# Progress And Challenges of Coronary Angiography in The Diagnosis and Treatment of Coronary Heart Disease

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**Abstract.** As living standards improve, the incidence of coronary heart disease (CHD) has been rising. Against this backdrop, coronary angiography has become a pivotal tool in cardiovascular medicine, establishing itself as the gold standard for the diagnosis and treatment of CHD. This review outlines the latest advancements in coronary angiography techniques, which have greatly enhanced the clarity with which physicians can view coronary artery structures and the precision of diagnoses. Clinically, coronary angiography not only plays a central role in diagnosing CHD but also exhibits unique advantages in managing acute coronary syndromes, myocardial infarctions, and interventional treatments. Real-time imaging technologies enable physicians to make swift and accurate clinical judgments and provide timely interventions for patients. This article also reviews the literature to discuss the symptoms and susceptibility factors of CHD, the fundamental principles and conditions of coronary angiography technology, the analysis of diagnostic results, and the potential to enhance the diagnostic efficiency of CHD using emerging algorithmic models.

**Keywords:** Coronary Heart Disease, Coronary Angiography, Image Segmentation, Deep learning.

## 1. Introduction

Coronary heart disease (CHD), also known as coronary atherosclerotic heart disease, is characterized by atherosclerotic lesions in the coronary arteries. These lesions lead to the narrowing or blockage of blood vessels, resulting in myocardial ischemia, hypoxia, or necrosis—commonly referred to as ischemic heart disease. According to the China Health Statistical Yearbook, the mortality rate of CHD in urban residents increased from 86.34 per 100,000 in 2010 to 121.59 per 100,000 in 2019 [1]. In rural areas, it rose from 69.24 per 100,000 to 130.14 per 100,000 over the same period. These statistics underscore that as modern society advances and living standards improve, the incidence and mortality rates of CHD continue to climb annually, posing significant threats to public health and safety in China.

Recent clinical studies have identified the primary factors contributing to the onset of CHD as smoking, poor diet, lack of physical activity, overweight, obesity, and psychological stress. Early identification and intervention targeting these risk factors can effectively prevent CHD, reduce its prevalence, and lead to better patient outcomes.

Currently, the principal clinical diagnostic methods for CHD include electrocardiography, echocardiography, and coronary angiography. Among these, coronary angiography is considered the gold standard for diagnosing CHD due to its crucial role in accurately assessing the condition.

## 2. Coronary arteries of the heart

The coronary arteries are the arteries of the coronary circulation, which carry oxygenated blood to the heart muscle. The heart needs a constant supply of oxygen to function and survive, just like any other tissue or organ in the body. The coronary arteries surround the entire heart. The two main branches are the left coronary artery (LCA) and the right coronary artery (RCA). Arteries can also be classified based on the area of the heart where they provide circulation. These categories are referred to as epicardium (above the pelvis, or the outermost layer of the heart) and microvascular (tissue near the endocardium or the innermost layer of the heart) [2]. Any disease or disease of the coronary arteries can have serious health effects and can lead to angina, heart attack, and even death.

### 2.1. Causes of coronary heart disease

Causes Coronary artery disease is manifested as coronary artery stenosis, which is mainly caused by atherosclerosis (the most common), arteriosclerosis and arteriolar sclerosis. It occurs when plaque (made up of deposits of cholesterol and other substances) builds up in the walls of the arteries over time, and as the disease progresses, plaque buildup can partially block blood flow to the heart muscle. The heart doesn't work properly without an adequate blood supply, especially with increased pressure. A heart attack is caused by a plaque that suddenly ruptures and forms a blood clot (blood clot), completely blocking blood flow to a part of the heart, leading to tissue death (infarction). Coronary artery disease can also lead to heart failure or arrhythmias. Reduced blood flow can lead to chronic hypoxia, which can lead to heart failure. At present, the types of theories are lipid infiltration, thrombosis and platelet aggregation, endothelial injury response, and smooth muscle cell cloning [3].

