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Hierarchical Part-based Generation for Realistic 3D Coronary Artery

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2024.12.4

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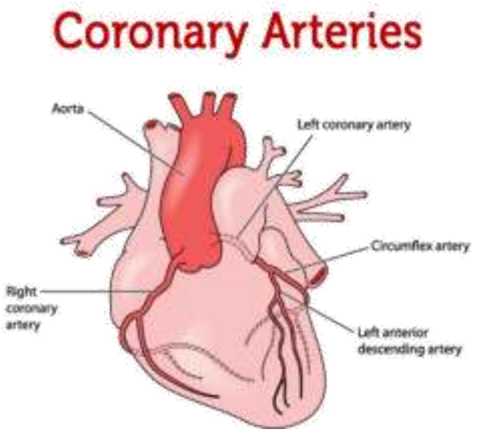
Introduction

Background

- **3D Vision in Medicine**: 3D vision plays a vital role in analyzing and modeling medical data.
- **Why 3D Vessel Modeling Matters**: Accurate modeling of blood vessels is key for many applications, including auxiliary diagnosis, data augmentation, biomedical simulation and education.
- **Early but Promising Field**: While 3D vessel generation is still in its early stages, it holds great potential, as generative models can be applied to downstream tasks such as vessel segmentation.

However, Current methods struggle to handle the complexity of real-world vascular geometries.



Introduction

Challenge

The inherent complexity of vascular system makes 3D vessel modeling a highly challenging task:

a. Complex curvature geometry
b. Extensive branching structures
c. Variations among samples: number of branches, different scale

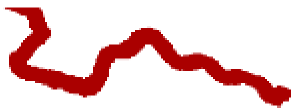
a. b. c.

How can we generate high-fidelity, realistic 3D vascular structures?

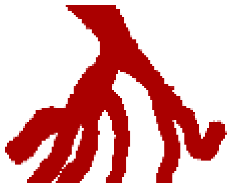
Introduction

Main Question

- What is the better **3D representation** for capturing the structure of coronary arteries?
- How can we accurately model **bifurcation structures**, including the number and structure of branches?

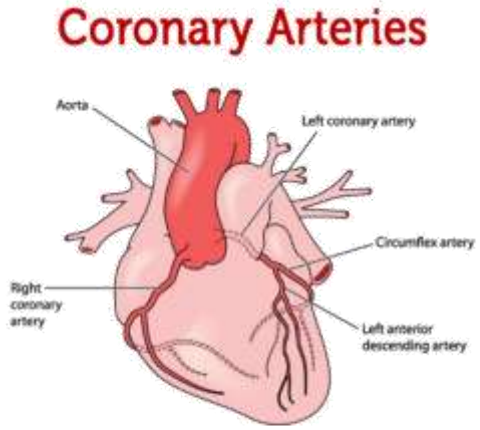


a.



b.

c.

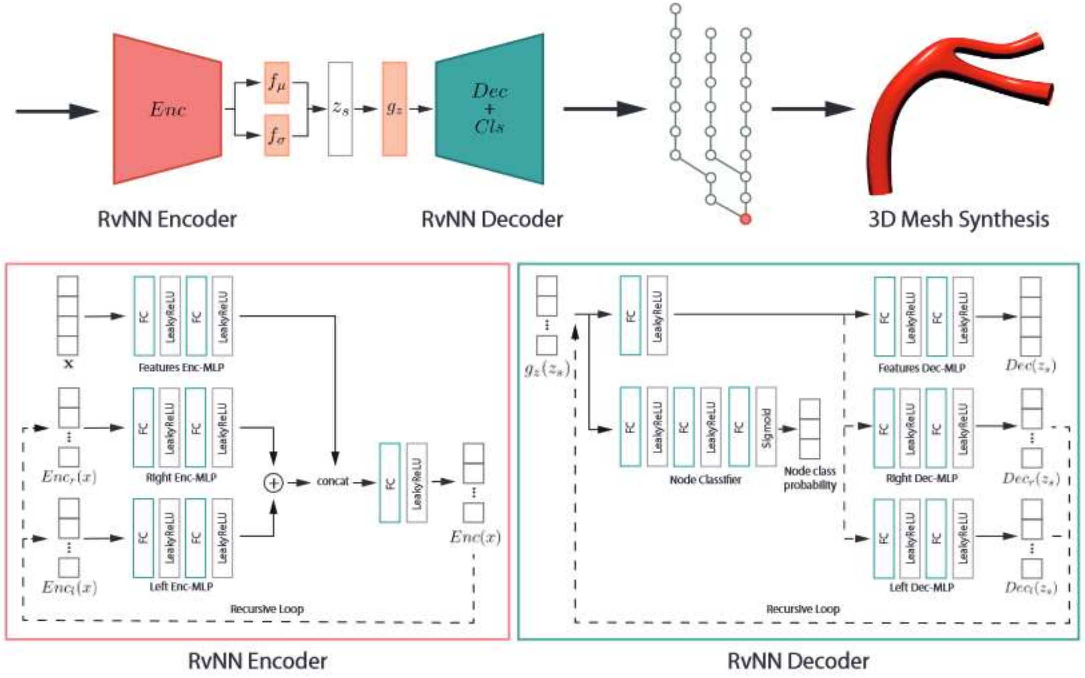


Related Work

Vessel Generation

- 3D Representation: Sequential Points and Tree Structure Graph
- Recursive VAE for tree structure graph

