Road network reconstruction from satellite images via TDA + ML

Presented by Jiayuan Wang

Department of Computer Science and Engineering ,

The Ohio State University

Joint work with Tamal K. Dey and Yusu Wang

Outline

- Road network reconstruction from satellite images framework pipeline
- Persistence guided discrete-Morse based graph reconstruction
- Semi-automatic framework
- Fully-automatic framework

Road network reconstruction from satellite images framework pipeline

Persistence guided discrete-Morse based graph reconstruction

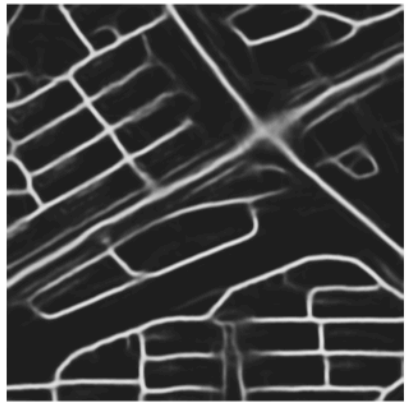
Stage1

Stage2

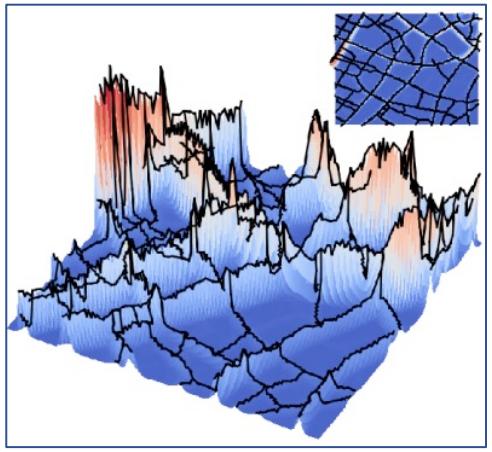
Satellite Images

A ML-framework to segment it to identify foreground (roads)

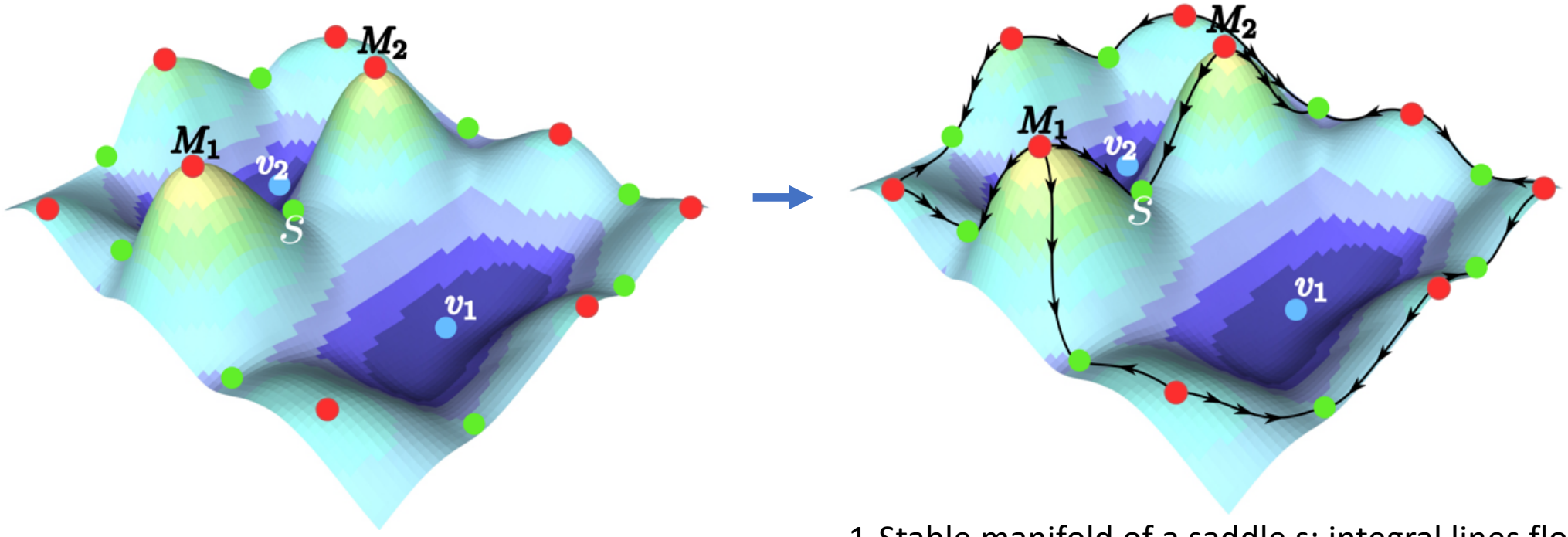
Extract road network from segmented images



