Blood Flow Speed Estimation with Optical Coherence Tomography Angiography Images

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Introduction

- Motivation: current blood flow measurements techniques are complex, slow and prone to system artifacts, any alternative?

- Solution: use vascular structure imaging (OCTA) to directly estimate blood flow speed.

- Justification:
  - vascular structure and blood flow are **highly correlated**
  - **paired structure and flow data** can be collected for model training
  - possible to **learn the relation** between structure and flow with **network**

Introduction

Proposed OCTA-Flow:

- First perform OCTA scan
- Then feed OCTA images to a neural network
- Generate blood flow estimation results

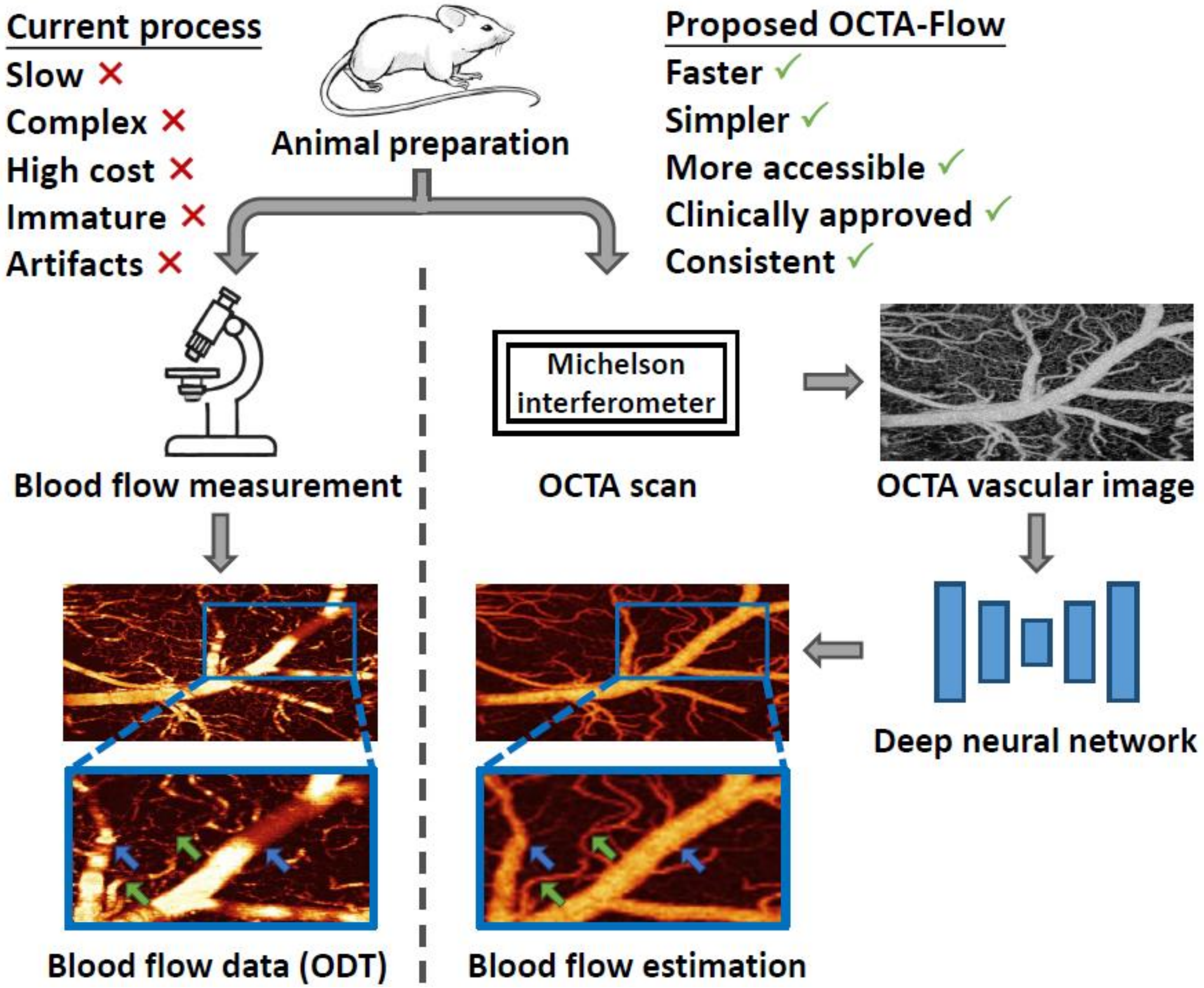

Figure 1. Current measurement process and our solution.

