

# Partial Vessels Annotation-based Coronary Artery Segmentation with Self-training and Prototype Learning

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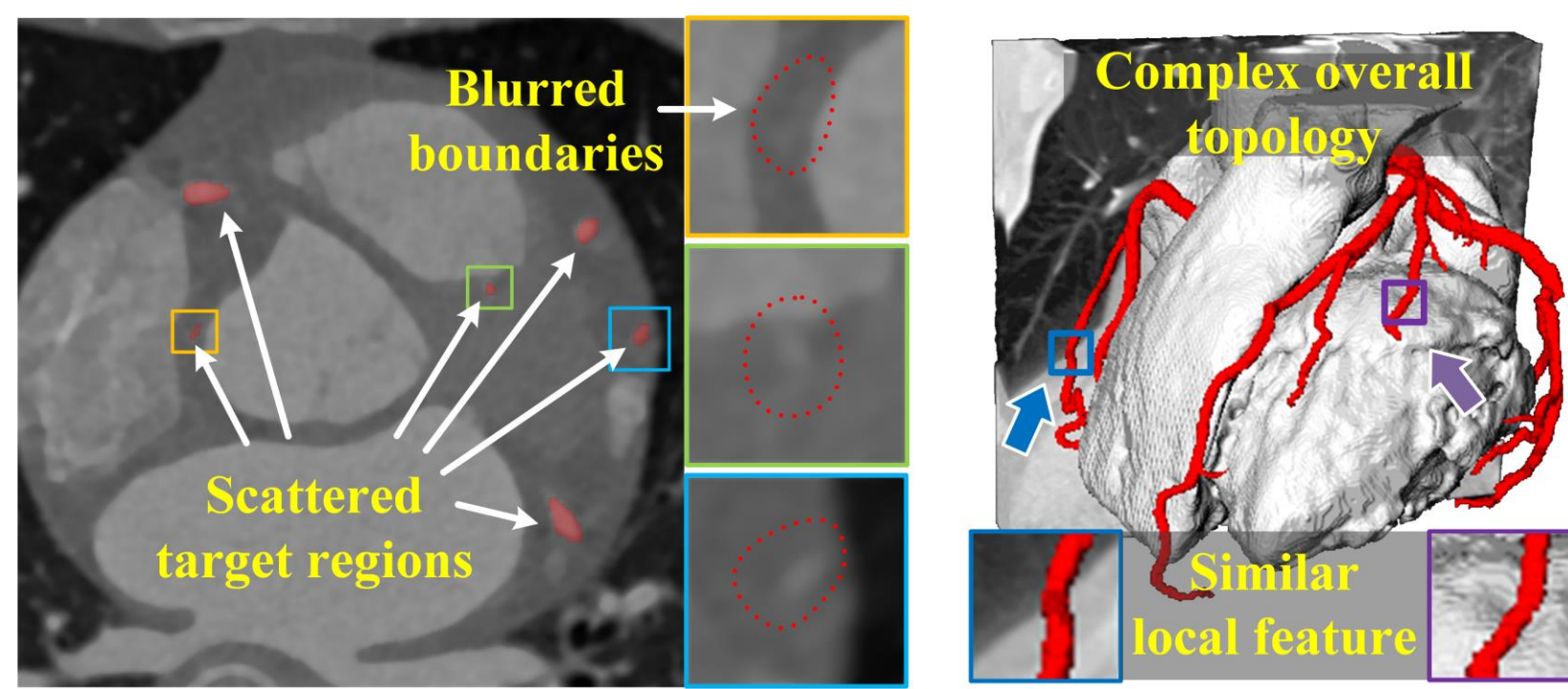
## Motivation

### 1. Difficult labeling on 3D CCTA images

The **scattered target regions** as well as the **blurred boundaries** make the annotating process time-consuming.

### 2. Complex topology and similar local feature

Coronary artery shows complex and slender structures but **similar feature in a local perspective**.