### 2.2. Classification of coronary heart disease in clinical practice

Clinical classification According to the clinical manifestations, coronary heart disease can be divided into three categories:

## 3. Exertional angina

Angina pectoris induced by increased myocardial oxygen consumption due to strenuous activity, emotional agitation, cold, satiety, etc., can relieve symptoms by rest or sublingual nitroglycerin. (1) Stable angina refers to the fact that there is no change in the nature of exertional angina within 1-3 months after the onset of exertional angina. (2) Primary angina, the course of angina pectoris is less than one month. (3) Aggravating angina, angina pectoris progressively worsens within 3 months.

## 4. Spontaneous angina

As the name suggests, the onset of spontaneous angina is not significantly related to the increase in myocardial oxygen consumption caused by overwork, but is related to the decrease in coronary blood flow reserve. (1) Recumbent angina pectoris, which often occurs at rest or while asleep. (2) Variant angina, which often occurs at night and during sleep, and ST-segment elevation can be seen on ECG during the attack. (3) Acute coronary insufficiency, also known as intermediate syndrome, occurs at rest or sleep, and the onset lasts for a long time, which can develop into myocardial infarction. (4) Angina pectoris after infarction, angina pectoris that occurs again within one month of acute myocardial infarction, and there is a possibility of recurrence of infarction at any time.

## 5. Mixed angina

Clinical symptoms The typical manifestation of angina pectoris attack is sudden onset of pressure, bloating or ventricular pain, which is generally located in the upper or middle part of the sternal body, and may also affect the predistracted area, which can radiate to the left shoulder, the inner side of the left upper limb, and reach the ring finger and little finger, occasionally accompanied by a sense of near-death fear, which often forces the patient to stop activities immediately, and in severe cases, sweating. The onset of pain usually takes about 1-5 minutes, rarely more than a quarter of an hour, and the pain disappears within 1-2 minutes with rest or sublingual nitroglycerin [4].

At present, the methods used in clinical practice include electrocardiogram (ECG), radionuclide examination, nuclear myocardial scintigraphy and stress test, radionuclide cardiography, positron emission tomography (PET) technology, and other examinations of multi-slice spiral CT coronary angiography (CTA), echocardiography and the "gold standard" coronary angiography for coronary heart disease diagnosis.

# 6. Treatments for Coronary Heart Disease

## 6.1. Management During Seizure

Immediate rest during a seizure typically alleviates symptoms swiftly. Pharmacological intervention involves the use of fast-acting nitrate preparations, such as sublingual nitroglycerin, which can take effect within 2-3 minutes to relieve symptoms effectively.

## 6.2. Management During Remission

Lifestyle modifications are crucial during the remission period. Patients are advised to avoid factors that trigger angina, adjust their diets by reducing the intake of fats and sweets, and limit the consumption of fish and meat. Additionally, quitting smoking and alcohol alongside enhancing physical activity are recommended. Pharmacologically, nitrates like glycyl nitrate and isosorbide dinitrate, along with calcium channel blockers such as verapamil and nifedipine, can effectively improve ischemia and reduce symptoms of angina. Medications such as aspirin, clopidogrel, and statins are also prescribed to prevent myocardial infarction and improve prognosis [5].

## 6.3. Interventional Treatments

Percutaneous coronary intervention (PCI) [6] is a pivotal interventional technique aimed at revascularization, significantly improving patient quality of life and reducing the incidence and mortality of myocardial infarction in high-risk individuals. This includes several procedures:

Percutaneous Coronary Intervention (PCI): This method uses transcardiac catheter technology to clear blocked or narrowed coronary arteries, thereby enhancing myocardial blood perfusion.

Percutaneous Transcoronary Angioplasty (PTA) [7]: Typically involves the placement of a stent, a small guidewire mesh tube that helps keep the artery open and reduces the risk of re-narrowing.

Rotational Atherectomy (RA) [8]: This procedure utilizes a diamond-coated grinding wheel to safely remove calcified plaque, thus restoring smooth blood flow.

Percutaneous Mechanical Thrombectomy (PMT) [9]: Specialized devices are used for this procedure to extract thrombus from blood vessels, performing functions such as impregnating, chopping, clearing, and dissolving thrombus.