OCTA-Flow

- Training: use paired ODT data with artifacts as pseudo label.

- Inference: feed the OCTA images to the neural network to get blood flow estimation.

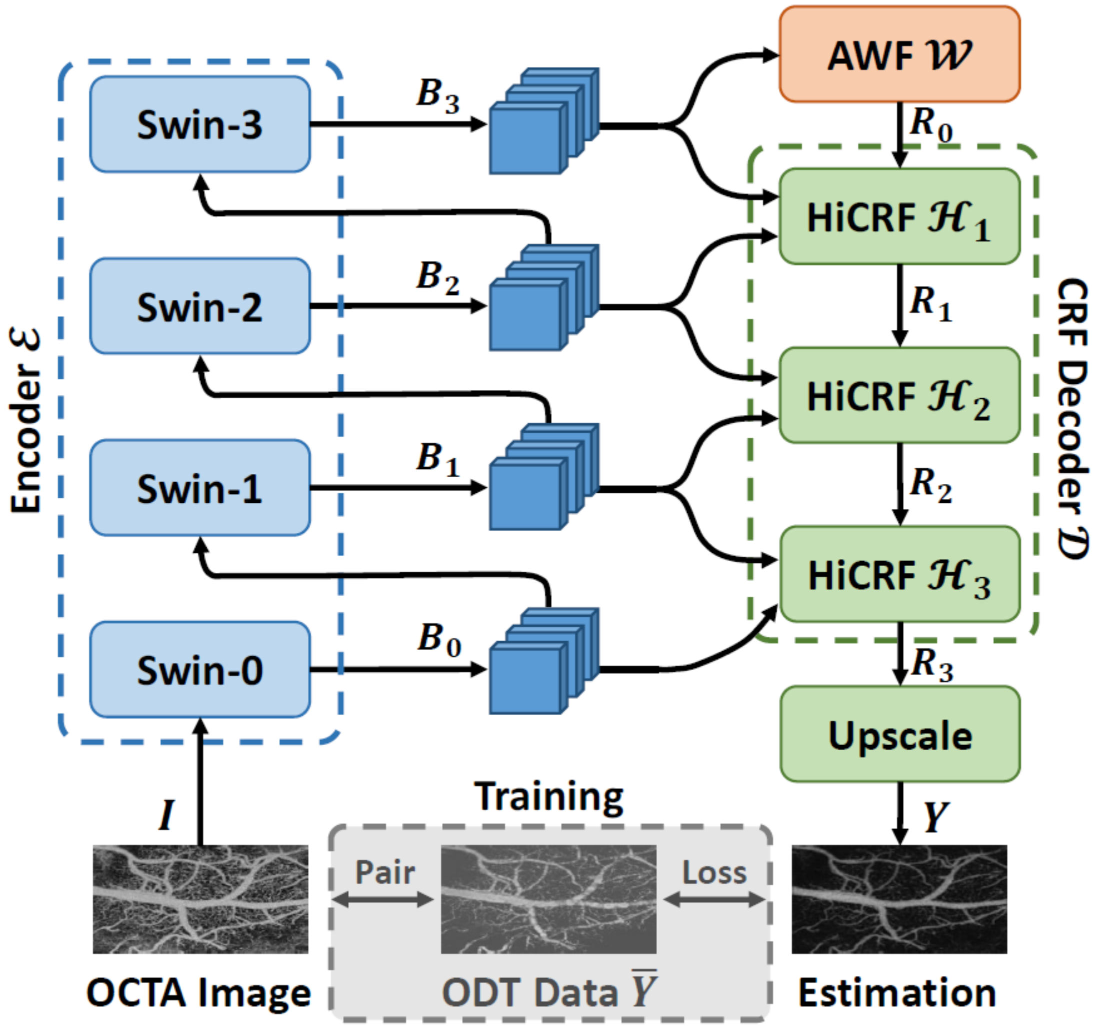

Figure 2. OCTA-Flow method overview.