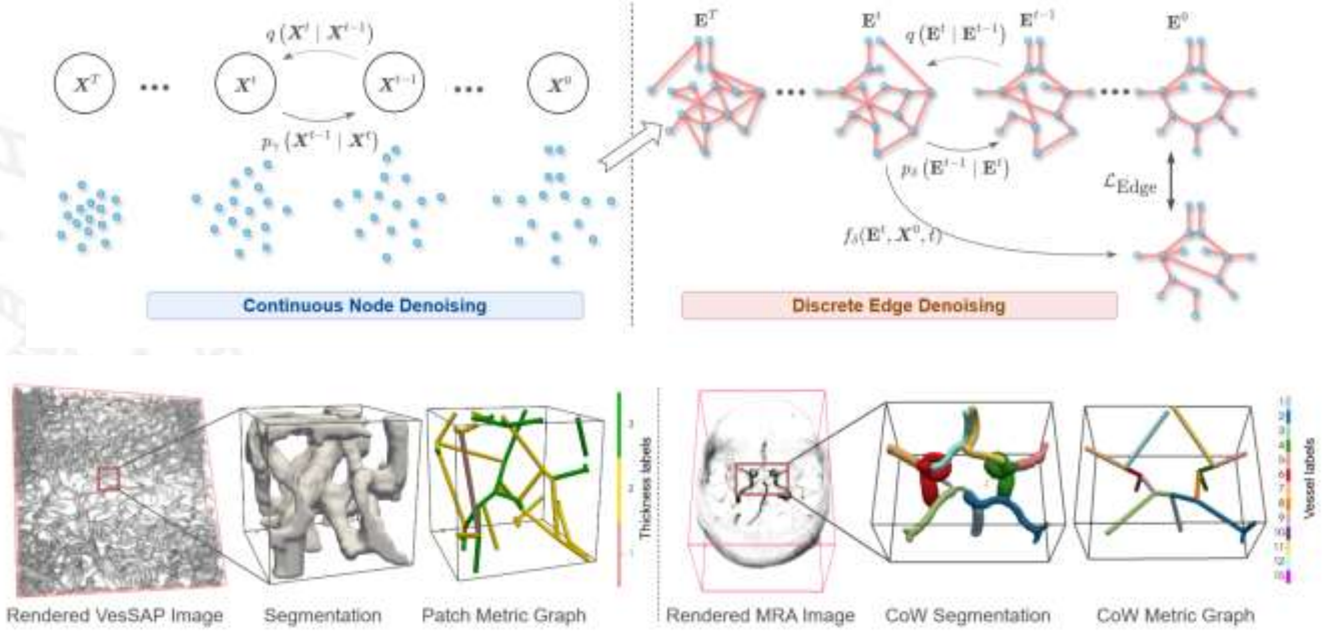
- Lack of anatomically plausibility
- Only model the vessel segment on simulated dataset



P. Feldman, M. Fainstein, V. Siless, C. Delrieux, and E. Iarussi, 'VesselVAE: Recursive Variational Autoencoders for 3D Blood Vessel Synthesis', 2023, MICCAI.

Related Work

Vessel Generation



- 3D Representation: Geometric Graph
- Graph Generation using Diffusion Model

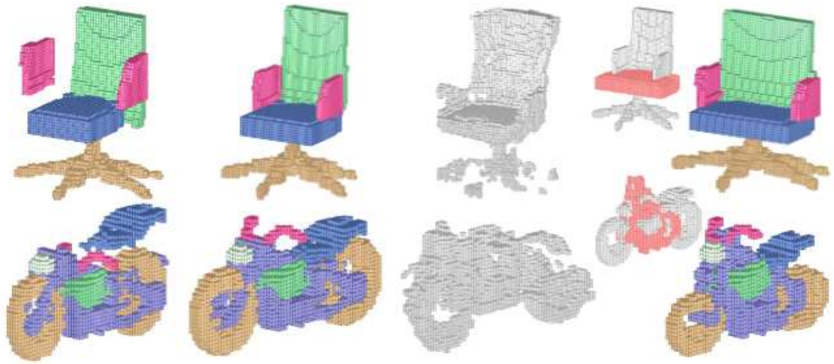
- only captures the global graph structure and does not model the complete blood vessel