Excimer Laser Ablation Angioplasty (ELA) [10]: This technique employs ultraviolet radiation to ablate atherosclerotic plaques. The UV energy is absorbed by the plaques, vaporizing them and effectively eliminating the obstruction within the target blood vessel.

These interventions are integral to managing coronary heart disease, providing various options for significantly improving outcomes for affected patients.

# 7. Coronary Heart Disease with Advanced Imaging Technology

Indications for percutaneous coronary intervention are divided into the following points: (1) Patients with chronic stable angina and symptoms of extensive myocardial ischemia. (2) High-risk patients with unstable angina and non-ST-segment elevation myocardial infarction. (3) Patients with acute ST-segment elevation myocardial infarction should be treated as early as possible to open the blocked blood vessels, save the myocardium as much as possible, reduce the patient's risk of death and improve the prognosis [11].

Conventional diagnostic methods for coronary heart disease include electrocardiography, imaging diagnosis, etc., and imaging is the most popular diagnostic method, among which the most widely used are computed tomography (CT) and cardiovascular magnetic resonance imaging (Cardiovascular magnetic resonance imaging). resonance, CMR) and single photon emission computed tomography (Single photon emississ computed tomography, SPECT), etc. Imaging technology can formulate precise and individualized diagnosis and treatment plans, but because the interpretation of imaging data is affected by objective factors such as doctor level and mental state, different diagnostic results may occur. With the rapid development of information technology and big data, computer-aided diagnosis mode has improved the processing speed and diagnostic accuracy of imaging data [12]. Among them, deep learning (DL) is the most commonly used algorithm. Among them, a series of image segmentation methods such as Full convolution network (FCN), Pyramids scene parsing network (PSPNet), DeepLab, and Mask RCNN have emerged in segmentation methods, which have continuously improved segmentation accuracy. The segmentation process is also more intelligent. These methods are used to segment lesions in coronary heart disease angiography images in the cardiovascular system, which will improve the diagnosis efficiency and reduce the workload of doctors. Contribute to the diagnosis and treatment of patients with coronary heart disease [13].

Medical imaging serves as a crucial medium for conveying medical information, and extracting information from key regions is essential for diagnostics. Prior to utilizing machine-based identification or classification of tissue information, the technology of image segmentation becomes particularly important. Indeed, image segmentation is foundational to image recognition, image processing, and the extraction of critical information. In the context of diagnosing coronary heart disease, medical professionals analyze cardiovascular angiography images to assess lesions. However, manual diagnostics can be hindered by the subjective factors such as the physician's diagnostic skill and clinical experience, as well as objective factors like the quality of angiography images or unique growth locations of the patient’s cardiovascular tissues, which can lead to inaccuracies in assessing patient conditions. Therefore, employing image segmentation techniques for lesion segmentation in cardiovascular angiography is beneficial for assisting diagnoses and reducing workload.

### 7.1. Traditional Segmentation Methods

This section primarily discusses segmentation techniques driven by model-based and machine learning-based approaches, comparing the characteristics of various methods. For specific comparative details, refer to Table 1. Each method's principles and applications within the realm of image segmentation are then discussed.

**Table 1.** Comprehensive Comparison of Algorithms

| Segmentation Method | Target Image | Complexity | Time Comsumption | Disadvantages |
|---|---|---|---|---|
| Statistic-based model | Most images | Simple | Short | Does not consider semantic features |
| Threshold segmentation | High contrast between target and background | Simple | Short | Does not consider semantic features |
| Edge detection segmentation | Pixels with significant grayscale changes | Moderate | Short | Insensitive to gradual grayscale changes |
| Region-based segmentation | Obvious inter-class characteristics | Difficult | Long | Uneven grayscale and noise can lead to over-segmentation |
| Segmentation based on clustering | Similar characteristics within target classes | Difficult | Longer | Time-consuming to traverse samples |

### 7.2. Model-Driven Segmentation Methods

Model-driven segmentation methods involve pre-setting models based on the characteristics needed to be segmented (such as grayscale and shape) and fitting these models to the target regions to achieve segmentation. However, it can be challenging to find a suitable model and correctly estimate its parameters.

