Topological Map Extraction From Overhead Images

Supplementary Material

A. Self-collected Dataset

As mentioned in the main paper, we collected our own dataset that contains annotations of building footprints and road networks. This dataset was created by following the same procedure used to obtain the datasets of crowdAI [6] and RoadTracer [1]. The overhead images are from Google Maps and the annotations are from OpenStreetMap [2]. To obtain the satellite imagery from Google Maps, an API key from the link is required. For OpenStreetMap, there is no such limitation.

For building annotations, we do not distinguish between different types of buildings but discard those that are not visible (this information is provided by OpenStreetMap). In terms of roads, very small roads such as pedestrian and sidewalk, as well as invisible roads are ignored (the same procedure was adopted for RoadTracer [1]).

The detailed statistics of our PolyMapper dataset are presented in Tab. 1.

Table 1: Statistics of PolyMapper dataset

City	Boston	Chicago	Sunnyvale
Min Latitude	42.3085	41.7500	37.3419
Max Latitude	42.4335	41.9800	37.4210
Min Longitude	-71.1840	-87.7300	-122.1269
Max Longitude	-71.0000	-87.5600	-121.9370
#Images	150,768	151,776	104,544
Area (km^2)	172.804	173.959	119.824
#Buildings	872,932	1,530,192	659,262
Road Length (km)	3003.66	3908.67	1992.96

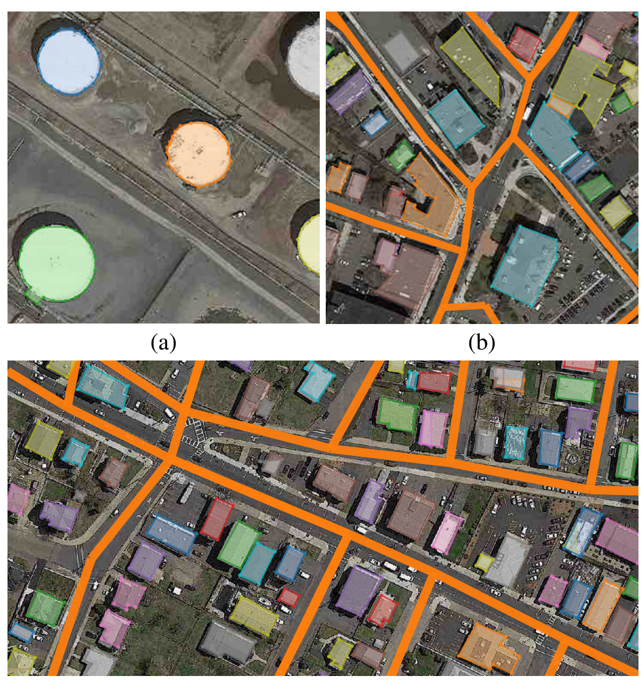
B. Detailed Quantitative Results

In the main paper, we compare PolyMapper with state-of-the-arts (Mask R-CNN [3] and PANet [4] for buildings, DeepRoadMapper [5] and RoadTracer [1] for roads) on our own collected dataset. We report a weighted average among the three cities Boston, Chicago and Sunnyvale. Here the detailed experiment results on each city of the PolyMapper dataset can be seen in Tab. 2 (buildings) and Tab. 3 (roads). Results show that PolyMapper is able to outperform or be on par with state-of-the-art methods.

C. Zoomed-in Qualitative Results

In the main paper, we showed topological maps predicted by PolyMapper on some selected areas of the three cities in the dataset. Here we further provide zoomed-in maps on several selected local areas in Fig. 1 (Boston), Fig. 2 (Chicago) and Fig. 3 (Sunnyvale).

We can see that in Fig. 1a, PolyMapper can even deal with buildings with round shapes (which are approximated using polygons). Fig. 1b and Fig. 1c show the predicted topological maps on areas whose road networks are quite complicated and are not vertically or horizontally aligned. The road networks in Fig. 2 present a shape of chess-board and the buildings are mostly rectangular. Fig. 3 further shows the superiority of PolyMapper in building footprints segmentation. Compared to the output of pixel-level segmentation models, the building footprints predicted by PolyMapper have sharp corners and exhibit more compact representations.



(a) (b) (c)

Figure 1: Sample areas of Boston

Table 2: Evaluation on the PolyMapper dataset for each city: Buildings

Boston	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	AR	AR_{50}	AR_{75}	AR_S	AR_M	AR_L
Mask R-CNN	23.8	57.0	**14.0**	7.6	32.4	44.1	30.5	59.8	**27.5**	8.1	41.8	55.5
PANet	**24.1**	57.2	13.9	7.1	**33.2**	**48.4**	30.5	59.7	27.4	7.2	**42.2**	**57.9**
Ours	23.3	**61.8**	11.0	**12.2**	29.1	38.6	**33.0**	**69.5**	26.8	**16.8**	40.8	57.8
Chicago	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	AR	AR_{50}	AR_{75}	AR_S	AR_M	AR_L
Mask R-CNN	46.5	74.5	54.3	30.5	61.5	**54.0**	51.1	75.6	60.8	35.6	67.0	**62.6**
PANet	46.2	75.6	53.5	32.0	59.6	50.6	51.3	76.2	61.0	37.7	65.4	57.2
Ours	**51.2**	**87.0**	**56.7**	**40.1**	**61.6**	42.1	**58.0**	**89.1**	**66.2**	**47.6**	**68.6**	61.0
Sunnyvale	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	AR	AR_{50}	AR_{75}	AR_S	AR_M	AR_L
Mask R-CNN	42.9	66.8	50.3	10.7	53.6	32.5	48.0	68.8	56.8	12.6	59.2	56.2
PANet	45.0	70.6	**52.8**	13.0	56.1	28.5	50.6	72.8	59.6	15.1	62.0	54.1
Ours	**47.7**	**78.5**	**52.8**	**19.3**	**56.9**	**35.6**	**56.2**	**83.4**	**63.4**	**28.3**	**65.2**	**60.3**