Adaptive Window Fusion

- Utilize the window attention mechanism with varying window sizes to capture multiscale context information from the deep features.

- Integrate multiscale context information dynamically, conditioned on the input vasculature feature.

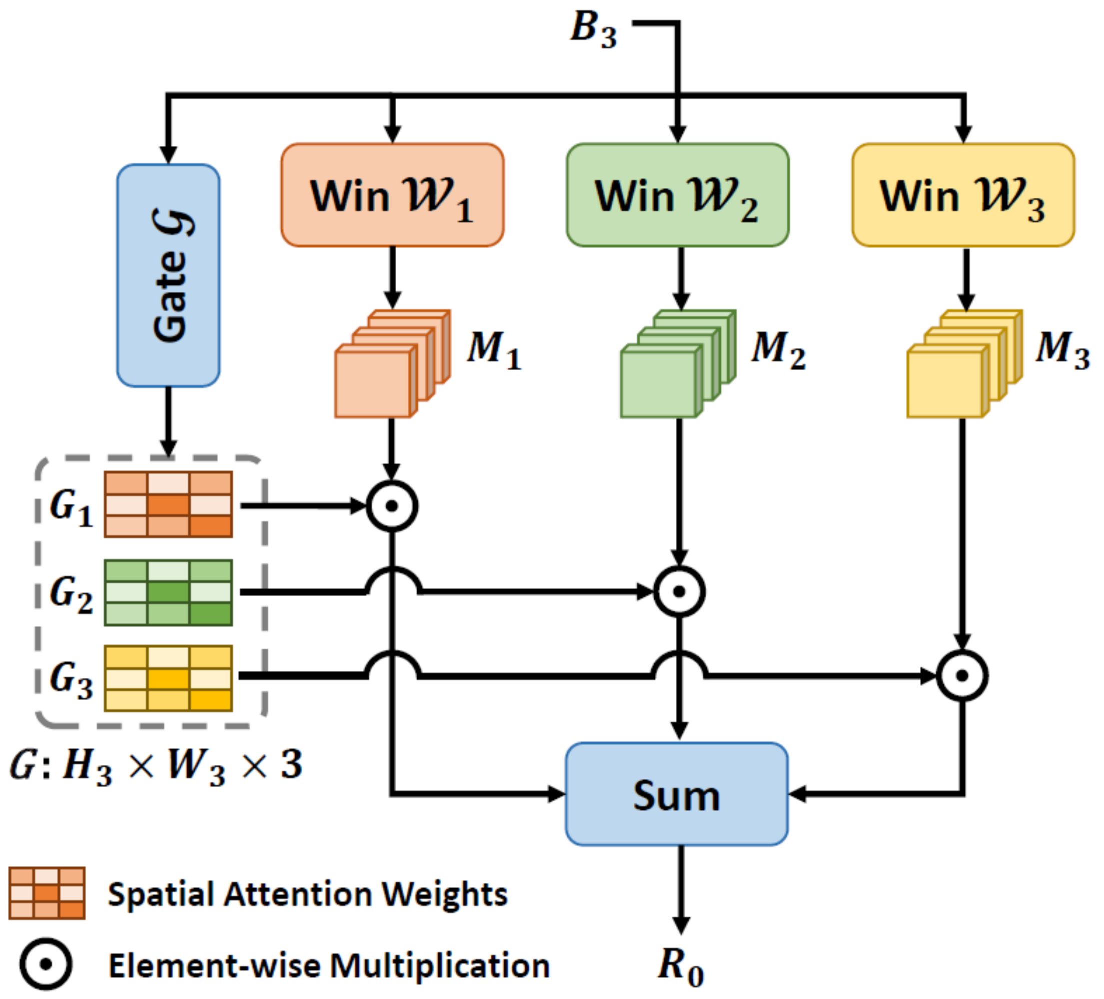

Figure 3. The Adaptive Window Fusion module.