Graph reconstruction - Smooth case



- Input: a density field sampled from a graph
- Capture the mountain ridged by 1-stable manifold from Morse theory



1-Stable manifold of a saddle s: integral lines flow into s

Graph reconstruction

- Discrete Morse theory:
  - Efficient and numerically stable computation
- Persistent homology:
  - Capture importance of different pieces of 1-stable manifolds

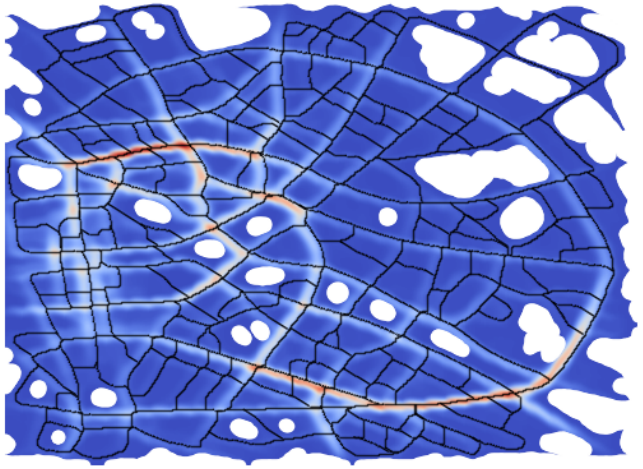
[Wang, Li, Wang, SIGSPATIAL 2015]
- Application on road reconstruction from GPS trajectories

[Dey, W., Wang, SIGSPATIAL 2017] [Dey, W., Wang, SoCG 2018]
- Further simplification of the algorithm/editing strategy
- Reconstruction guarantees under a (simple) noise model

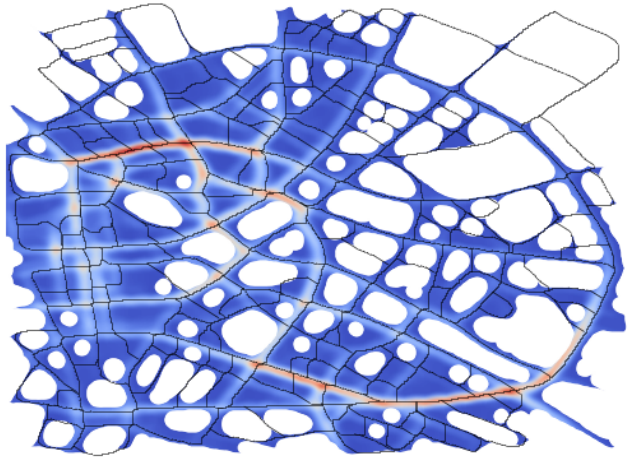
Graph reconstruction – Advantages

- Robust to noise
- Handle non-uniform sampling

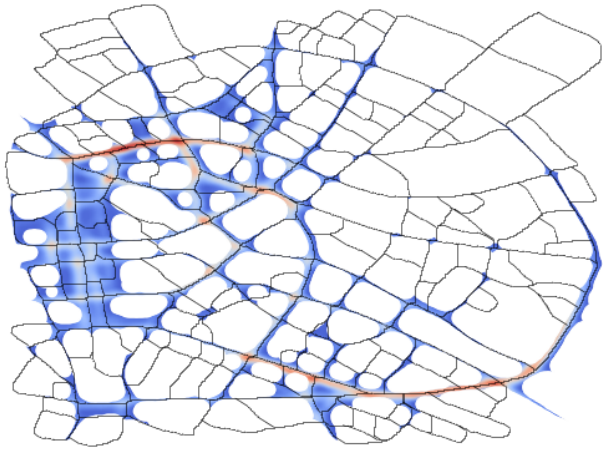
No single threshold value can capture all features due to the non-homogeneousness