## Proposed Annotation

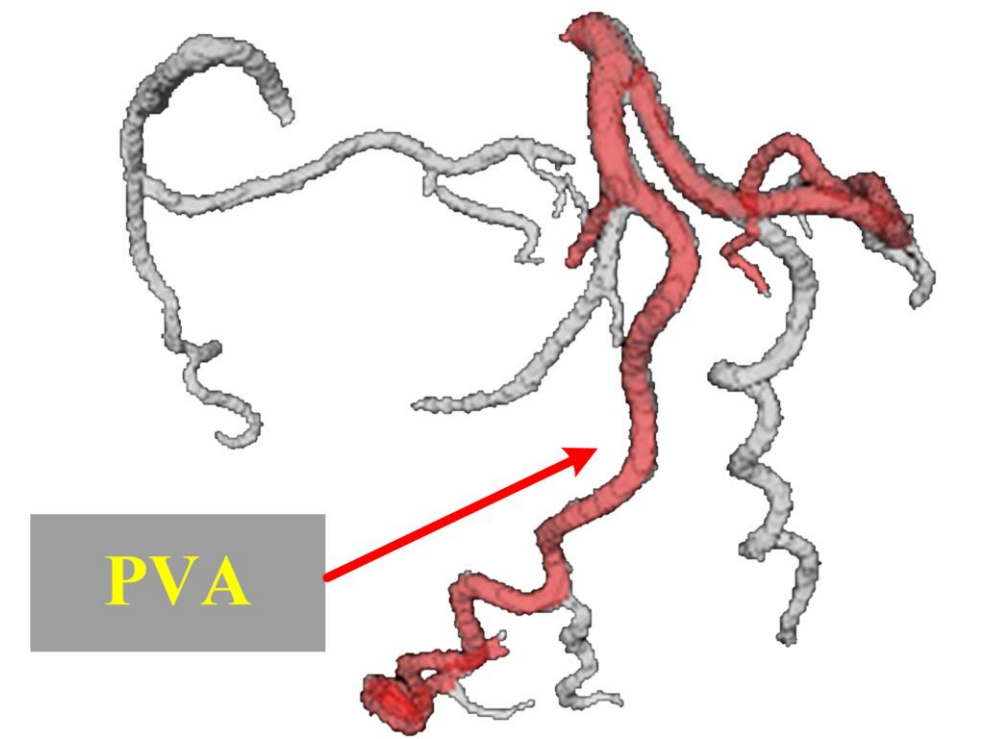
### What is Partial Vessels Annotation (PVA) ?

PVA is a **special form of partial annotation (PA)**, under which only a limited part of target regions are labeled. PVA labels vessels continuously from the proximal end to the distal end, while the labeled regions of PA are typically randomly selected.

### What are the merits of PVA?

1. PVA **balances efficiency and informativity**. PVA only requires clinicians to label vessels within restricted regions in adjacent slices.

2. PVA **provides flexibility**. PVA allows clinicians to focus their labeling efforts on vessels of particular interest.

