Supplementary Material for
LPD-Net: 3D Point Cloud Learning for Large-scale Place Recognition and Environment Analysis

1. Contents

In this supplementary material we provide:

- Detailed differences between our LPD-Net and existing networks, in Sec. 2.
- Detailed environment analysis results, in Sec. 3.
- Detailed robustness test results, in Sec. 4.

2. Detailed differences between our network and existing networks

Comparison of the proposed network with existing methods is shown in Table 1. PointNet [3] provides a simple and efficient point cloud feature learning framework that directly uses the raw point cloud data as the input of the network, but failed to capture fine-grained patterns of the point cloud due to the ignored local features of points. PointNet++ [2] considers the hierarchical feature learning, but it still only operates each point independently during the local feature learning process, which ignores the relationship between points, leading to the missing of local feature. Then, KCNet [4] and DGCNN [6] have been designed based on PointNet. With the kNN-based local feature aggregating in the feature space, the state-of-the-art classification and segmentation results are obtained on small-scale object point cloud dataset. Moreover, RWTH-Net [1] achieved fine-grained segmentation results on the large-scale outdoor dataset based on local feature aggregating and clustering in Feature space and Cartesian space, respectively. However, the above networks all focus on capturing the similarity of point clouds, and it is hard to generate effective global descriptors of the point cloud in large scenes. On the other hand, PointNetVLAD [5] can learn the global descriptor of the point cloud in a large scene, but it only performs feature aggregation in the feature space, ignoring the distribution of features in Cartesian space, which makes it difficult to generalize the learned features.

3. Detailed environment analysis results

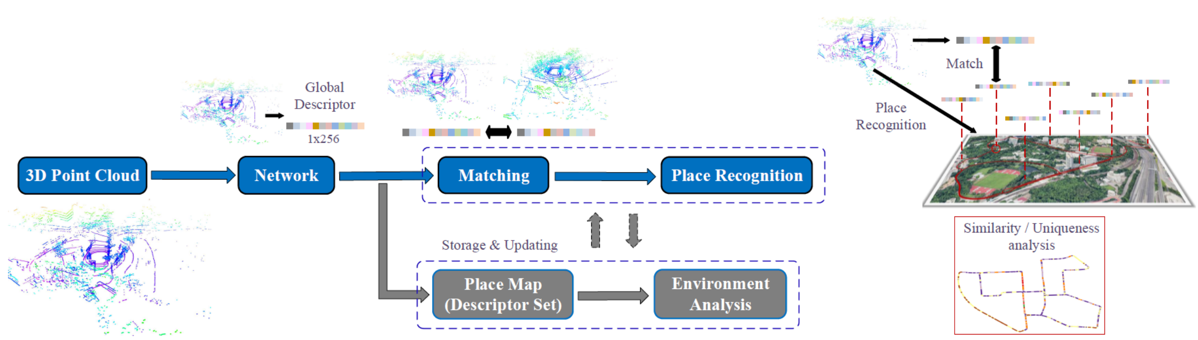

Figure 1. System structure.

Our LPD-Net extracts discriminative and generalizable global descriptors of an input point cloud, so we can resolve the large-scale place recognition and environment analysis problems. The system structure is shown in Fig. 1. The original

3D Lidar point cloud is used as system input directly. We use LPD-Net to extract a global descriptor which will be stored in a descriptor set. On the one hand, when a new input point cloud is obtained, we match its descriptor with those in the descriptor set to detect that whether the new scene corresponds to a previously visited place, if so, a loop closure detection accomplished. On the other hand, we analyze the environment by investigating the statistical characteristics of the global descriptors of the already visited places to evaluate the similarity/uniqueness of each place. The similarity between two point clouds is calculated from the distance between two corresponding global descriptors. Then for a given point cloud, we can calculate the similarity index of this point and plot a similarity map as shown in Fig. 3 (in KITTI dataset). With normalization, the sum of the similarity with all the other point clouds in the whole environment can be used to evaluate the uniqueness of the given point cloud (the given place). Fig. 4 shows the uniqueness evaluation results of the whole environment in KITTI dataset.

We also cluster the global descriptors generated by our LPD-Net to see the places in the same cluster. We collect the point cloud data with a VLP-16 LADAR in our university campus. In Fig. 5, we show the clustered places which are also near with each other in the geographical location, and in Fig. 6, we show the clustered places which are far from each other in the geographical location.

4. Detailed robustness test results

The detailed results of the robustness test presented in the main paper are shown in Tab. 2 and Fig. 2. In Tab. 2, we show the average (max) number of place recognition mistakes under different degrees of input point cloud rotations. We consider 1580 places in the university campus dataset and also add 10% white noise in the tests. Both results from our network and PointNetVLAD are shown. Fig. 2 shows an example of the failure cases in PointNetVLAD in the robustness tests.

