

SGLC: Semantic Graph-Guided Coarse-Fine-Refine Full Loop Closing for LiDAR SLAM

(Supplementary)

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A. Experimental Setup

We evaluate our method in KITTI [1], KITTI-360 [2], Ford Campus [3] and Apollo datasets [4]. For loop pairs selection, many existing methods with different settings, mainly divided into distance-based and overlap-based. For a comprehensive evaluation, we select loop pairs using both distance-based and overlap-based criterion.

(1) Distance-based: following SSC [5], we regard LiDAR scan pairs as positive samples of loop closure when their Euclidean distance is less than 3 m and as negative samples if the distance exceeds 20 m.

(2) Overlap-based: following OverlapTransformer [6], we regard LiDAR scan pairs as positive samples of loop closure when their overlap ratio exceed 0.3, otherwise, it is regarded as negative.

Taking the 00 sequence as a case, we present the distribution of rotations and translations of loop pairs across different criteria. As shown in Fig. 1, the number of loop pairs based on overlap criteria is significantly higher than those based on distance, and they exhibit larger viewpoint changes in rotation and translation.

B. Generalization Evaluation

We provide visual results of semantic segmentation in the Ford Campus and Apollo dataset for readers to assess the labels quality.

C. Loop Pose Estimation

Further visualization results of alignment are presented as Fig. 4:

D. Runtime

We provide full runtime comparison with 6-DoF pose estimation baselines, helping readers understand the real-time performance of our system. From the results, our method achieves the fastest running speed even when the time of semantic segmentation is included.

TABLE I: The runtime comparison.

Method	Descriptors Generation	Retrival	Pairwise Registration	Total
BoW3D	17.4	60.6	40.0	118.0
LCDNet(fast)	142.0	5.7	81.7	229.4
LCDNet	142.0	5.7	429.1	576.8
Ours	67.1*+4.5	5.7	20.8	98.1

* denotes the semantic segmentation time, i.e., SegNet4D.

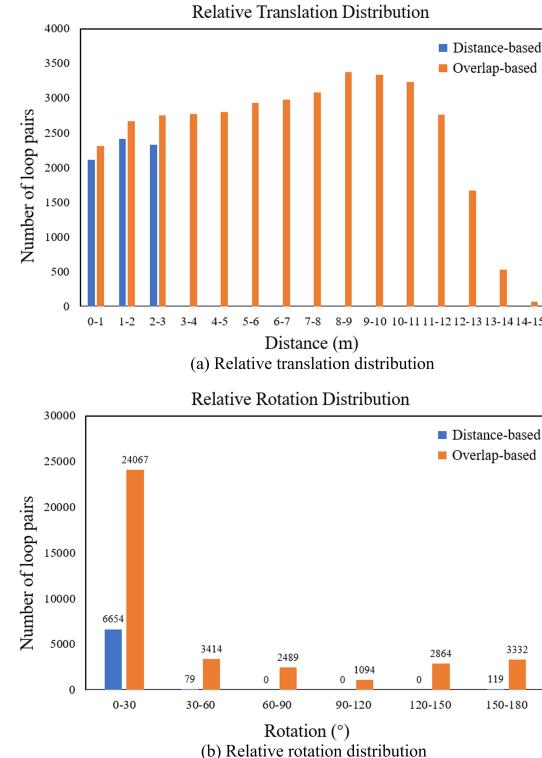


Fig. 1: The distribution of rotations and translations of loop pairs across different criteria on KITTI sequence 00.