#### 4.2.1 Statistical Model Method

Statistical models primarily analyze the histogram of data, segmenting based on probability models within the histogram, such as the proportion of values within a certain range in the image. Because the medical imaging scenes are straightforward with clear background and target distinctions, segmentation in this field is often done through simple threshold-based methods for rough pixel-level segmentation.

#### 4.2.2 Machine Learning-based Segmentation Methods

Threshold-based image segmentation fundamentally involves clustering an image's grayscale histogram by setting different grayscale thresholds. Pixels within the same grayscale range are classified as belonging to the same category based on their similarity. The challenge in this method lies in selecting the appropriate threshold size, which is crucial for segmentation accuracy. Optimal grayscale thresholds can be determined by maximizing the differences between categories. Additional methods include entropy-based thresholding, minimum error thresholding, co-occurrence matrix methods, moment preservation, simple statistical approaches, probabilistic relaxation, fuzzy set methods, and hybrid thresholding techniques [14].

In image segmentation, if a pixel significantly differs in grayscale value from its neighbors, it is likely located on an edge. Identifying these pixel clusters and connecting them forms an edge contour, thus dividing the image into distinct regions. This method relies on discontinuities in grayscale values between adjacent areas, such as sudden changes in grayscale, color, or texture. These discontinuities are typically detected using derivative operations, which can be calculated using differential operators [15], including generalized first-order differential operators like the Prewitt and Sobel operators [16].

Region-based segmentation methods divide an image based on spatial information and pixel similarity. Common algorithms include region growing and split-and-merge techniques. Region growing starts with a set of seed points and iteratively groups pixels with similar properties into a region according to predefined criteria related to image color and texture. The thresholds set during this process are crucial and directly affect the segmentation outcome. In split-and-merge, the image is initially divided into regular regions, which are then split or merged based on similarity criteria until no further changes occur.

Clustering-based segmentation techniques use feature space clustering to segment pixels in the image space according to their aggregation in the feature space. Pixels with similar features group together in the same region, and the clustering results are iteratively refined until convergence. Finally, all pixels are classified into several categories, and these categories are mapped back to the original image space to produce the segmentation result [17]. The most commonly used clustering algorithm is K-means, which clusters samples based on distance to form compact and independent clusters as the clustering goal.

#### 4.2.3 Emerging Frontiers in Image Analysis

Traditional segmentation techniques are not suitable for tasks involving semantic information, which has made convolutional neural networks a crucial tool in image processing, particularly in semantic segmentation. Semantic segmentation involves assigning a semantic label to each pixel in an image. The main components are: (1) identifying the objects in an image, (2) delineating object boundaries, and (3) marking the target regions at the pixel level. Current mainstream methods include FCN, PSPNet, DeepLab, and Mask R-CNN. The advent of these deep learning-based segmentation methods has continuously improved segmentation accuracy and intelligence.

The **Full Convolutional Network (FCN)** is a pioneering work in deep learning for semantic segmentation, particularly suited for biomedical image segmentation. It consists of an encoder, bottleneck module, and decoder, establishing a universal network model framework for image semantic segmentation. Unlike traditional CNNs, which use several fully connected layers following multiple convolution layers to map the produced feature maps to fixed-length feature vectors for classification, FCN adopts a "fully convolutional" approach, upsampling the feature maps to perform deconvolution, followed by classification via a SoftMax layer, ultimately outputting segmentation results. FCNs can perform pixel-level classification, effectively solving semantic segmentation challenges and can input images of any size, marking it as the first end-to-end segmentation network model, holding significant importance in the segmentation field. The specific architecture of an FCN is illustrated in Figure 1.