C. Prabhakar *et al.*, '3D Vessel Graph Generation Using Denoising Diffusion', 2024, MICCAI.

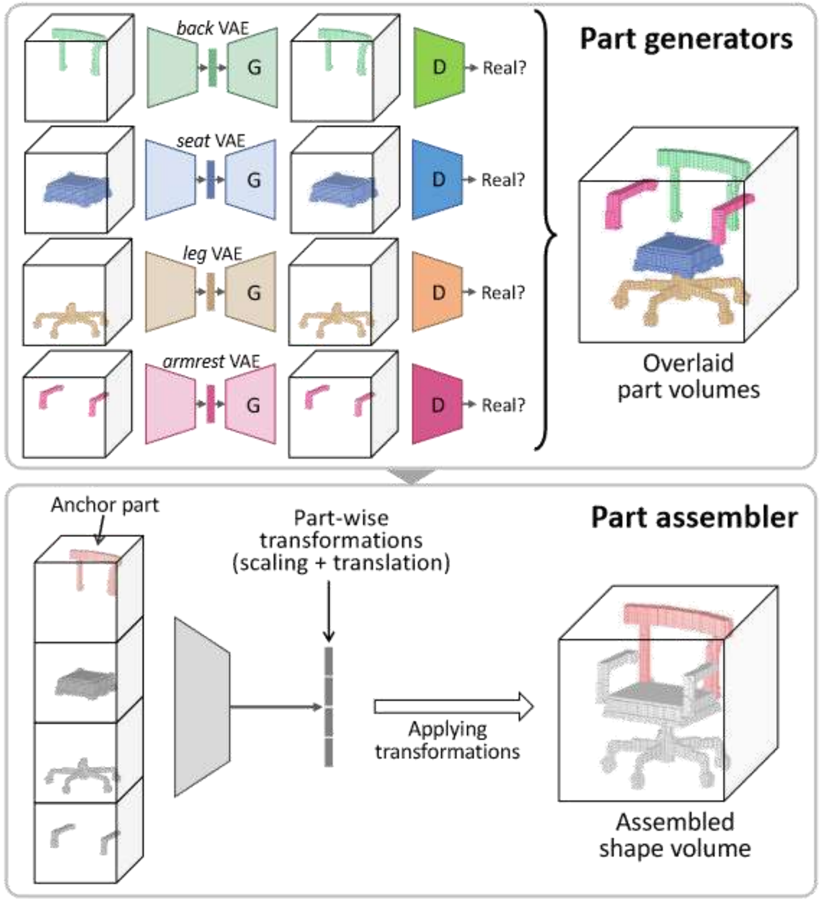
Related Work

Part-based 3D Shape Modeling

- Consider shapes as an assembly of parts
- Refine shape modeling
- Structure-aware



(a) Part-wise generation (b) After assembling (c) Holistic generation (d) Part-based editing

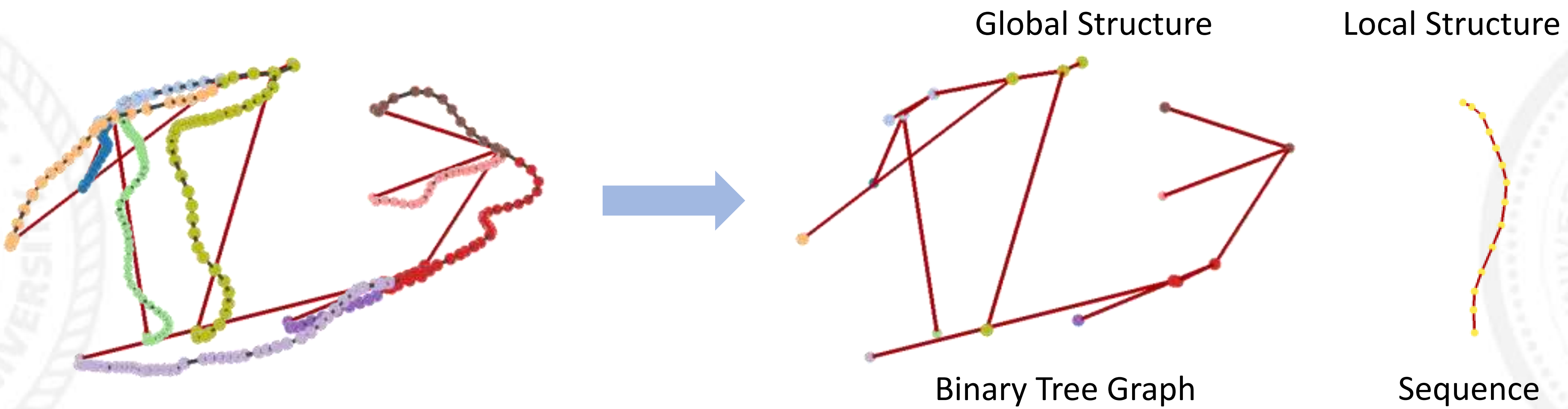


Li J, Niu C, Xu K. Learning Part Generation and Assembly for Structure-Aware Shape Synthesis. AAAI. 2020 Apr 3;34(07):11362–9.