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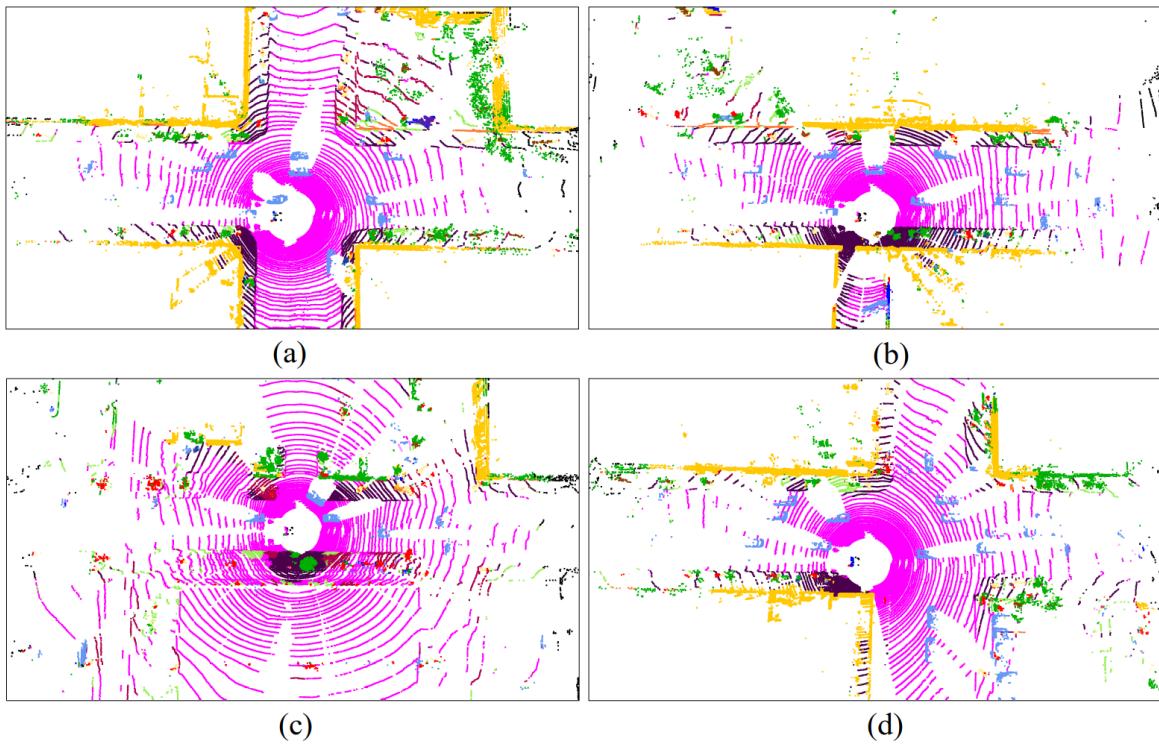


Fig. 2: Semantic labels from SegNet4D on the Ford dataset. Many moving vehicles on the road.