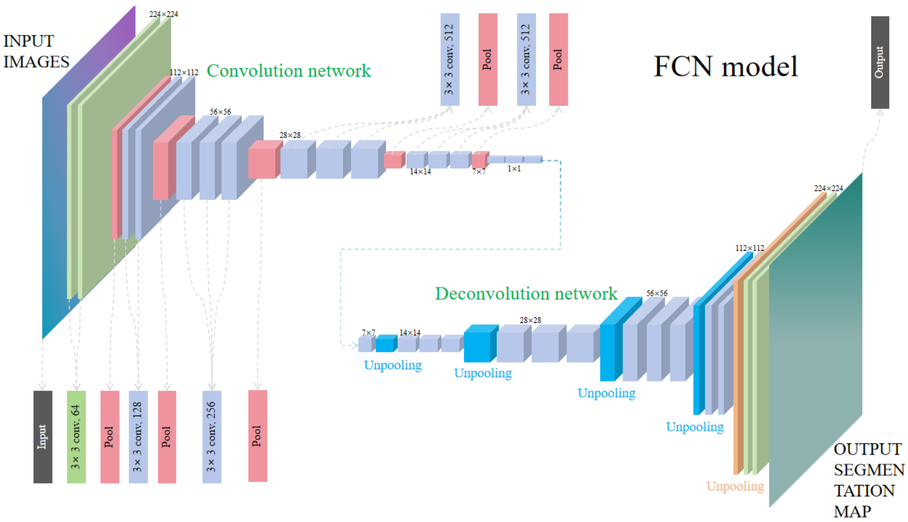


**Figure 1.** FCN Model Diagram

Introduced by Ronneberger et al. at the 2015 MICCAI conference, **U-Net** has marked a breakthrough in medical image segmentation using deep learning. U-Net, a full convolutional network (FCN), incorporates a U-shaped structure combining contextual information, making it highly effective and efficient with minimal data use. Its design is particularly well-suited for medical image segmentation. The U-Net model was originally developed for 2D image processing and has been adapted into a 3D U-Net to address challenges in volumetric biomedical imaging where traditional 2D image processing algorithms struggle in 3D medical imaging contexts [18].

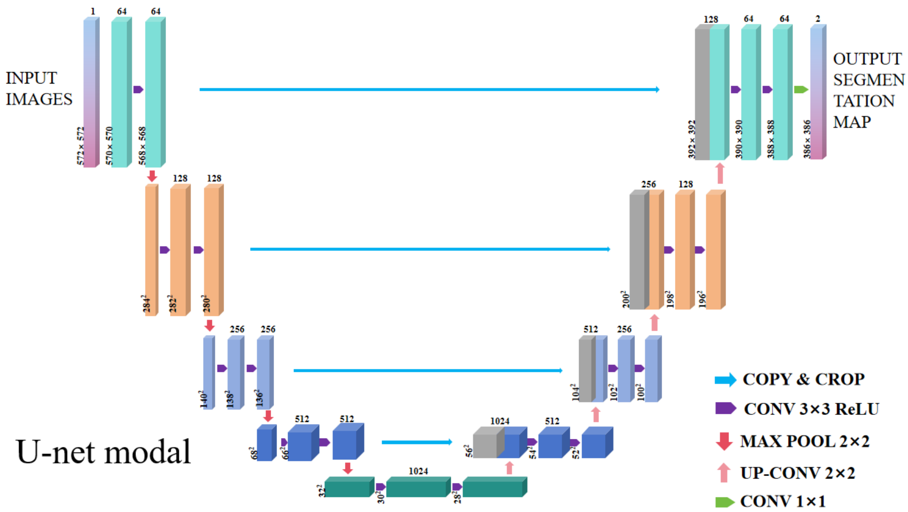


**Figure 2.** U-net Model Diagram

Figure 2 shows the model architecture of U-net. In recent years, several U-net variants have been developed for different application scenarios. The enhancements and basic parameters of different variants are compared in Table 2.