Method

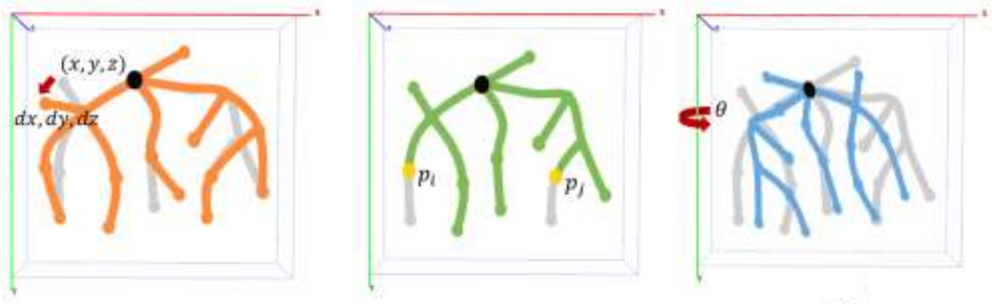
3D Representation

- 3D Coordinate + Radius (x_i, y_i, z_i, r_i)
- **Objective：** Modeling Tree Structure Graph and Sequence



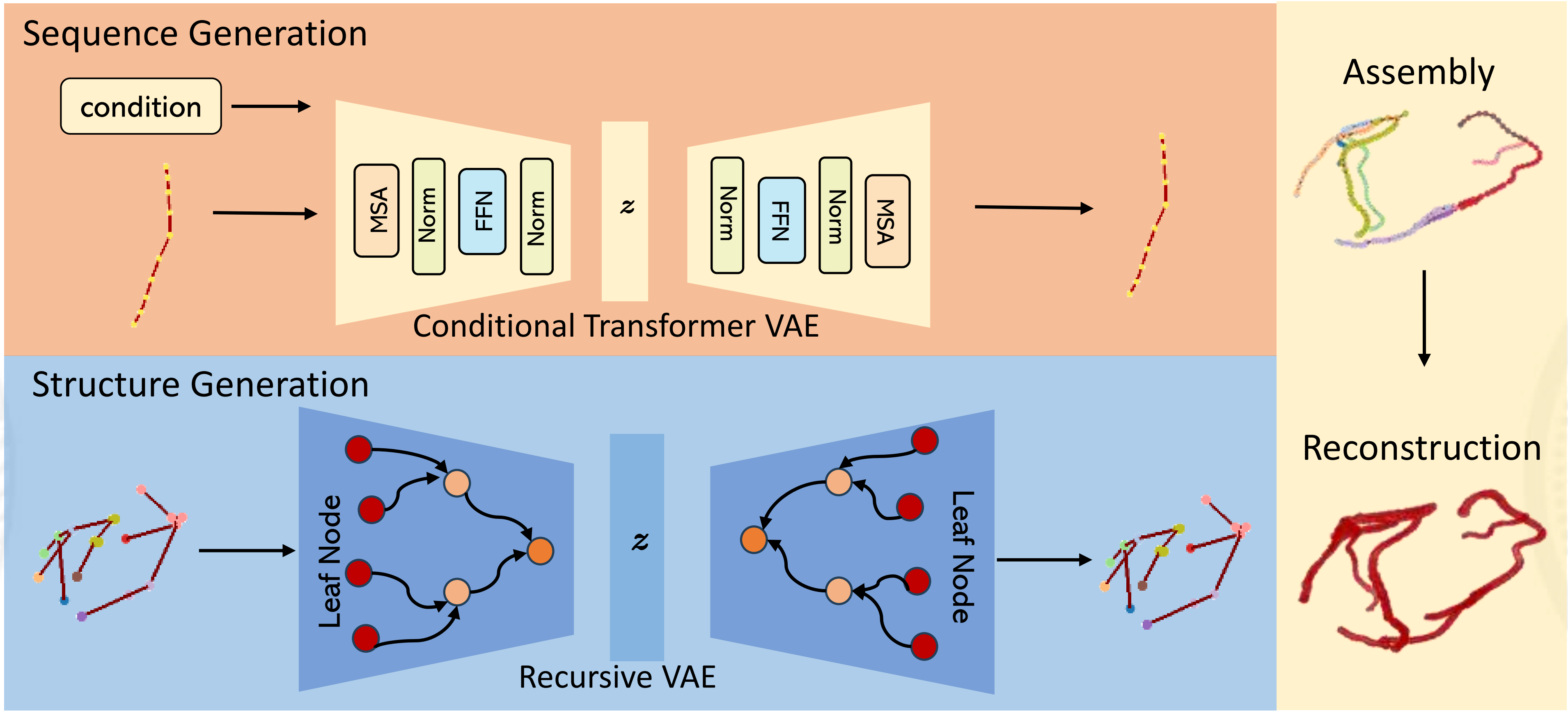
Method

- Data Processing
  1. Data processing pipeline
  2. Identify key points by Depth First Search
- Data Augmentation
  1. Node Perturbation
  2. Branch Dropping
  3. Rotation and Translation