Keep 90% lowest density value



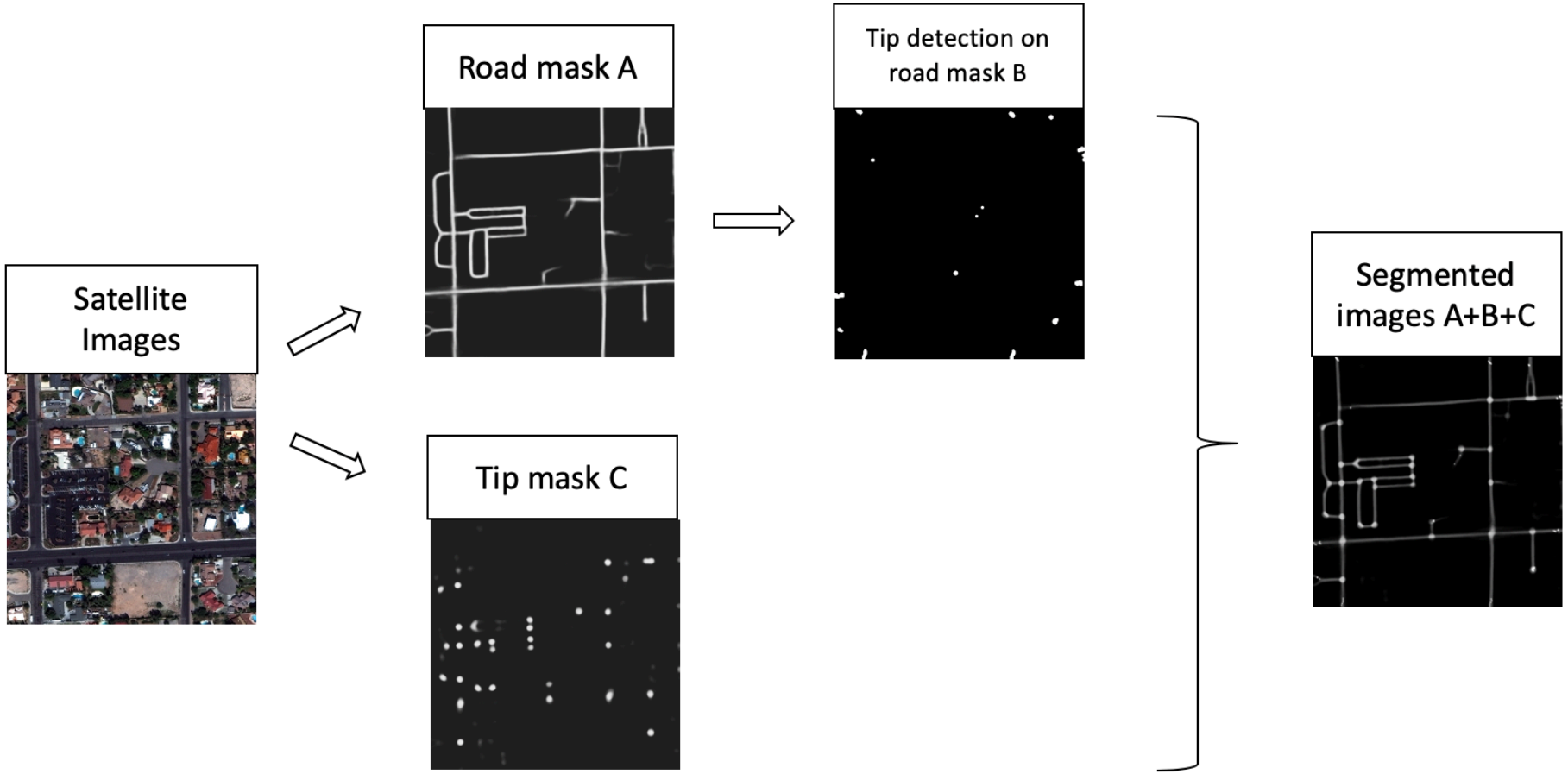
70%



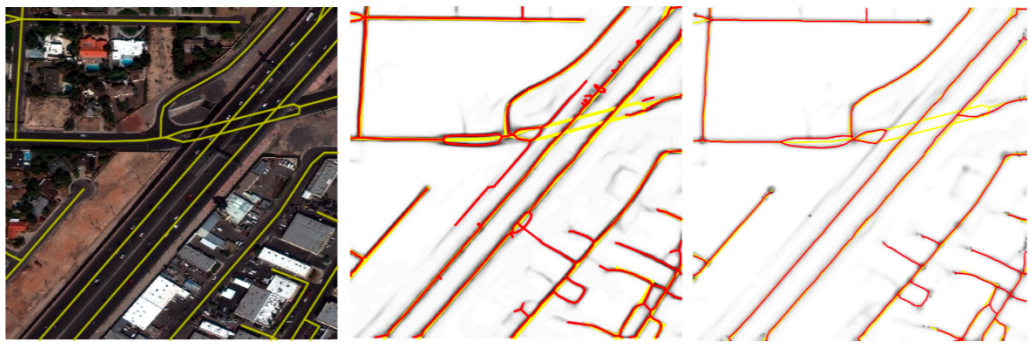
40%

- Close small gaps

Semi-automatic framework pipeline – Stage1

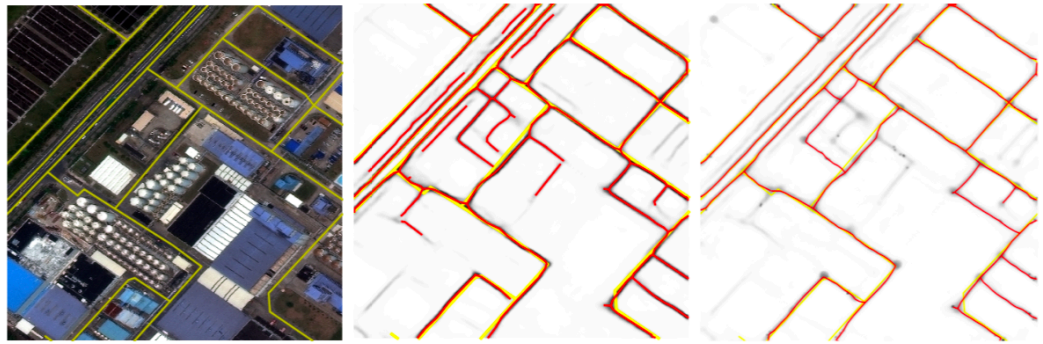


Experiment results for semi-automatic framework



AOI_2-Id: 1462 | 0.5700 / 18.6828 | 0.6655 / 14.2246

AOI_3-Id: 217 | 0.6194 / 20.7057 | 0.8193 / 16.8086



AOI_4-Id: 267 | 0.4721 / 29.5151 | 0.5693 / 21.6930