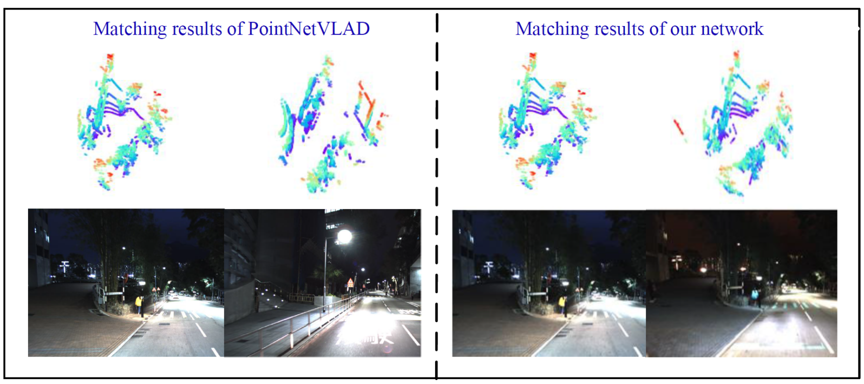

Figure 2. An Example of the failure cases in PointNetVLAD in the robustness tests. In this case, we rotate the input point cloud with 10 degrees and add 10% random white noise. Our network recognizes the place correctly, however, PointNetVLAD retrieves a wrong place.

References

[1] F. Engelmann, T. Kontogianni, J. Schult, and B. Leibe. Know what your neighbors do: 3d semantic segmentation of point clouds. In *Proceedings of the IEEE European Conference on Computer Vision Workshops*, 2018.

[2] C. R. Qi, L. Li, H. Su, and L. J. Guibas. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In *Proceedings of the Conference on Neural Information Processing Systems*, 2018.

[3] C. R. Qi, H. Su, K. Mo, and L. J. Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017.

[4] Y. Shen, C. Feng, Y. Yang, and D. Tian. Mining point cloud local structures by kernel correlation and graph pooling. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018.

[5] M. A. Uy and G. H. Lee. Pointnetvlad: Deep point cloud based retrieval for large-scale place recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018.

[6] Y. Wang, Y. Sun, Z. Liu, S. E. Sarma, M. M. Bronstein, and J. M. Solomon. Dynamic graph cnn for learning on point clouds. In *arXiv preprint arXiv:1801.07829v1*, 2018.

Table 1. Where our work fits into the literature.

	Local features	Feature space aggregation	Cartesian space aggregation	Feature distribution	Large-scale scene
PointNet [3]					
PointNet++ [2]			✓		
PointNetVLAD [5]		✓			✓
DGCNN [6]		✓			
KCNet [4]		✓			
RWTH-Net [1]		✓	✓		✓
Our LPD-Net	✓	✓	✓	✓	✓

Table 2. Results in the robustness test: with different rotation angles (degree).

	1	2	3	4	5	10	20	30
PointNetVLAD	4.5(6)	5.25(7)	7.75(13)	10.75(12)	29.25(31)	229.25(232)	908.75(918)	1298.75(1301)
Our LPD-Net	4.75(6)	6(8)	6.5(8)	7.25(9)	8(10)	17.25(21)	75.5(87)	202(217)

A(B): A is the average number across eight repeated experiments in each case, B is the max number in the eight experiments.

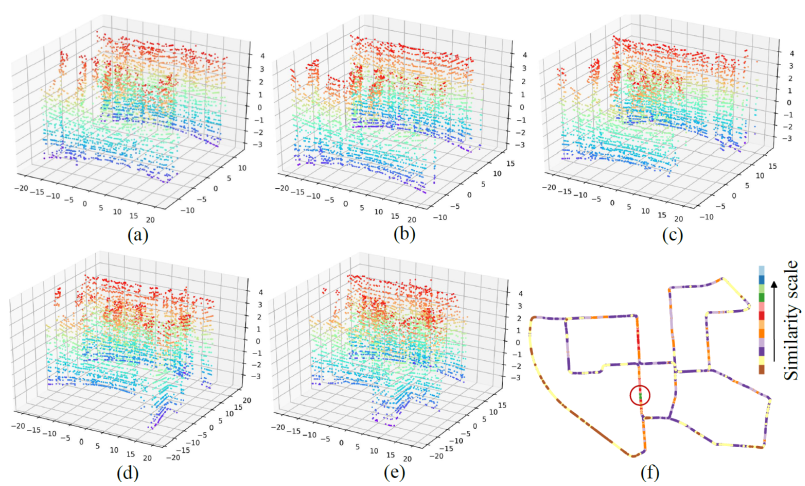

Figure 3. Similarity evaluation. (a)-(e) show a sequence of point clouds with near locations (correspond to the places within the red circle in f). (f) shows the similarity between the point cloud in (b) and all the other point clouds in the whole environment.

