Global-to-Focal: Topology-Guided Progressive Refinement Network for Accurate Coronary Artery Segmentation

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Abstract— **Automatic coronary artery segmentation is crucial for computer-aided diagnosis and treatment planning of coronary artery disease (CAD). It helps clinicians identify potential stenotic lesions and formulate treatment plans, thereby improving the efficiency and effectiveness of diagnosis and treatment. However, the complex tree-like tubular structure of the coronary artery makes it challenging to accurately identify small branches, leading to incomplete topology. This paper proposes a topology-guided progressive refinement network (TPRNet) that progresses from global to focal perspective, leveraging the anatomical topology of the coronary artery to accurately identify small branches and reconstruct vascular structure. Specifically, the globalnet branch performs global segmentation to capture the spatial location information of the coronary artery in the image; the localnet branch segments local vessel regions based on location information and extracts vascular topology; the focalnet branch performs fine-grained segmentation along the centerline to capture vascular details; and finally, the refinement branch reconstructs and optimizes the topology. Experiments show that TPRNet outperforms existing methods on the public coronary artery segmentation dataset ARCADE. The code is available at https://github.com/IPMI-NWU/TPRNet.**

I. INTRODUCTION

Accurate coronary artery segmentation can help clinicians identify lesions during imaging examinations, especially in the early stages of coronary artery disease (CAD). However, automatic coronary artery segmentation still faces two major challenges: 1) The coronary artery have a complex tree-like tubular structure, making it difficult for models to correctly reconstruct the vascular topology; 2) The small branches of the coronary artery have low contrast and occupy a minimal proportion of the image pixels, making them difficult to detect and prone to mis-segmentation.

Currently, several deep learning-based methods have made significant progress in coronary artery segmentation tasks [1]–[3]. U-Net adopts an encoder-decoder architecture, significantly improving segmentation accuracy [4]; while nnU-Net achieves automatic network configuration, enabling adaptive architecture selection and hyperparameter optimization, further enhancing model performance [5]. U-mamba and LKM-UNet introduce the mamba structure, which strengthens the model's ability to handle long-range

dependency [6], [7]. CoANet [8] and DSCNet [9] design specialized convolutions for tubular structures, improving the feature extraction capability. However, these methods often overlook local details and fail to accurately segment the small branches of the coronary artery, leading to incorrect topology. Progressive segmentation methods improve accuracy by gradually refining segmentation results. For example, FocusCut combines global predictions and local refinement to progressively refine boundaries [10]; MagNet uses a multi-scale framework to integrate local details with global context, employing an uncertainty selection branch to optimize outputs [11]. However, despite adopting the global-to-local multi-scale strategy, these methods still do not account for the special anatomical topology structure of the vessel, resulting in incorrect vascular topology.

To address the aforementioned challenges, we propose a topology-guided progressive refinement network (TPRNet), which efficiently learns the tree-like tubular features of small vessel branches and reconstructs anatomically consistent topological structures. Our main contributions are as follows: 1) We design a topology-guided progressive refinement network that improves the detection of small vascular branches. 2) We propose a refinement method based on topological structure and spatial location information to reconstruct the topological consistency of the vessel. 3) Through comprehensive experiments on the publicly available ARCADE dataset [12], we demonstrate that TPRNet outperforms existing methods, achieving higher segmentation accuracy.

II. METHODS

As shown in Fig.1, TPRNet consists of four branches, aiming to achieve high-precision coronary artery segmentation. GlobalNet performs global segmentation, obtaining the spatial location of the vessel. LocalNet conducts local segmentation on the cropped small vascular region to extract complete topological structure information. Guided by the topological information, FocusNet further focuses on even smaller regions to extract finer vascular structural details. The Refinement branch integrates global, local, and focus information to generate the most accurate segmentation results.

