Automatically Gather Address Specific Dwelling Images Using Google Street View



BACKGROUND: Exciting research is being conducted using Google's street view imagery. Researchers can have access to training data that allows CNN training for topics ranging from assessing neighborhood environments to estimating the age of a building. However, due to the uncontrolled nature of imagery available via Google's Street View API, data collection can be lengthy and tedious. To help researchers gather address specific dwelling images efficiently, we developed an innovative and novel way of automatically performing this task. It was accomplished by exploiting Google's publicly available platform with a combination of 3 separate network types and post-processing techniques. Our uniquely developed NMS technique helped achieve 99.4%, valid, address specific, dwelling images.

METHODS: In this work, we have taken a step towards reducing the time required and the tedious nature of the data collection and labeling step. First, we retrieve the image of our desired dwelling by entering its address into Google SV API. To acquire the most accurate view of each dwelling, we adjusted the pitch parameter to point the camera up by 10 degrees. A scene classification network was utilized as a mechanism to filter out undesired dwelling images. We employed 6 Keras-RetinaNet models pre-trained on the Google Open Images data set. The bounding boxes produced by the networks were merged based on heuristic NMS techniques to get as close to one bounding box per object. To obtain the dwelling of interest, we chose the dwelling bounding box whose center is closest to the image's center. This logic works 100% of the time as long as we do not have unwanted scenes present. Last step is to ensure that there are no trees present in front of our chosen dwelling. For this, we utilized a pre-trained semantic segmentation network.



Bounding Boxes

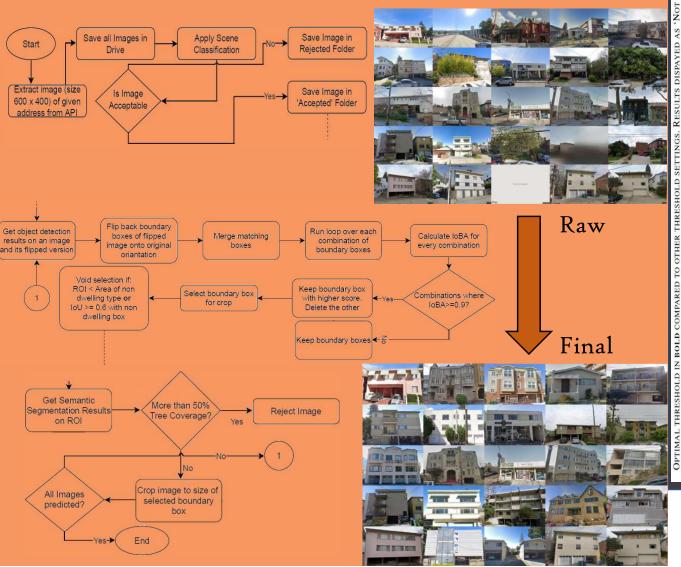






c) Cropped Image: 3326 SE Milwaukie Ave, Portland, OR

The final result of each Google Street View API extraction is a cropped image consisting of the desired building at an accuracy of 99.4%.



Results of our Automatic Dwelling Data Generation Pipeline Accepted Post Scenes NMS 258 321 136 1106 453 587 1620 Santa Mor 1490 1191 322 0.428% 99.29%

Results of our Automatic Dwelling Data Generation Pipeline if our heuristic methods are not applied

City	Total Im- ages	Accepted Scenes	Post NMS	Final Cropped Images	Not ROI	Err/ Prc/ Rcl
SF Bay Area	321	258	256	217	14	6.45%/ 93.55%/ 89.82%
Seattle	1106	749	673	475	23	4.84%/ 95.15%/ 84.96%
Portland	1620	993	954	704	59	8.34%/ 91.61%/ 73.13%
Santa Monica	1490	1191	1124	860	191	22.20%/ 77.79%/ 86.43%
Vancouver	726	569	558	348	14	4.02%/ 95.97%/ 82.2%
Averaged Results:	Avg Err:	9.17%	Avg Prc:	90,81%	Avg Rcl:	83.31%

Results of Automatic Dwelling Data Generation with SOTA Semantic Segmentation Network

	City	Total Im- ages	Accepted Scenes	Post NMS	Final Cropped Images	Not ROI	Err/ Prc/ Rcl
1.92/0	SF Bay Area	321	258	136	96	1	1.04%/ 98.95%/ 82.05%
	Seattle	1106	749	453	417	1	0.24%/ 99.76%/ 86.12%
	Portland	1620	993	587	551	3	0.54%/ 99.45%/ 73.36%
	Santa Mon- ica	1490	1191	322	267	4	1.50%/ 98.50%/ 72.65%
10	Vancouver	726	569	349	285	1	0.35%/ 99.65%/ 85.03%
5 1710	Averaged Results:	Avg Err:	0.734%	Avg Pre:	99.26%	Avg Rel:	79.84%

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