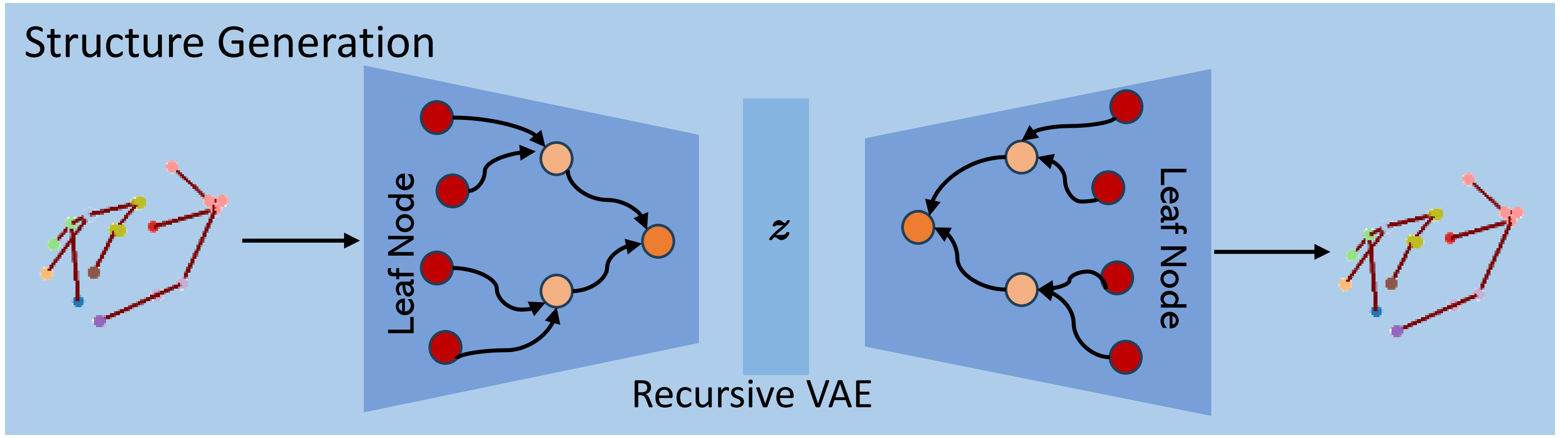
Method

Overview



Method

Stage 1: Global Graph Generation

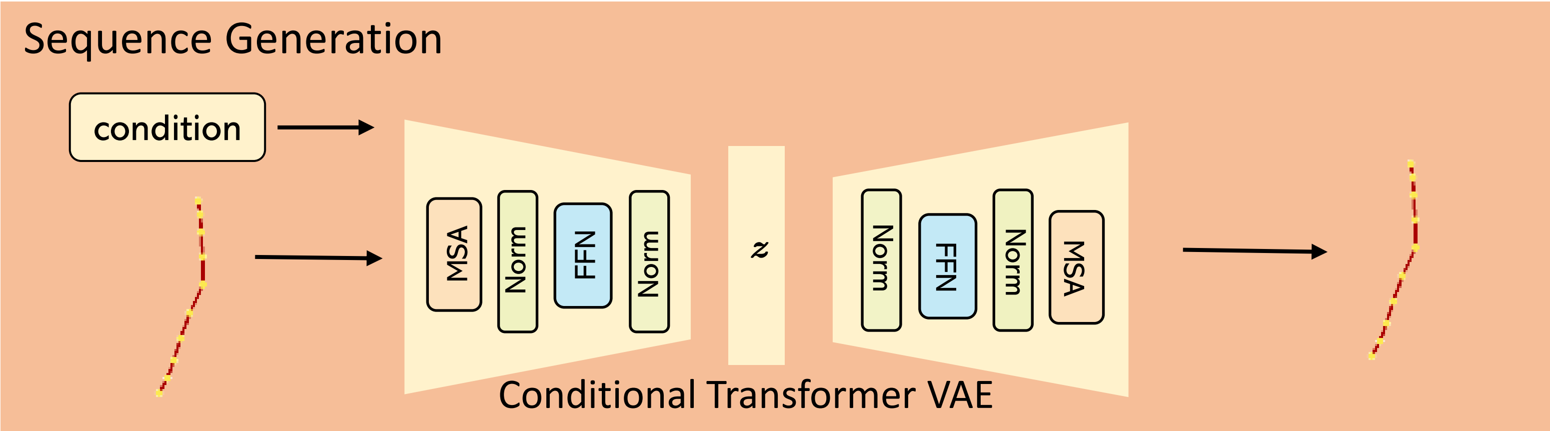


- Recursive variational Neural Network (RvNN) are particularly designed for tree-like structure graph.
- Recursively encode and decode each level of nodes.
- The attributes of each node include spatial coordinates and geometric conditions $(l_i,\, d_i,\, c_i)$

$$L = L_{\text{recon}} + \alpha_1 L_{\text{cls}} + \alpha_2 L_{\text{KL}}$$

Method

Stage 2: Local Sequence Generation



- Input: ordered sequential point cloud data
  condition (cumulative length, distance, curvature) $(l_i,\ d_i,\ c_i)$ $c_i = 1 - \frac{l_i}{d_i}$
- Both encoder and decoder are based on the Transformer architecture
- Each point is treated as a token

$$L = L_{\text{recon}} + \alpha L_{\text{KL}}$$

Method

Stage 3: Assembly

Merging global and local structures through transformations.