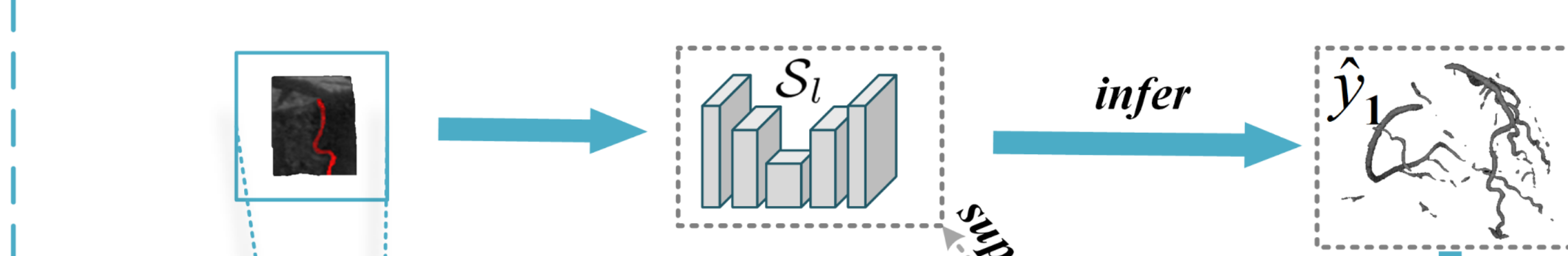


## Proposed Framework for Coronary Artery Segmentation under PVA

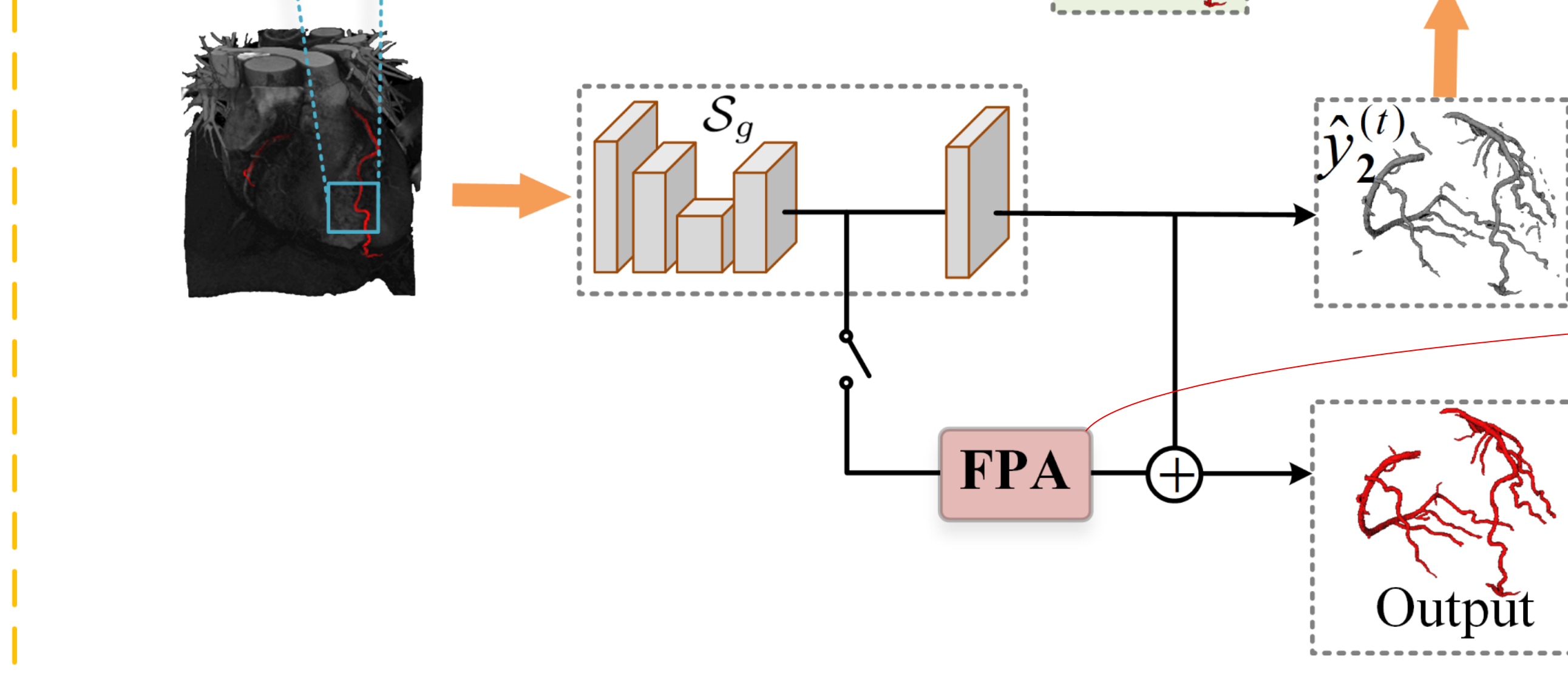
The framework works in two stages.

1. LFE stage **extracts the local features** of coronary artery, and then **propagates the knowledge to unlabeled regions**.
2. GSR stage **leverages prediction consistency to correct the errors** during the iterative self-training process.