A. GlobalNet Branch

The coronary artery is usually located in a part of the overall image. To locate the coronary artery in the image, GlobalNet performs a coarse segmentation of the overall
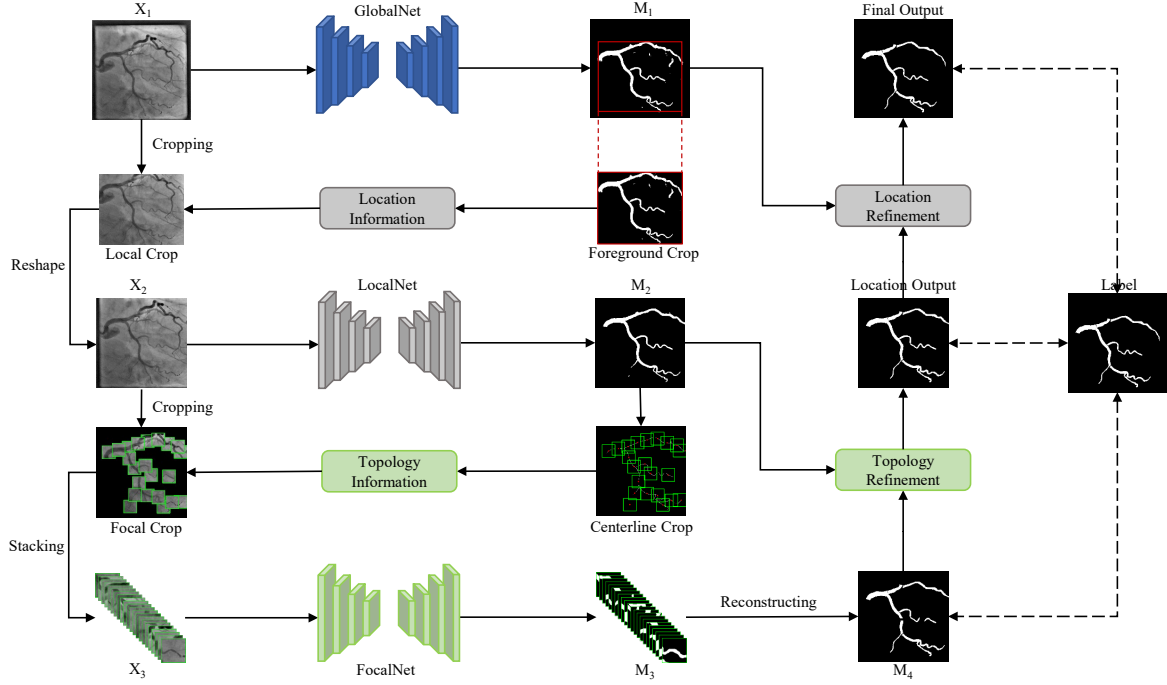
Fig. 1. The architecture of TPRNet. 1) GlobalNet segments the global anatomical region and obtains the spatial position information of the coronary artery relative to the whole image. 2) LocalNet segments the local anatomical region to obtain the topological structure information of coronary artery. 3) FocalNet segments the fine-grained anatomical regions along the centerline to obtain the fine-grained features of blood vessels. 4) Refinement branch reconstructs and optimizes the segmentation.

image, capturing vascular overall structure and spatial position. Its key innovation lies in dynamically determining the minimum bounding rectangle of the vascular region, thereby providing adaptive spatial guidance for subsequent local processing.

Specifically, GlobalNet generates a coarse binary segmentation mask M_1 from input X_1. In order to focus on the foreground region of the coronary image, the minimum bounding rectangle, defined by corners A and B, is computed to outline the vascular region:

$$A = (\min\{x \mid \exists y, \ M_1 = 1\}, \min\{y \mid \exists x, \ M_1 = 1\}),$$
$$B = (\max\{x \mid \exists y, \ M_1 = 1\}, \max\{y \mid \exists x, \ M_1 = 1\}), \quad (1)$$

where A and B denote the top-left and bottom-right corners of the minimum bounding rectangle, providing spatial guidance for LocalNet to refine and enhance the segmentation.

B. LocalNet Branch

After obtaining the spatial location information of the vessel, cropping the vascular region not only eliminates irrelevant information but also allows the model to focus more on the meaningful vascular area, leading to segmentation results with the well-defined topological structure that guides FocusNet in segmenting smaller vascular regions.

To ensure the uniformity and compatibility of input, the rectangular area is reshaped into a square area. Specifically, for the vertices A and B of the minimum bounding rectangle, the midpoint C of AB is chosen as the center of a square region ($a \times a$) representing the vessel area. To ensure that the

cropped area does not exceed the boundary, C is checked for validity as follows:

$$C'_x = \max\left(\frac{a}{2}, \min\left(C_x, n - \frac{a}{2}\right)\right),$$
$$C'_y = \max\left(\frac{a}{2}, \min\left(C_y, n - \frac{a}{2}\right)\right), \quad (2)$$

where C' represents the valid cropping center.

Based on the valid cropping center C' and cropping size a, X_1 is cropped to obtain the local input X_2:

$$X_2 = \text{Cropping}(X_1, C', a), \quad (3)$$

where "Cropping" represents cropping the local region from X_1 based on the cropping parameters C' and a.