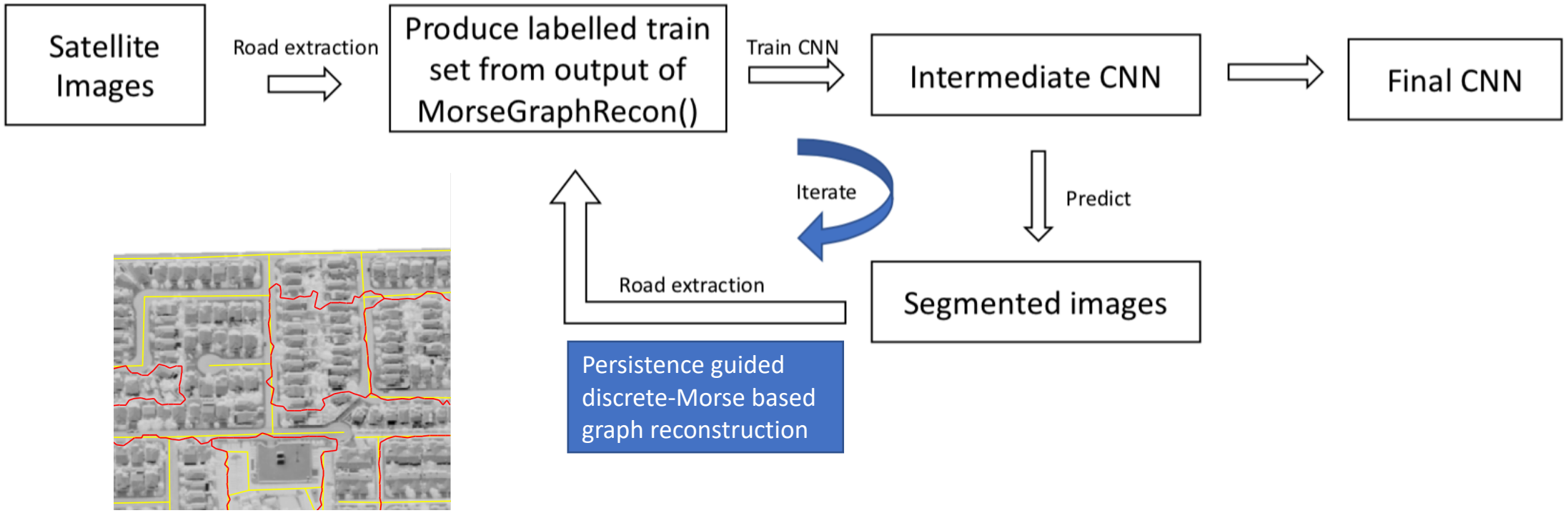
AOI_5-Id: 207 | 0.6334 / 30.0484 | 0.7287 / 24.9911

Better connectivity and less noise

Experiment results for semi-automatic framework

	APLS		S_H	
	Buslaev[2]	ours	Buslaev[2]	ours
AOI_2	0.8211	**0.8278**	18.3539	**17.7841**
AOI_3	0.5848	**0.6324**	291.0188	**289.9532**
AOI_4	0.6630	**0.6632**	69.5775	**68.9596**
AOI_5	0.6069	**0.6477**	44.4201	**41.6037**
ave.	0.6689	**0.6927**	105.8425	**104.5751**

