Efficient Neuron Segmentation in Electron Microscopy by Affinity-Guided Queries

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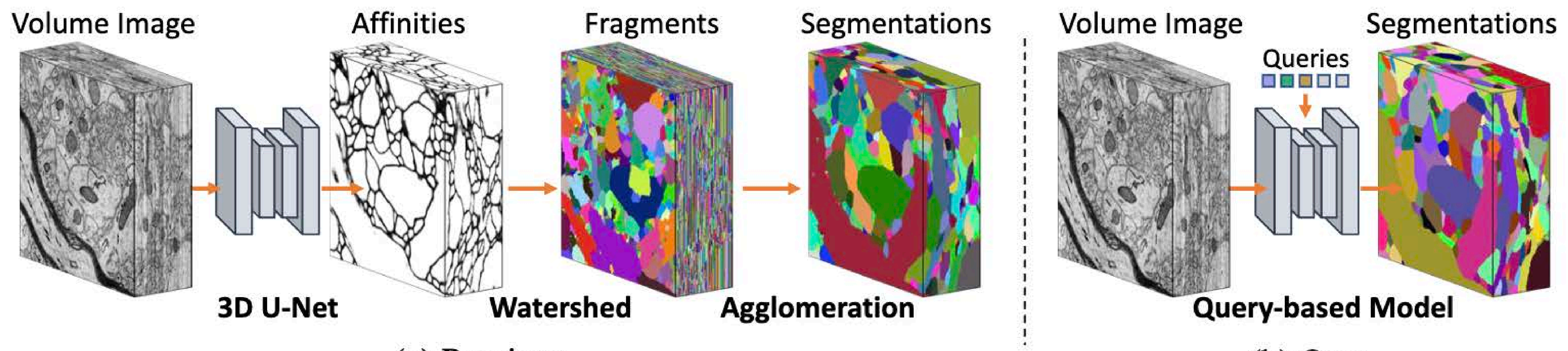
Summary

- ***Problem***: watershed-based methods suffer from inaccuracy and inefficiency that limit their application;
- ***Contribution***: we propose the first query-based model for neuron segmentation;
- ***Results***: Compared with state-of-the-art methods, our method achieved lower errors with significantly speedup (200 ~ 300%)