Input: global graph model; local sequence model
Output: complete vessel skeleton graph

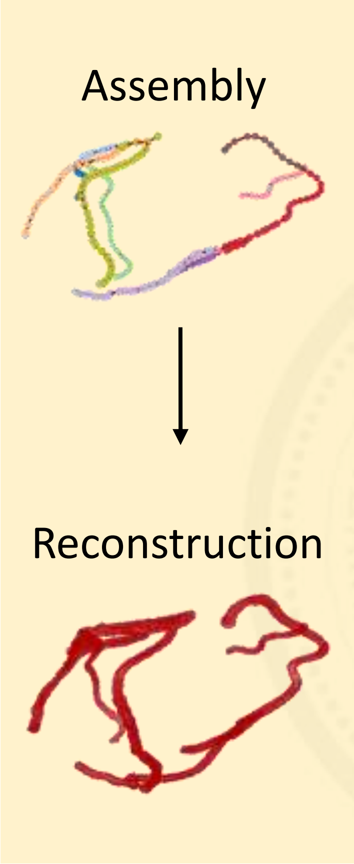
sample *key point graph G*

for *branch* **in** *key point graph*:

  sample *sequence s_i based on conditions* $(l_i,\ d_i,\ c_i)$

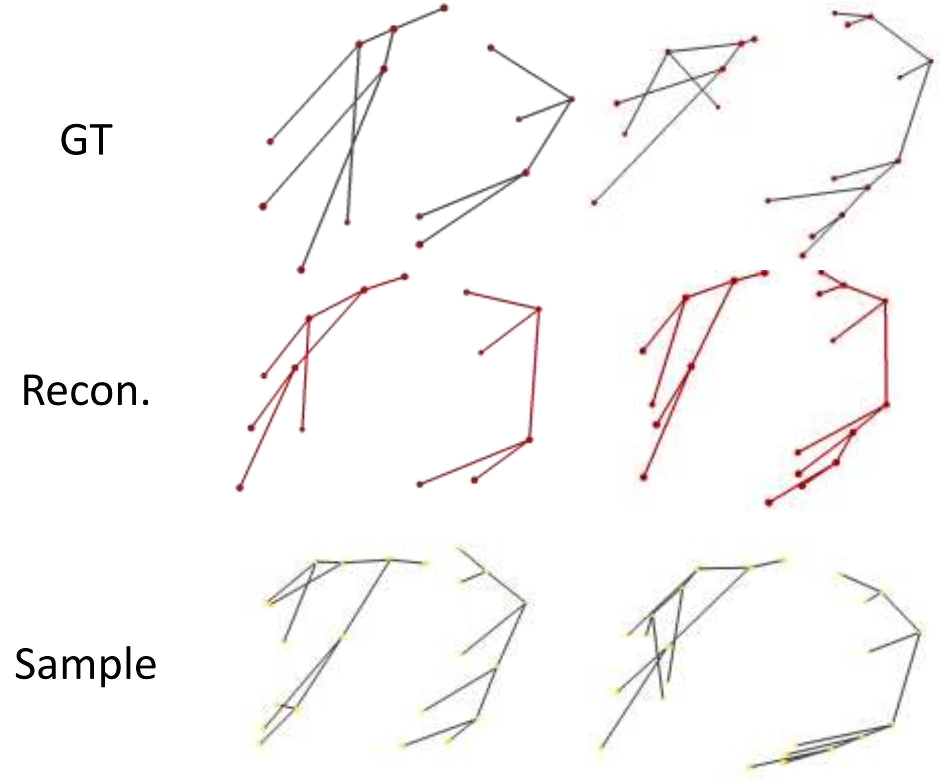
  transformation *s_i*

end
concatenate *s*



Result

Global Graph Reconstruction and Generation



	Graph	
	MMD-degree↓	MMD-spectral↓
Base (Test/Train)	0.0063	0.0452
Gen	0.0082	0.0473