Fully-automatic framework pipeline

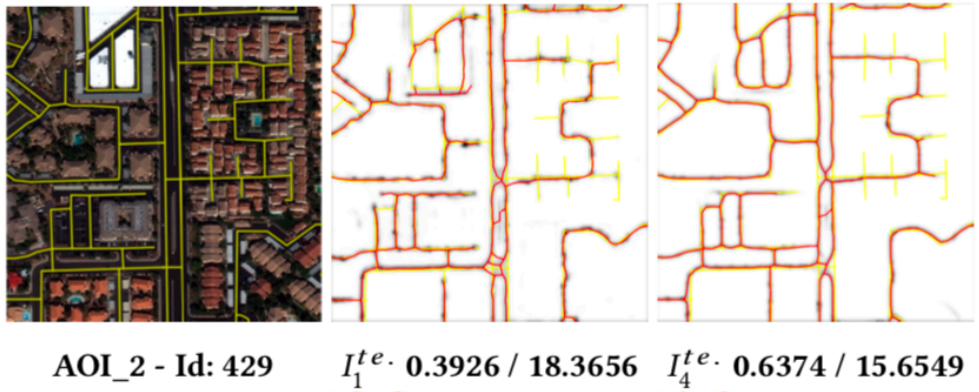


Experiment results for fully-automatic framework – label free

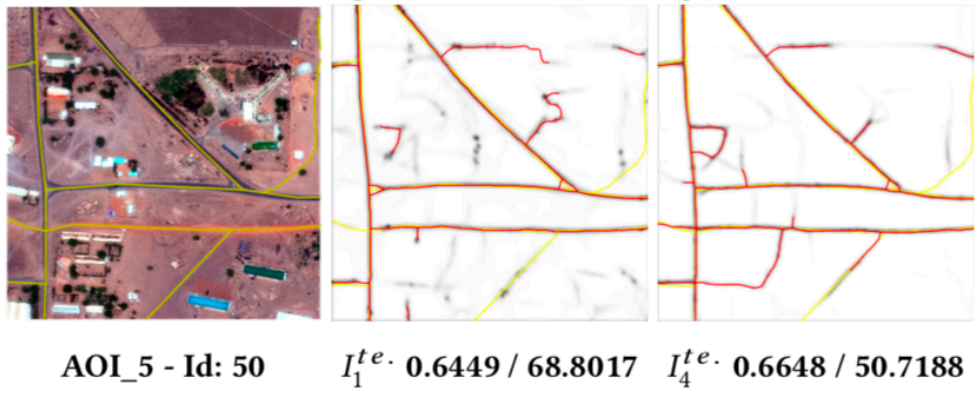
AOI_2	I_1^{test}	I_2^{test}	I_3^{test}	I_4^{test}	I_5^{test}	I_6^{test}	I_7^{test}	I_8^{test}	I_9^{test}	I_{10}^{test}	I_{11}^{test}
MorseLabelTrain()	0.2523	0.3340	0.3886	0.4173	0.4332	0.4655	0.4829	0.5252	0.5497	0.5813	0.5922
SkeletonLabelTrain()			0.2677	0.2643	0.2763	0.2753					