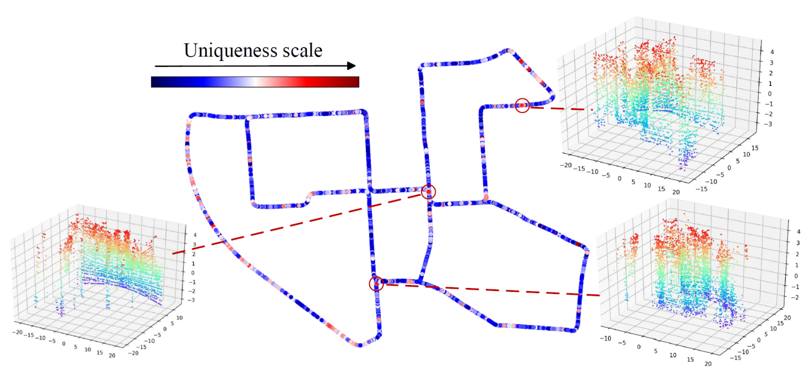

Figure 4. Uniqueness evaluation. The corresponding point clouds of three places with high uniqueness are shown.

Figure 5. Examples of the place clustering results: the clustered places which are also near with each other in the geographical location.

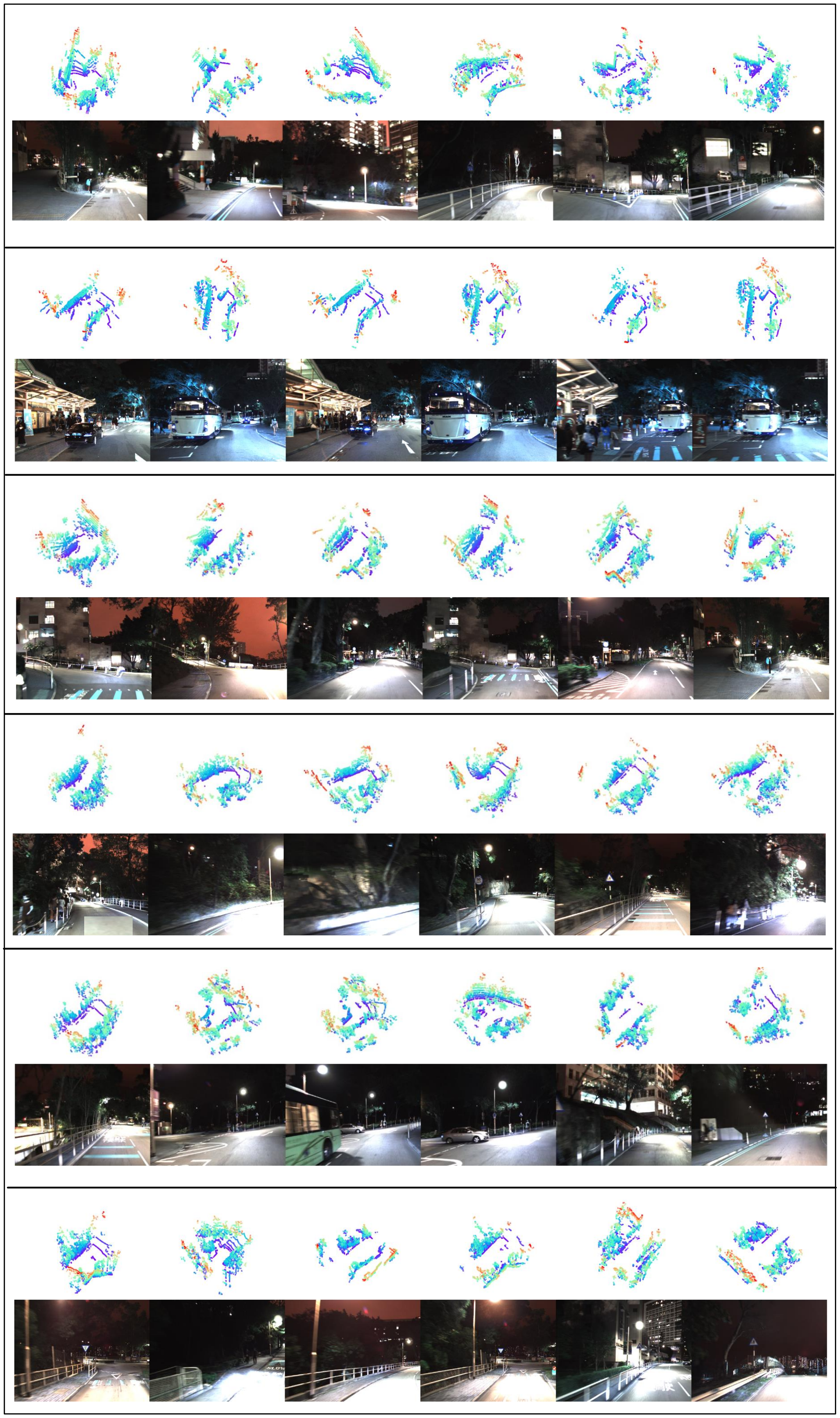

Figure 6. Examples of the place clustering results: the clustered places which are far from each other in the geographical location.