L^3-Net: Towards Learning based LiDAR Localization for Autonomous Driving

CVPR 2019 Supplementary Material

Weixin Lu* Yao Zhou* Guowei Wan Shenhua Hou Shiyu Song†
Baidu Autonomous Driving Business Unit (ADU)
{luweixin, zhouyao, wanguowei, houshenhua, songshiyu}@baidu.com

1. More about RNNs

RNNs plays an important role in our network architecture. In order to further illustrate the effectiveness of RNNs, two zoomed-in views of the estimated trajectories are included in the left corner of Figure 1. The trajectories of our method with RNNs are smoother than those without RNNs as seen Figure 1 and is also closer to ground truth. This demonstrates that RNNs doesn't only improve our localization accuracy, but also smoothes the estimated trajectories by making them conform to the vehicle's dynamics. On the right corner of Figure 1, the localization errors of our longest testing dataset, SunnyvaleBigLoop is displayed; in which the collection time interval between mapping and testing the data is one year. As our LiDAR localization method largely depends on the similarity of the online data and map data, the area that has larger errors, can be considered as having larger environmental changes.

Figure 1. (Left) Comparison with/without RNNs. The effectiveness of RNNs is clearly demonstrated. (Right) The localization errors of the longest dataset, SunnyvaleBigLoop. The magnitude of the localization errors reflects the level of environmental changes.

2. More about Apollo-SouthBay Dataset

Our dataset contains six routes, BaylandsToSeafood, ColumbiaPark, Highway237, MathildaAVE, SanJoseDowntown, and SunnyvaleBigLoop covering different scenarios including but not limited to residential areas, urban downtown areas and highways. Our dataset contains 3D LiDAR scans (as well as point clouds generated by accumulating scans with motion compensation), camera images, post-processed ground truth poses and online estimated poses from the GNSS/IMU integrated solution. In Figure 2, the six routes in southern San Francisco Bay area are shown for reference. In Figure 3, the camera images of four selected scenarios in the datasets are shown to demonstrate the coverage diversity of our datasets.

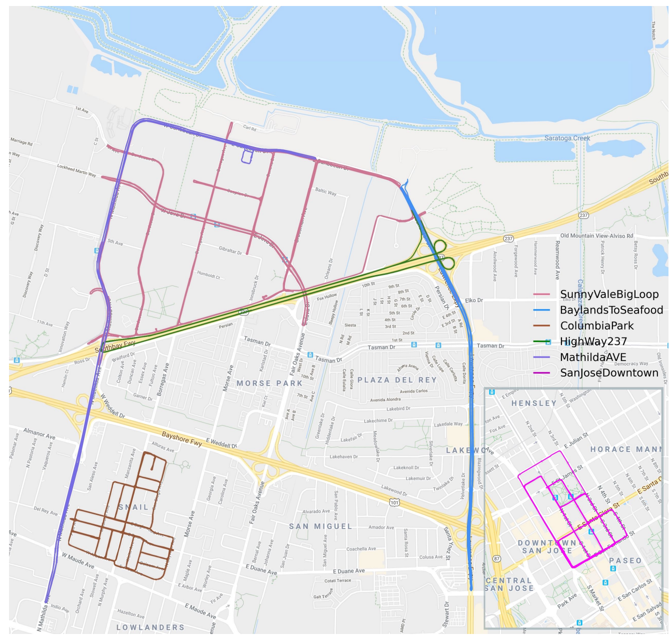

Figure 2. The six routes of the collected datasets in southern San Francisco Bay area. The routes are carefully selected to cover the different scenarios.

Figure 3. Illustration of the different scenarios in our datasets. The multiple trials of repetitive data collection in these different scenarios makes our datasets ideal for testing localization systems.

* Authors with equal contributions
† Author to whom correspondence should be addressed