Table 3: Evaluation on the PolyMapper dataset for each city: Roads

Boston	$SP_{\pm 5\%}$	$SP_{\pm 10\%}$	AP_{85}	AP_{90}	AP_{95}	AR_{85}	AR_{90}	AR_{95}
DeepRoadMapper	24.8	40.7	60.7	41.4	23.5	61.6	44.1	25.6
RoadTracer	52.6	70.6	72.5	64.2	45.1	82.5	72.7	53.6
Ours	**59.6**	**80.0**	**88.0**	**81.2**	**61.3**	**87.8**	**80.7**	**59.1**
Chicago	$SP_{\pm 5\%}$	$SP_{\pm 10\%}$	AP_{85}	AP_{90}	AP_{95}	AR_{85}	AR_{90}	AR_{95}
DeepRoadMapper	80.0	86.1	87.1	83.8	77.0	90.0	86.9	80.4
RoadTracer	70.5	75.9	92.0	87.2	76.1	80.7	76.2	70.6
Ours	**89.8**	**95.5**	**98.4**	**96.0**	**90.1**	**98.5**	**96.0**	**88.5**
Sunnyvale	$SP_{\pm 5\%}$	$SP_{\pm 10\%}$	AP_{85}	AP_{90}	AP_{95}	AR_{85}	AR_{90}	AR_{95}
DeepRoadMapper	40.9	57.9	75.1	60.1	42.8	76.0	60.7	42.1
RoadTracer	**74.0**	**86.5**	84.0	74.7	59.3	**93.2**	**87.0**	**74.5**
Ours	69.1	80.3	**90.8**	**82.2**	**69.8**	90.8	82.1	70.2

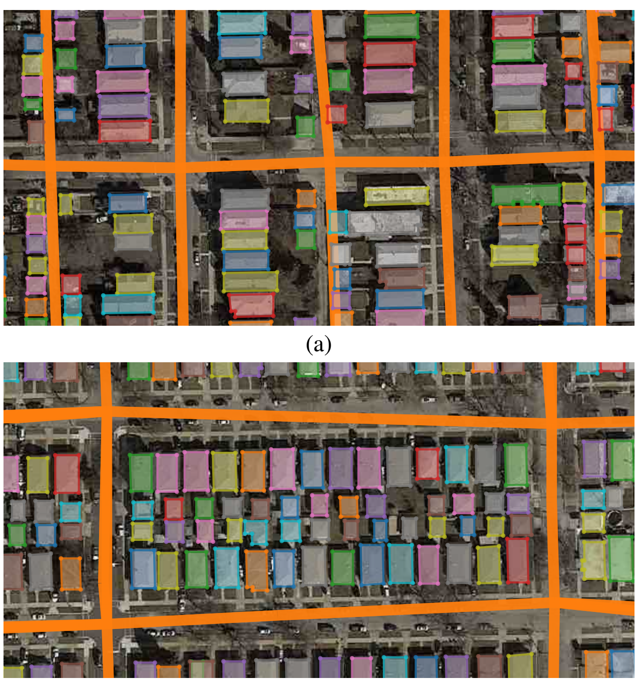


Figure 2: Sample areas of Chicago

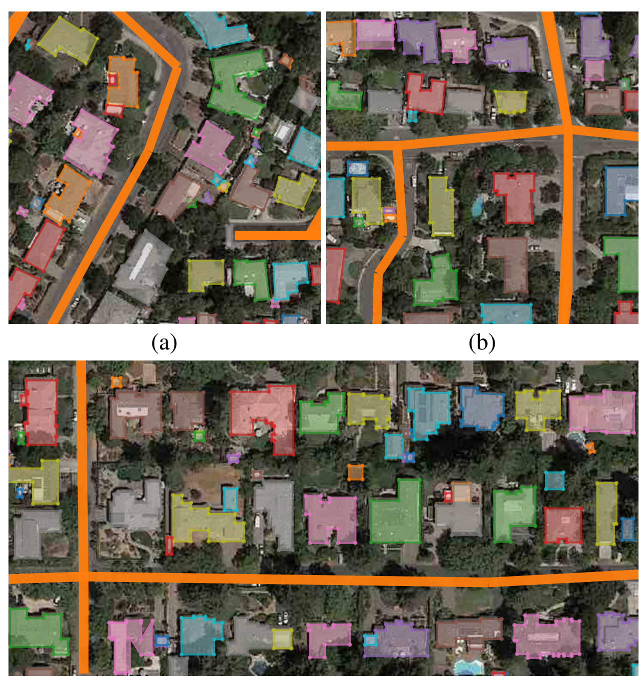


Figure 3: Sample areas of Sunnyvale

References

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