	Point Cloud	
	CD↓	EMD↓
Gen	0.0114	0.1523

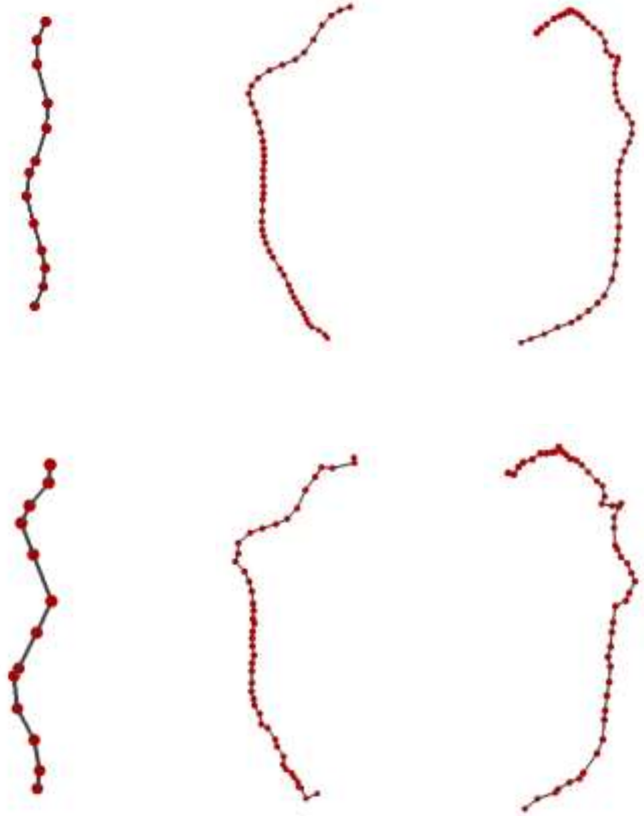
Result

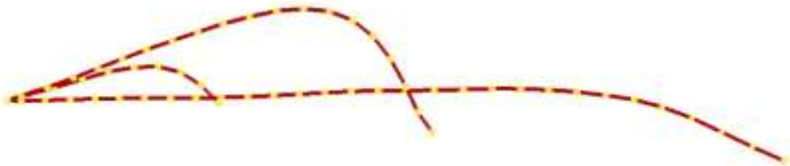
Local Sequence Reconstruction and Generation

sequence reconstruction

GT

Recon.