Motivation

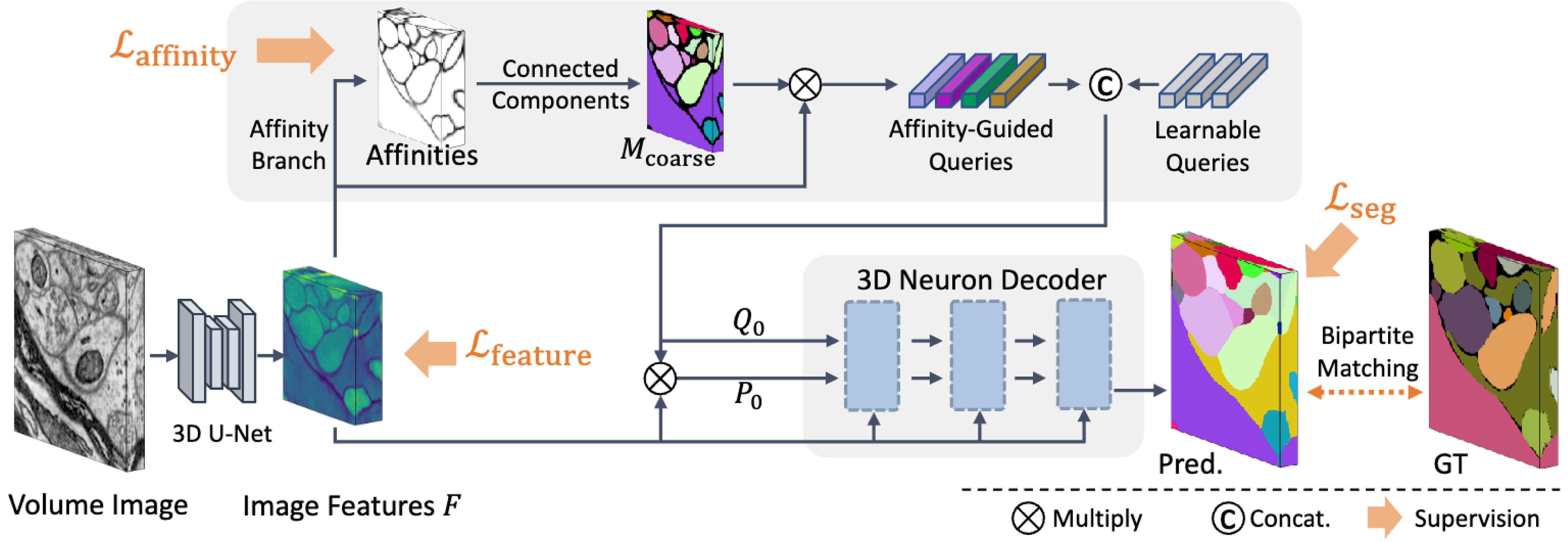


(a) Previous (b) Ours

- ***Drawbacks of watershed-based methods:***
  - *Inaccuracy*: easily produces fragments with unnatural boundaries (artifacts);
  - *Inefficiency:* watershed is unsuitable for GPU acceleration;
- ***Ours: a query-based modeling manner***:
  - predict N potential segmentation probability maps $P \in (0,1)^{N \times D \times H \times W}$;
  - directly obtain the segmentation results:

$$S = \operatorname{argmax}_{i \in \{1,\dots,N\}} \left(P_{i,:,:,:}\right) \in \mathbb{N}^{D \times H \times W}$$

Framework



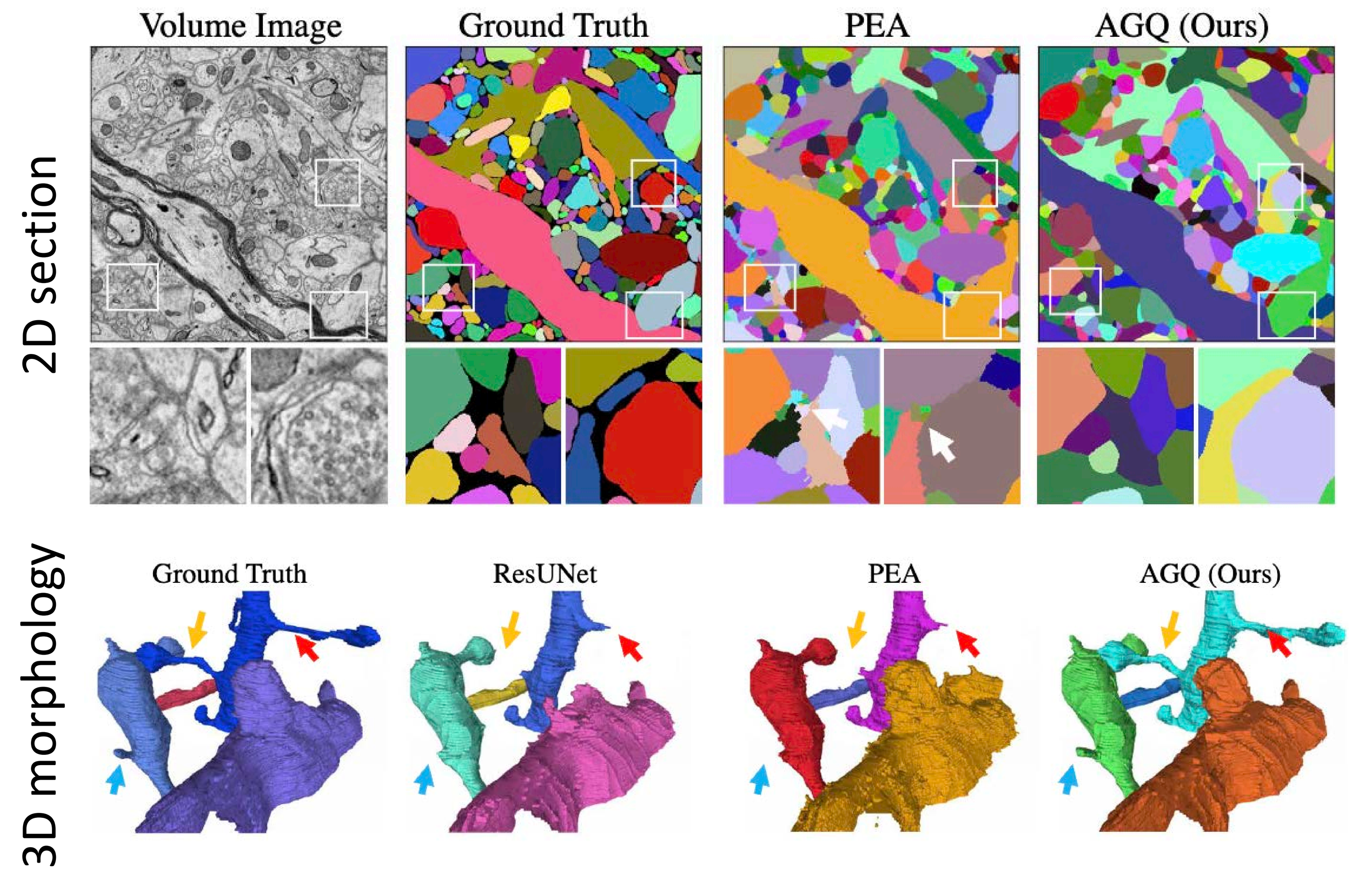
- ***Backbone:*** a 3D U-Net backbone to extract volume image features;
- ***3D neuron decoder:*** a K-Net-style 3D mask decoder to directly predict segmentation;
- ***Query Generator:*** generate N queries (corresponding to N potential neurons);
  - *AGQ*: to include coarse neuron structure information from bottom-up cues;
  - *LQ*: to further refine the incorrectly merged and missing neurons.