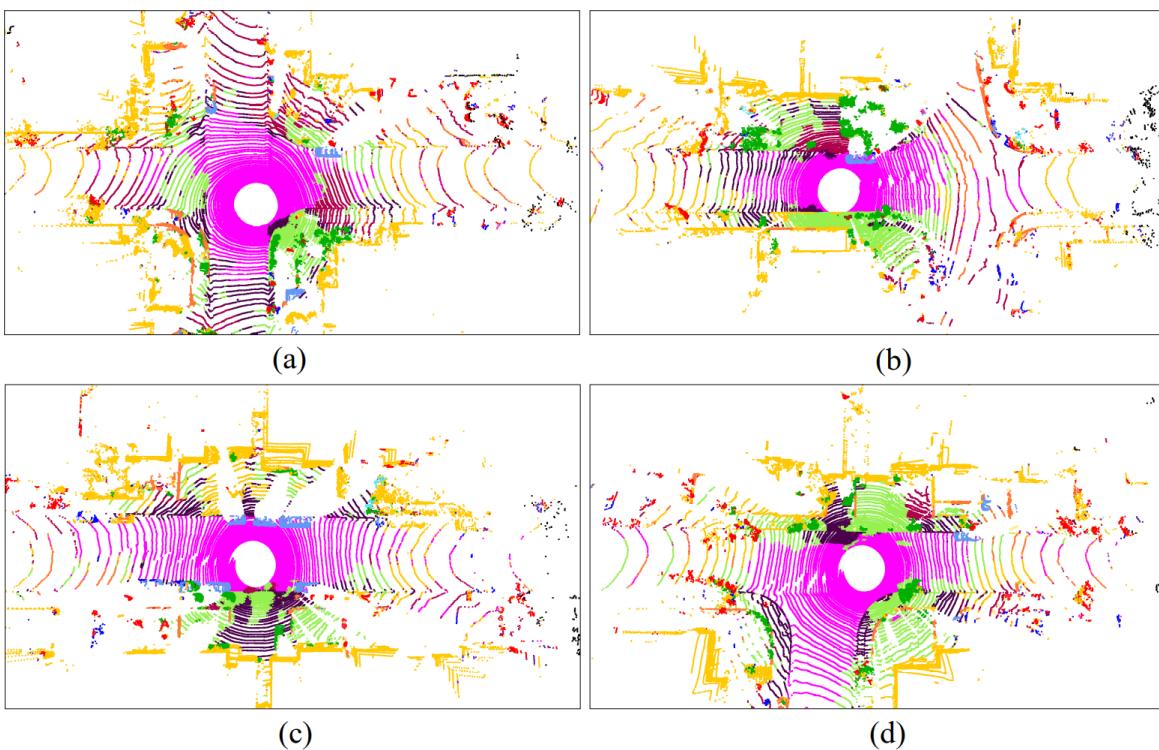


Fig. 3: Semantic labels from SegNet4D on the Apollo dataset. The quality of semantic segmentation has significantly declined.

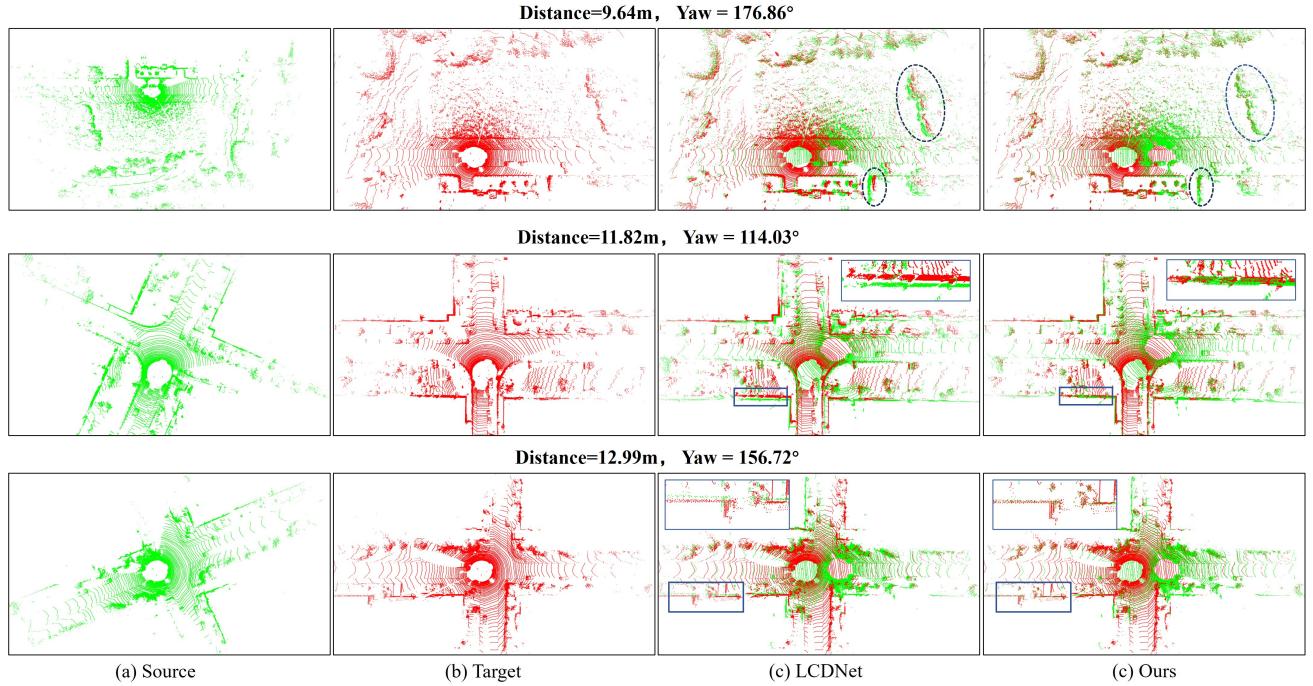


Fig. 4: The qualitative comparison of loop pose estimation on the KITTI dataset using overlap-based loop pairs. Dashed ellipses are directly annotated on the registration results, while solid boxes indicate local magnification. The top displays the ground truth distance and yaw angle difference of the loop pair.