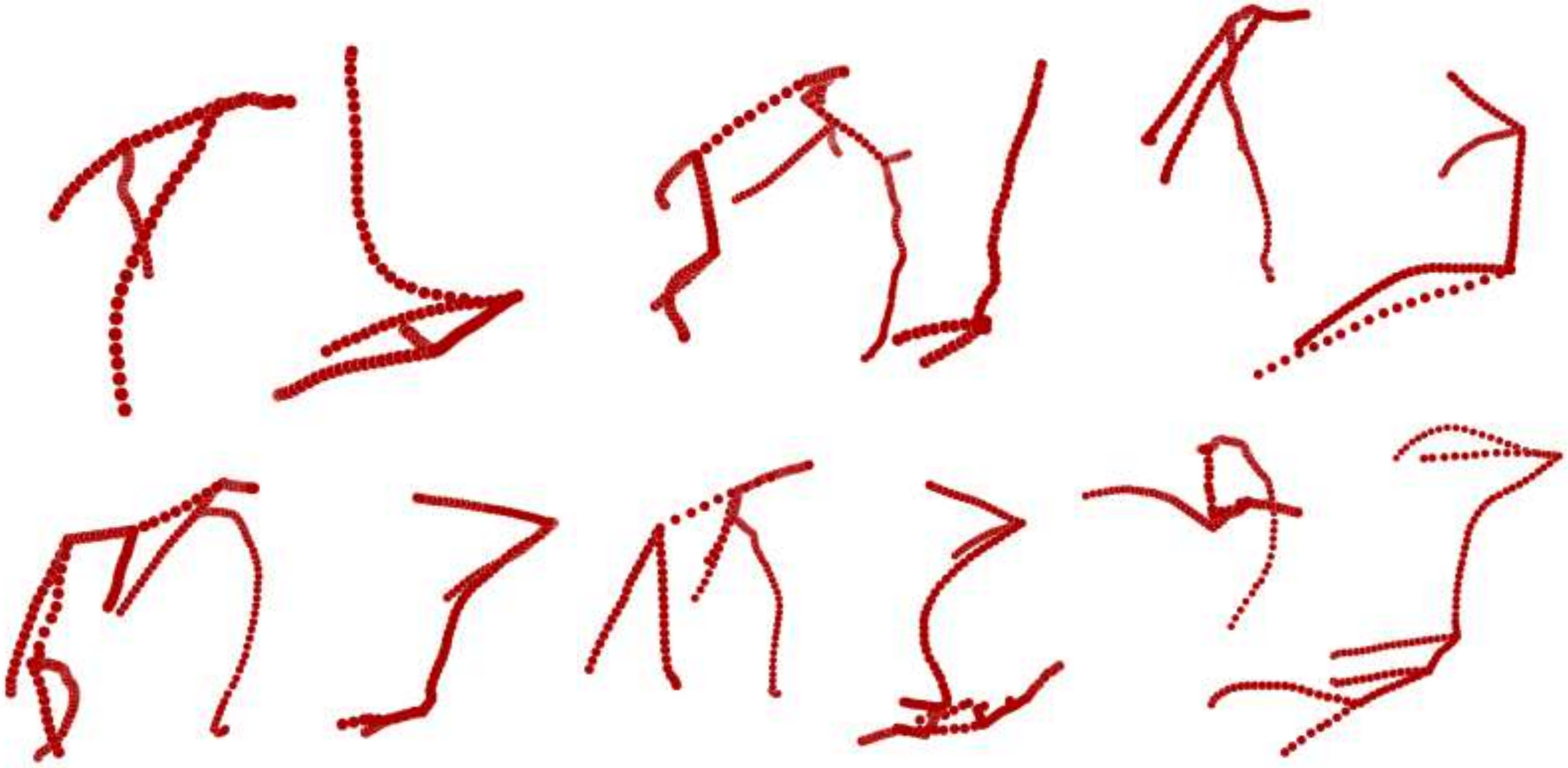


sequence generated under different conditions

sequence generation

Result

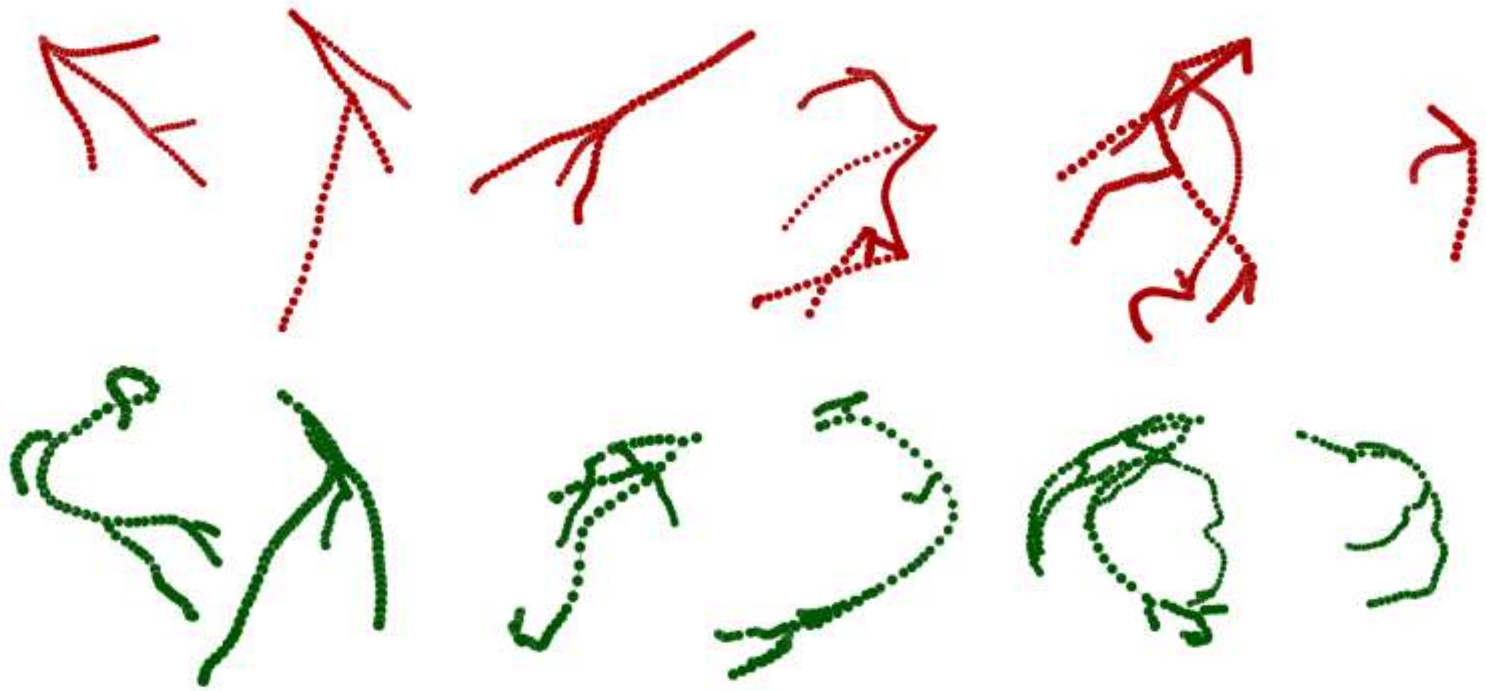
Assembly Result



Result

Recon.

GT



Conclusion

In this study, we proposed a hierarchical part-based approach for 3D vessel generation:

- Introduced a **part-based** method that combines **global graph** representation for overall structure and **local sequence** representation for detailed geometric modeling

- Utilized Recursive Variational Neural Networks (RvNN) for tree-like global structures and Transformer-based VAE for local geometric details.

- applied the approach to **real-world** coronary artery datasets, achieving promising preliminary results

Future Work

1. Adding global geometric constraints to ensure smoothness and fidelity.
2. Improve the evaluation metrics and conduct comparative experiments.
3. Apply to multiple datasets.

The above work will be completed before January.

THANK YOU