AOI_2 - Id: 323 $I_1^{te.}$ **0.0653 / 57.0400** $I_{11}^{te.}$ **0.5564 / 30.3855**

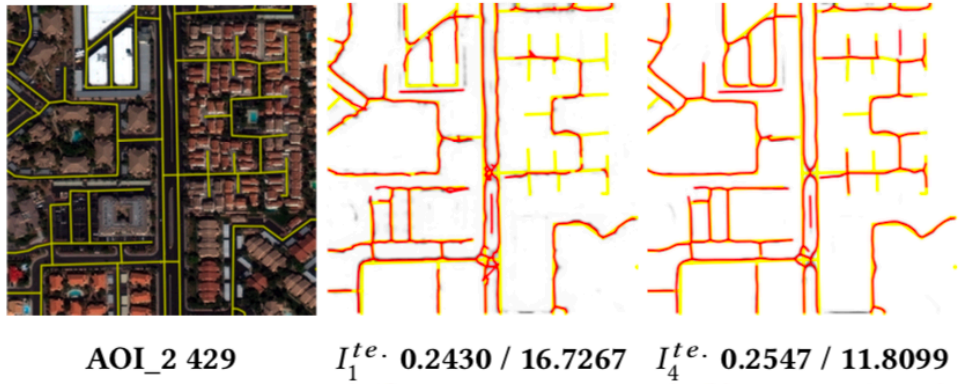
Experiment results for fully-automatic framework – partial label



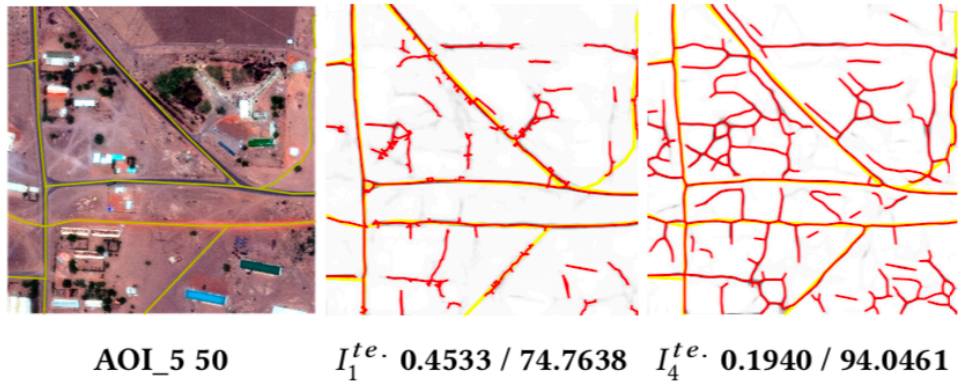
AOI_2 - Id: 429 $I_1^{te\cdot}$ 0.3926 / 18.3656 $I_4^{te\cdot}$ 0.6374 / 15.6549



AOI_5 - Id: 50 $I_1^{te\cdot}$ 0.6449 / 68.8017 $I_4^{te\cdot}$ 0.6648 / 50.7188



AOI_2 429 $I_1^{te\cdot}$ 0.2430 / 16.7267 $I_4^{te\cdot}$ 0.2547 / 11.8099



AOI_5 50 $I_1^{te\cdot}$ 0.4533 / 74.7638 $I_4^{te\cdot}$ 0.1940 / 94.0461