### Stage1: Local Feature Extraction



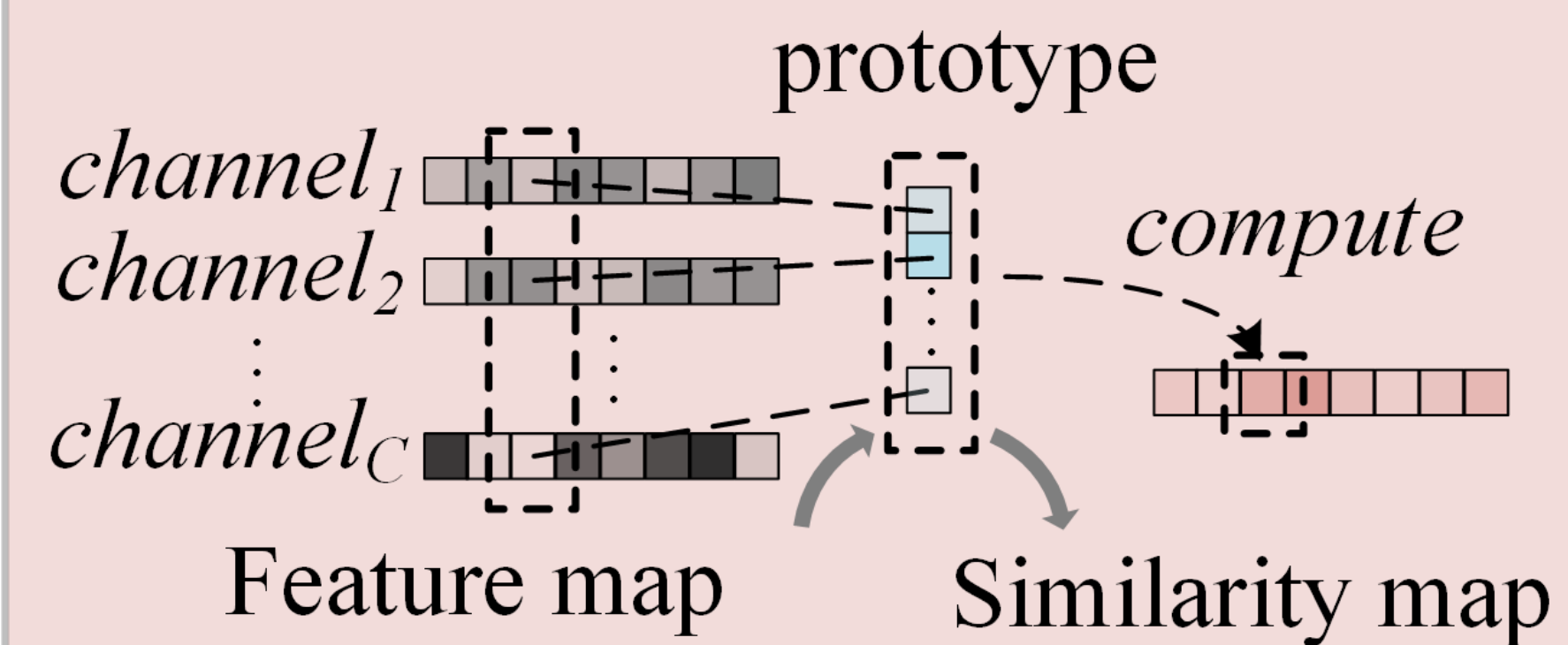
### Stage2: Global Structure Reconstruction



### Label Propagation Unit (LPU)

$$y_{PL}^{(t)} = \begin{cases} \max(y_{PVA}, \hat{y}_1) & , t = 0 \\ \eta^{(t)} \hat{y}_2^{(t)} + (1 - \eta^{(t)}) y_{PL}^{(t-1)} & , t > 0 \end{cases}$$