**Table 2.** Comparison of U-net Variants

| Model structure | Dimension | Improved structure | Params | Kernel size |
|---|---|---|---|---|
| U-net | 2D | The decoder is deepened by convolution | 30M | 3×3;2×2;1×1 |
| U-net++ | 2D | Densenet-like structure is combined;<br>Deep supervision was used | 35M | 3×3;1×1 |
| 3D U-net | 3D | The convolution operation in 2D becomes 3D | 19M | 3×3×3;2×2×2;1×1×1 |
| Attention U-net | 2D | Add attention mechanisms to skip connections | 123M | 1×1 |
| V-net | 3D | Introduce a novel objective function,based on Dice coefficient | NA | 2×2×2 |
| U2-net | 2D | RSU was used as the unit for encoding and decoding | 176M | 3×3 |
| nnU-net | 2D/3D | Leaky ReLU and instance normalization is used ;<br>Multi-unet cascade segmentation | NA | 4×4×4 |
| TranU-net | 2D | Transformer model is added after the decoder | 2.93M | 1×1 |

### 4.2.4 Other Emerging Applications of Deep Learning

In recent years, weakly supervised and semi-supervised learning with Deep Convolutional Neural Networks (DCNN) have emerged as effective algorithms for semantic image segmentation. Prior to this, the DeepLab method utilized Fully Convolutional Networks (FCN) to generate coarse segmentation maps interpolated to the size of the original image, then refined the segmentation details using fully connected Conditional Random Fields (CRF) borrowed from FCN [19]. DCNN research, building on DeepLab, explored using bounding boxes and image-level labels as training data, employing the Expectation Maximization (EM) algorithm to estimate unlabeled pixel classes and CNN parameters. For training images labeled with bounding boxes, this method employs CRF for automatic segmentation, followed by fully supervised learning. Experiments have shown that relying solely on image-level labels yields poor segmentation results, whereas training with bounding boxes achieves better outcomes.

Just as with Multi-Head Attention and marked MHA, Vision Transformers like DETR, CNN, and ViT are being applied. Some teams have utilized the PyTorch library to implement Convolutional Long Short-Term Memory (ConvLSTM) network architectures for training deep learning models for coronary artery segmentation. Compared to U-Net, ConvLSTM networks, which are a mainstream method for image segmentation, split into two branches. The first branch uses ConvLSTM to capture spatial-temporal information by learning dependencies between sequence images, extracting features from the current cross-section and five adjacent ones. The second branch extracts features from the current vascular cross-section using DenseNet blocks. The trained network outperforms U-Net in terms of Dice coefficient for vascular walls (0.94 vs 0.83; $P < 0.0001$) and lumen and plaque (0.90 vs 0.83; $P < 0.0001$). The proposed model, with its 13 layers utilizing dilated convolutions and max pooling for feature extraction, increases resource consumption. Meanwhile, some teams have proposed the Ghost model to eliminate redundant features, simplifying the process and reducing neural network complexity. Its accuracy rate is 96.05%, with a precision of 98.2% and a recall rate of 95.78%.

### 4.2.5 Image Segmentation Evaluation Metrics

The percentage of correctly segmented pixels in the segmented image, i.e., the proportion of correctly classified pixels to the total number of pixels. The formula is as follows:

$$PA=\frac{\sum_{i=0}^{n} p_{ii}}{\sum_{i=0}^{n}\sum_{j=0}^{n} p_{ij}}=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Here are the explanations for the parameters formula mentioned:

$n$ : Total number of categories, including the background, making it $n+1$ categories in total.

$P_{ii}$ : The total number of pixels that are truly of category $i$ and are correctly predicted as category $i$ . This represents the total number of pixels correctly segmented for the actual category $i$ .

$P_{ij}$ : The total number of pixels that are truly of category $i$ but are predicted as category $j$ . This indicates the number of pixels that are misclassified from their true category $i$ to another category $j$ .

TP (True Positives): The number of pixels that are positive according to the label and are also predicted as positive by the model.

TN (True Negatives): The number of pixels that are negative according to the label and are also predicted as negative by the model.

FP (False Positives): The number of pixels that are negative according to the label but are predicted as positive by the model.

FN (False Negatives): The number of pixels that are positive according to the label but are predicted as negative by the model.