The local input X_2 is passed to LocalNet to produce local output M_2 of size $a \times a$. In order to focus on smaller vessel regions, the centerline L of M_2 is extracted, and farthest-point sampling is applied along L to select a set of sample points P, with each point P_i chosen for its maximum distance from previously selected points:

$$P_i = \underset{p \in L \setminus \{P_0, P_1, \dots, P_{i-1}\}}{\arg\max} \ \text{distance}(p, \{P_0, P_1, \dots, P_{i-1}\}). \quad (4)$$

For each sample point P_i in P, a square region with center P_i and side length b is cropped from X_2. To ensure that the cropped region stays within the image boundaries, the sample point P_i is performed the same validity check as C. The valid sample points P', along with the side length b, are transmitted as topological structure information to the FocalNet branch for subsequent fine-grained feature extraction.
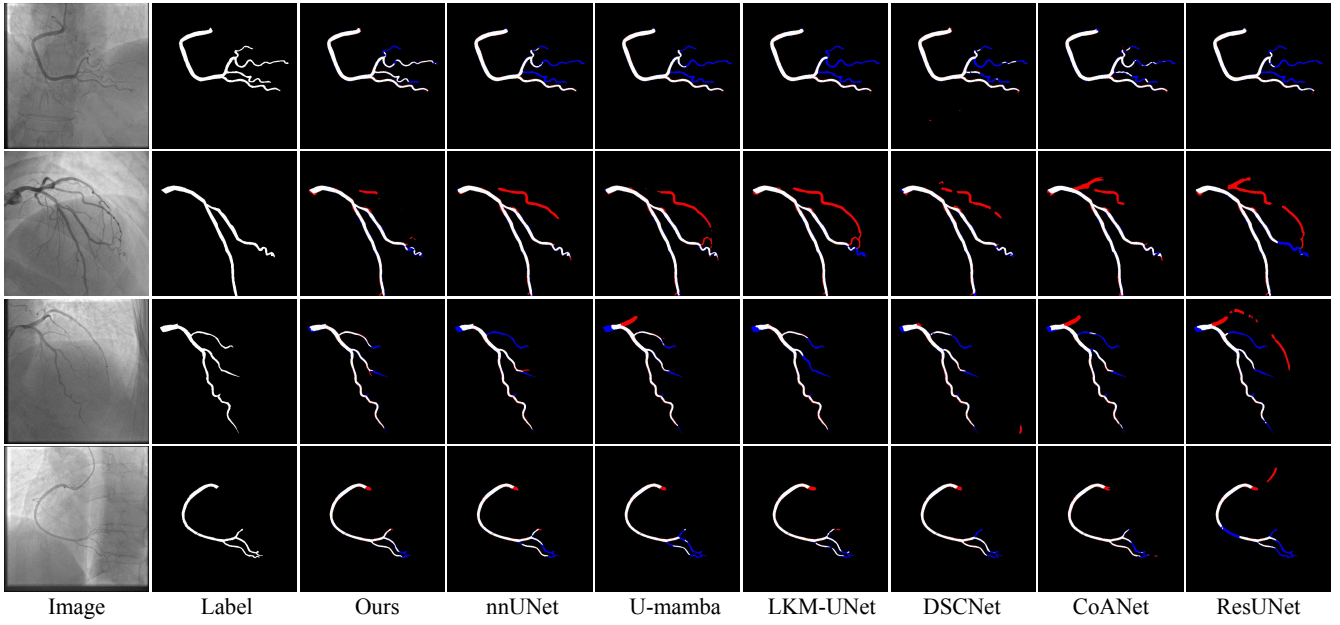
Fig. 2. Qualitative comparison of our TPRNet with other state-of-the-art methods. The red part of the prediction results indicates false positive (over-segmentation), and the blue part indicates false negative (mis-segmentation).

C. FocalNet Branch

Guided by the topological structure information provided by LocalNet, FocalNet focuses on smaller vascular regions to capture more fine-grained details and perform more precise vessel segmentation. By specifically processing small branch regions, FocalNet can extract detailed features of small branches, thereby enhancing segmentation accuracy and achieving more precise results.

Specifically, the focal input X_3 is cropped and stacked from X_2 based on P' and b:

$$X_3 = \text{Stacking}(\text{Cropping}(X_2, P', b)), \qquad (5)$$

where "Stacking" refers to concatenating the cropped blocks along the z-axis.

The focal input X_3 is processed by FocalNet to yield a fine-grained segmentation M_3 of size $s \times b \times b$, where s corresponds to the number of cropping centers in P'. M_3 is then reconstructed using the topological information P' to form a detailed vascular segmentation mask M_4:

$$M_4 = \text{Reconstructing}(M_3, P'), \qquad (6)$$

where "Reconstructing" refers to the process of rebuilding each segmentation mask of M_3 into a complete structure based on the topological structure information P'.

By analyzing smaller focal regions in greater detail, the FocalNet branch can learn more fine-grained features, significantly enhancing the model's ability to detect small vessel branches.

D. Refinement Branch

The Refinement branch combines the fine-grained information from FocusNet, the topological structure from Local-Net, and the spatial location from GlobalNet, progressively merging them to optimize the coronary artery segmentation. Through multi-level, multi-perspective integration, the Refinement branch ensures topological consistency while significantly enhancing the ability to identify smaller vessel branches.