### Feature Prototype Analysis (FPA)

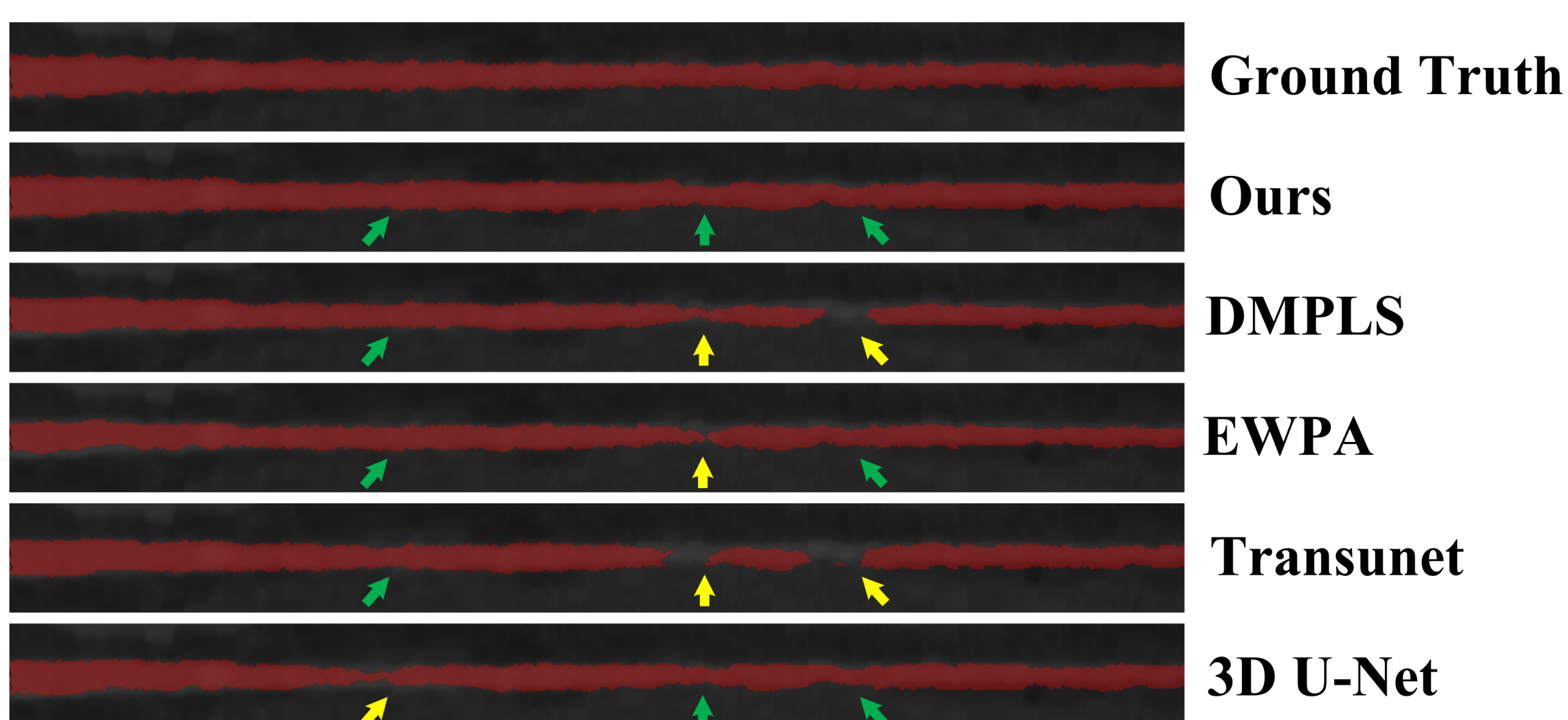


## Results

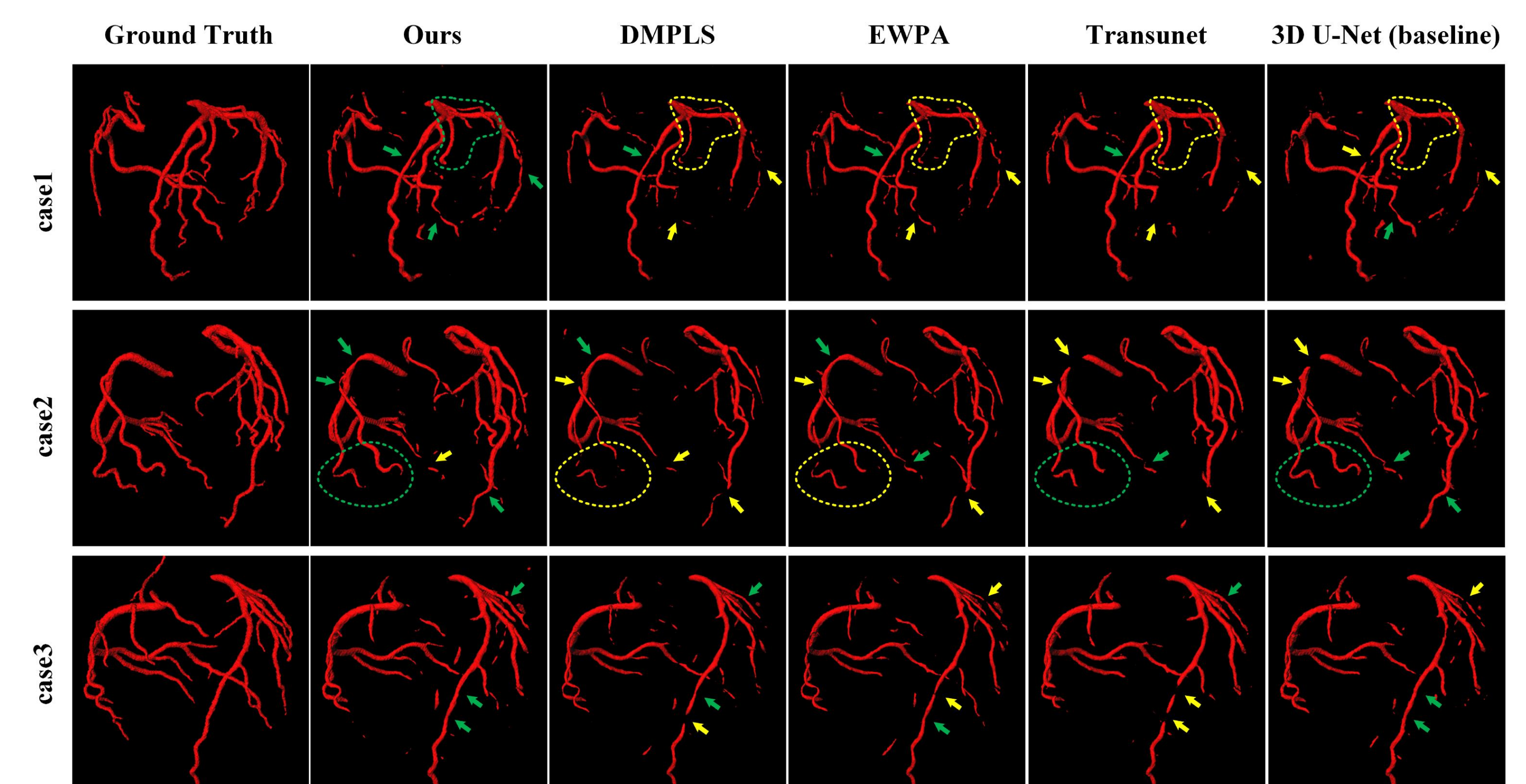
**Result 1:** Our proposed framework outperforms the competing methods under PVA (24.29% vessels labeled), the performance which is comparable to that of the baseline model using full annotation (FA, 100% vessels labeled).

Label	Method	Dice(%)↑	RDice(%)↑	OV(%)↑	OF↑		
					LAD	LCX	RCA
PVA	3D U-Net [3]	60.60±7.09	69.45±7.82	62.24±6.43	0.647±0.335	0.752±0.266	0.747±0.360
	HRNet [17]	48.72±7.16	52.31±7.96	37.81±6.61	0.490±0.297	0.672±0.301	0.717±0.356
	Transunet [1]	63.08±6.42	71.97±7.38	61.21±6.40	0.669±0.274	0.762±0.243	0.728±0.362
	EWPA [12]	55.41±6.15	61.54±6.83	60.48±5.17	0.659±0.334	0.759±0.286	0.749±0.364
	DMPLS [10]	59.12±7.69	65.81±8.15	59.99±5.80	0.711±0.292	0.775±0.284	0.711±0.358
