuity, confirming the effectiveness of the orthogonal projection and parametric curve fitting method in restoring the three-dimensional spatial position information of blood vessels. Simultaneously, this centerline accurately reflects the morphology of the main vascular trunk, providing a correct spatial

reference framework for subsequent spatial alignment of OCT cross-sectional sequences and three-dimensional volume reconstruction.

### 3.3 Construction of a 3D Model of Coronary Arteries and Plaques Based on Centerlines and OCT

Building upon the acquisition of three-dimensional centerline data, this study further integrates optical coherence tomography (OCT) data to perform detailed three-dimensional modeling of the coronary artery lumen and plaque composition. The core task of this process is to accurately arrange the two-dimensional OCT cross-sectional sequences along the centerline in three-dimensional space and generate a continuous mesh model. This involves the following two steps:

First, the ordered OCT sequence is input into a pre-trained 3D U-Net Attention model for pixel-level semantic segmentation, yielding a three-dimensional volume matrix containing distinct tissue labels, such as background, vascular walls, lipid plaques, fibrous plaques, and calcified plaques. Next, using the reconstructed 3D centerline as the central axis of the vessel, each OCT cross-sectional image is positioned to its corresponding center point. To ensure the slice plane remains perpendicular to the local direction of blood vessels, a local coordinate system is established by calculating the tangent vectors at each point along the centerline [9]. The slice undergoes rotational transformation, effectively preventing model distortion caused by vessel curvature and ensuring the geometric accuracy of the reconstructed model.

After completing the spatial alignment of OCT volumetric data, the Marching Cubes algorithm is employed to extract isosurfaces from the aligned three-dimensional volumetric matrix [10]. This algorithm efficiently generates smooth mesh models that accurately reproduce the three-dimensional geometry of the vascular intima and different plaque components (lipids, fibrous tissue, calcification). Ultimately, an integrated three-dimensional model combining the macroscopic geometry of the coronary artery with the microscopic composition of the plaque was obtained, providing an ideal geometric foundation for subsequent biomechanical analysis.

### 4. Closing Remarks

This study proposes a three-dimensional

automatic reconstruction method that integrates coronary angiography and OCT imaging. This method first utilizes the Attention 3D U-Net model to extract the vascular centerline from angiographic images. It then employs dual-view geometric reconstruction techniques to generate a smooth three-dimensional centerline. Subsequently, OCT cross-sectional sequences are aligned with this centerline, and the Marching Cubes algorithm is applied to construct a three-dimensional model of the coronary artery, containing distinct plaque components.

The results demonstrate that the proposed method can effectively reconstruct the three-dimensional spatial structure of coronary arteries from two-dimensional orthogonal projections. The generated centerlines exhibit excellent geometric rationality and anatomical authenticity, providing a viable solution for the geometric assessment of coronary lesions in clinical practice.

This study not only provides a novel technical tool for the precise quantitative analysis of coronary artery lesions but also establishes a three-dimensional geometric foundation for plaque biomechanical assessment and rupture risk prediction. Future research can validate the method's robustness on broader datasets and explore more optimal reconstruction algorithms to further enhance performance.

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