Hierarchical CRF

- Takes three features from different levels, and models the relation between them progressively and hierarchically.
- By passing features through cascaded HiCRF blocks, the model iteratively adjusts the features and refines predictions.

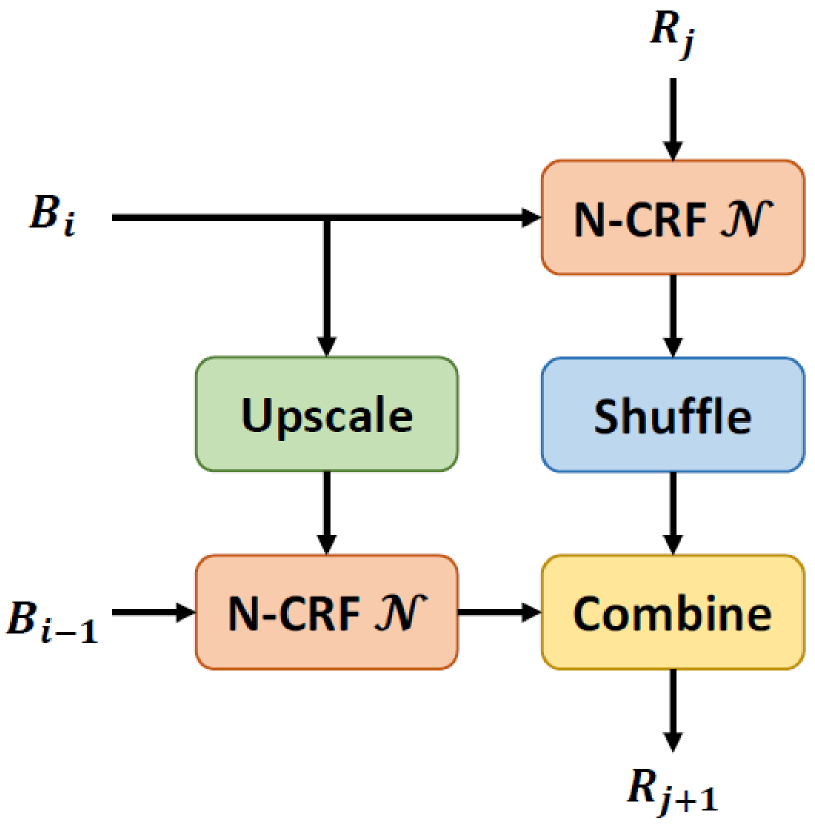

Figure 4. The Hierarchical CRF block.

Comparison w. Regression Models

Table 1. Five-fold cross validation results on self-built datasets.

Method	Architecture	Anesthetized Dataset		Awake Dataset	
		Abs Rel ↓	RMSE ↓	Abs Rel ↓	RMSE ↓
BTS [17]	DenseNet	0.374±0.033	6.777±0.532	0.366±0.026	6.336±0.776
IEBins [32]	Swin	0.377±0.057	7.217±0.730	0.364±0.056	7.958±1.197
NeuWin [46]	Swin	0.366±0.046	6.428±0.337	0.367±0.038	6.324±0.759
Ord Ent [47]	Swin	0.362±0.045	6.442±0.447	0.359±0.036	6.315±0.853
Diff Depth [6]	Diffusion	0.485±0.037	7.649±0.341	0.457±0.070	7.241±0.736
ECoDepth [27]	Diffusion	0.445±0.065	7.958±1.286	0.766±0.080	7.513±0.565
OCTA-Flow (ours)	Swin	**0.353**±0.042	**6.278**±0.480	**0.318**±0.018	**6.037**±0.674