	<b>Ours</b>	<b>71.45±6.07</b>	<b>83.14±6.72</b>	<b>75.40±6.15</b>	<b>0.895±0.226</b>	<b>0.915±0.190</b>	<b>0.879±0.274</b>
FA	3D U-Net	83.14±3.52	90.91±4.18	89.00±4.75	0.913±0.231	0.843±0.301	0.873±0.265

### Visualization 1: Comparison on MPR



### Visualization 2: Comparison of the segmentation results under PVA



**Result 2:** Different components are effective in our proposed method.

$S_l$	LPU		$S_g$	FPA	Dice(%)↑	RDice(%)↑	OV(%)↑	OF↑		
	PL	PLU						LAD	LCX	RCA
✓					60.60±7.09	69.45±7.82	62.24±6.43	0.647±0.335	0.752±0.266	0.747±0.360
✓	✓			✓	64.23±6.44	73.81±6.89	66.19±5.63	0.751±0.328	0.813±0.231	0.784±0.349
✓	✓	✓		✓	71.43±7.20	81.70±6.92	72.13±5.94	0.873±0.227	0.860±0.223	0.808±0.334
✓	✓	✓	✓	✓	<b>71.45±6.07</b>	<b>83.14±6.72</b>	<b>75.40±6.15</b>	<b>0.895±0.226</b>	<b>0.915±0.190</b>	<b>0.879±0.274</b>