Also known as the Jaccard index, it's one of the most commonly used metrics in semantic segmentation. It measures the overlap between the predicted segmentation and the label over their union (the intersection divided by the union). The metric ranges from 0 to 1 (0–100%), where 0 indicates no overlap and 1 indicates perfect overlap. The formula is as follows:

$$IoU=\frac{|A\bigcap B|}{|A\bigcup B|}=\frac{TP}{TP+FP+FN} \tag{2}$$

For detailed formula parameters, see Section 4.1.

Defined as twice the intersection divided by the sum of pixels, also known as the F1 score. The Dice coefficient is very similar to IoU and positively correlated with it. It ranges from 0 to 1, where 1 represents the highest similarity between prediction and reality. The formula is as follows:

$$Dice=\frac{2|A\bigcap B|}{|A|+|B|}=\frac{2TP}{2TP+FP+FN} \tag{3}$$

For detailed formula parameters, see Section 4.1.

Used to measure the accuracy of boundary segmentation. It quantifies the similarity between two sets of points, describing the distance between two point sets: given two sets A={a1,…,ap} and B={b1,…,bq}, the HD between them is defined as the maximum mismatch degree between the two sets.

$$H(A,B)=\max(h(A,B),h(B,A)) \tag{4}$$

$$h(A,B)=\max_{a\in A}\{\min_{b\in B}||a-b||\} \tag{5}$$

$$h(B,A)=\max_{b\in B}\{\min_{a\in A}||b-a||\} \tag{6}$$

Below is the explanation of the formula:

Equation (1) is known as the bidirectional Hausdorff distance, which is the most fundamental form of Hausdorff distance. Equations (2) and (3), $\mathrm{h}(A,B)$ and $\mathrm{h}(B,A)$, respectively, are known as the unidirectional Hausdorff distances from set A to set B and from set B to set A. Specifically, $\mathrm{h}(A,B)$ first calculates the distances $\left\|a_i - b_j\right\|$ between each point ai in set A and the closest point bj in set B, sorts these distances, and then takes the maximum of these distances as the value of $\mathrm{h}(A,B)$. Equation (3) $\mathrm{h}(B,A)$ is derived similarly.

From Equation (1), the bidirectional Hausdorff distance $\mathrm{H}(A,B)$ is the larger of the two unidirectional distances $\mathrm{h}(A,B)$ and $\mathrm{h}(B,A)$. It measures the greatest mismatch between the two sets of points.

Measures the error relative to the actual volume, comparing the segmented result with the ground truth.

$$RVE(R_a, R_b) = \frac{obs(|R_a| - |R_b|)}{|R_b|} \tag{7}$$

Here are the explanations for the parameters formula mentioned:

$R_a$: Segmentation result.

$R_b$: Surrounding true values (Ground truth).

## 8. Conclusion

Advancements in coronary angiography, fueled by innovations in imaging technology and the integration of artificial intelligence, have significantly enhanced the diagnosis and treatment of coronary heart disease (CHD). Modern high-resolution imaging techniques provide clearer, more detailed visualizations of coronary arteries, which are essential for accurate diagnostics. Meanwhile, automated algorithms have revolutionized the process by reducing the manual workload and increasing diagnostic precision, solidifying angiography as a diagnostic cornerstone.Despite these improvements, several challenges persist in the field of coronary angiography. Safety concerns, especially regarding radiation exposure, continue to be a significant issue. Although technological advancements have led to reduced radiation doses, the risk remains a critical consideration for both patients and healthcare providers. Additionally, the high cost of advanced imaging technology and AI integration poses a barrier to widespread adoption, limiting access in resource-constrained settings.

Ongoing research and development are directed towards overcoming these hurdles. Efforts are focused on refining imaging techniques to further reduce radiation risks and developing cost-effective solutions that can be more broadly implemented. Moreover, there is a concerted push to tailor these advanced technologies for personalized care, ensuring that they can be seamlessly integrated into standard clinical practices. This personalized approach aims to optimize treatment plans based on individual patient profiles, thereby enhancing the overall effectiveness and efficiency of healthcare delivery for CHD.

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