Comparison w. Flow Measurements

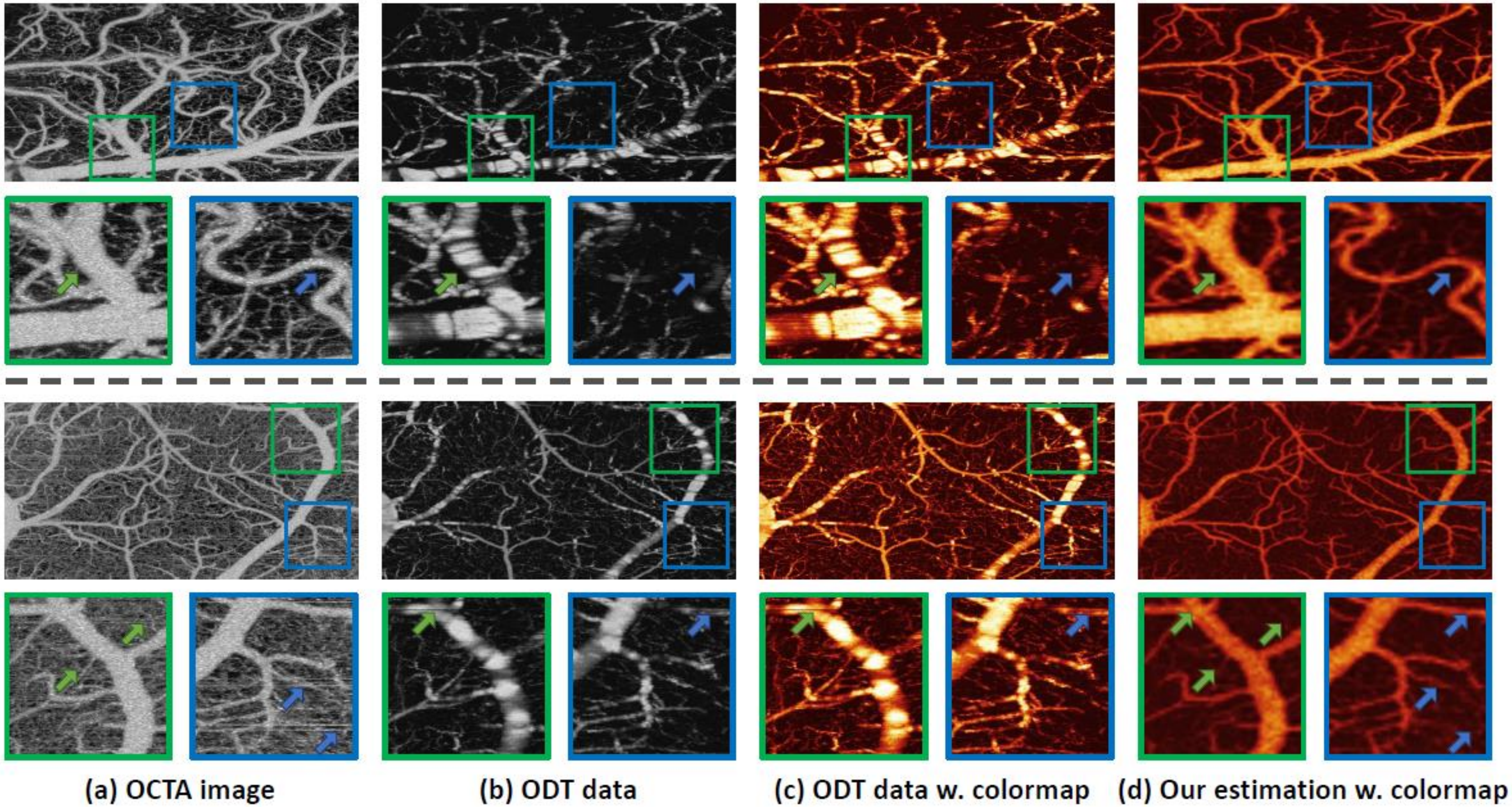

Figure 5. Qualitative results on self-built datasets.

Conclusion

- Using ODT data with artifacts as pseudo label is practical.
- Directly estimating blood flow speed from vascular structure is feasible.
- Learning-based method can mitigate artifacts in the ODT label.
- Collecting more paired data may further improve the performance.