Results

	Metrics ↓				Inference Time ↓			
	VOI_s	VOI_m	VOI	Arand	Model	Watershed	Agg.	Total
ResUNet (Xiao et al., 2018)	1.037	0.258	1.295	0.154	81.2	30.8	35.8	147.8
SeUNet (Lin et al., 2021)	1.031	0.251	1.282	0.156	83.1	30.7	36.0	149.8
UNETR (Hatamizadeh et al., 2022)	2.750	0.281	3.031	0.220	37.0	41.4	133.0	211.4
SwinUNETR (Hatamizadeh et al., 2021)	1.238	**0.191**	1.429	0.110	80.0	32.5	43.1	155.6
LSD (Sheridan et al., 2023)	1.448	0.229	1.677	0.134	229.9	29.7	26.5	286.1
ML-De (De Brabandere et al., 2017)	1.575*	0.615*	2.190*	0.196*	-	-	-	-
SuperHuman (Lee et al., 2017)	1.145*	0.263*	1.408*	0.122*	52.3	28.4	19.4	100.1
MALA (Funke et al., 2019)	1.304*	0.242*	1.546*	0.120*	-	-	-	-
PEA (Huang et al., 2022b)	0.852*	0.232*	1.084*	0.094*	60.2	37.1	25.4	122.7
FragViT (Luo et al., 2024)	0.868*	**0.191***	1.054*	0.093*	>60.2	≃37.1	≃25.4	>122.7
APViT (Sun et al., 2023)	0.767*	0.209*	0.976*	**0.078***	>60.2	≃37.1	≃25.4	>122.7
AGQ (ours)	**0.677**	0.290	**0.967**	0.095	**27.6**	**N/A**	**6.1**	**33.7**

- *Better accuracy*: exhibiting superior performance in metrics (lowest VOI and competitive Arand errors);
- *Better efficiency*: significantly surpassed previous methods, due to the concise modeling and framework.

Qualitative Results



Ablation Study

- ***Design of neuron decoder:***

	Block		Full			
	VOI	Arand	VOI_{split}	VOI_{merge}	VOI	Arand
Transformer Decoder	1.245	0.184	1.695	1.138	2.833	0.395
K-Net Decoder	0.710	0.087	1.131	0.562	1.693	0.160
Ours	**0.538**	**0.065**	0.781	0.397	**1.177**	**0.141**

- ***Effect of affinity-guided queries:***

	Block		Full			
	VOI	Arand	VOI_{split}	VOI_{merge}	VOI	Arand
LQ	0.710	0.087	1.131	0.562	1.693	0.160
Double LQ	0.695	0.082	1.078	0.650	1.729	0.209
AGQ	0.836	0.102	0.822	0.881	2.010	0.229
LQ+AGQ	**0.538**	**0.065**	**0.781**	**0.397**	**1.177**	**0.141**

- ***Different approaches of using bottom-up cues:***

	Block		Full			
	VOI	Arand	VOI_{split}	VOI_{merge}	VOI	Arand
Concat affinities	0.836	0.102	0.836	0.102	2.010	0.229
Concat coarse segmentation	0.869	0.104	0.975	0.917	1.893	0.213
Affinity guided queries	**0.538**	**0.065**	0.781	0.397	**1.177**	**0.141**