Specifically, the Refinement branch first merges the topological features from M_4 with the local details from M_2, producing a location output that blends fine-grained and topological information. The location output is then combined with M_1, which gives the overall position of the coronary artery, resulting in the final output.

III. RESULTS

A. Experimental Dataset

We conducted experiments on the publicly available AR-CADE dataset [12], which contains 1,200 annotated coronary artery X-ray images. Of these, 1,000 images were used as the training set and 200 images as the test set. During data pre-processing, we standardized and cropped the images to ensure consistency and usability for the model input. In the experiments, widely accepted evaluation metrics, including Dice coefficient, Intersection over Union (IoU), Precision, Recall, and Average Surface Distance (ASD), were used to compare the performance of TPRNet with other methods.

B. Quantitative Experiments

To demonstrate the superiority of our proposed method, we compared it with state-of-the-art methods, including ResUNet, DSCNet, CoANet, nnUNet, U-Mamba, and LKM-UNet, as shown in Table.I. It can be observed that our TPRNet outperforms other methods on multiple metrics. Specifically, its IoU score and Dice coefficient reached 72.59% and 83.70%, respectively, showing improvements

of 1.02% and 0.79% over nnUNet. Since the difficulty in coronary artery vessel segmentation lies in small branches (which occupy very few pixels), excellent results often show minimal improvement in Dice coefficient, but there is a significant enhancement in the overall coronary artery vessel topology (which can be seen in qualitative experiments). This advantage is attributed to our method's ability to extract fine-grained features and ensure topological consistency in the segmentation results, thereby improving segmentation quality.

TABLE I

QUANTITATIVE COMPARISON WITH THE STATE-OF-THE-ART METHODS

Method	Dice	IoU	Precision	Recall	ASD
ResUNet [13]	0.7699	0.6359	0.8315	0.7326	9.14
CoANet [8]	0.8101	0.6891	0.8554	0.7827	5.95
DSCNet [9]	0.8119	0.6899	0.8348	0.8006	6.18
nnUNet [5]	0.8291	0.7157	0.8615	0.8101	5.60
U-mamba [6]	0.8279	0.7139	**0.8669**	0.8030	5.72
LKM-UNet [7]	0.8277	0.7125	0.8433	0.8232	6.01
Ours	**0.8370**	**0.7259**	0.8602	**0.8247**	**5.22**

C. Qualitative Experiments

In addition to quantitative experiments, we also performed qualitative experiments by visualizing four typical samples. As shown in Fig.2, when coronary artery is interfered by other types of vessels, all comparison methods exhibit over-segmentation (red areas), whereas our method tightly adheres to the ground truth labels. Furthermore, in coronary artery scenes with many small branches, most comparison methods tend to suffer from segmentation discontinuities and mis-segmentation (blue areas). In contrast, our TPRNet preserves high topological accuracy, owing to the effective fine-grained feature extraction and topology consistency achieved through the progressive topological dissection and reconstruction strategy.

D. Ablation Experiments

To validate the effectiveness of our TPRNet, we conducted ablation experiments on different branches. No.1 represents the baseline method using only the GlobalNet branch with binary cross-entropy loss and Dice loss. No.2 adds the LocalNet branch to No.1, and No.3 further incorporates the FocalNet branch into No.2, as shown in Table.II. Compared to the baseline method, the proposed approach shows significant improvement in multiple metrics. For example, in terms of the Dice coefficient, incorporating the LocalNet branch on top of the baseline method results in a 0.65% improvement, while the additional integration of the FocalNet branch yields a further 0.90% increase.

IV. DISCUSSION & CONCLUSIONS

In this paper, we propose a topology-guided progressive refinement network that includes GlobalNet, LocalNet, FocalNet, and Refinement branches. Experimental results demonstrate that our method significantly improves overlap,

TABLE II

QUANTITATIVE RESULTS OF ABLATION ANALYSIS OF DIFFERENT BRANCHES

No.	GlobalNet	LocalNet	FocalNet	Dice	IoU	Precision	Recall	ASD
1	✓			0.8280	0.7136	**0.8634**	0.8074	5.80
2	✓	✓		0.8345	0.7228	0.8568	0.8236	5.41
3	✓	✓	✓	**0.8370**	**0.7259**	0.8602	**0.8247**	**5.22**

accuracy, and topological structure compared to existing state-of-the-art methods. Our main contribution lies in the design of a topology-guided progressive refinement network that detects small branches efficiently and reconstructs the topology. By dissecting and reconstructing the coronary artery, our method has learned fine-grained and topological features of the vessel, leading to more accurate segmentation results. In future work, we plan to improve FocalNet branch as a selective fine-grained feature extraction branch to further enhance the accuracy of coronary artery segmentation.

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