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# Robust Point Cloud Registration via Local-to-Global Geometric Feature Aggregation

Karim Slimani<sup>1</sup>, Catherine Achard<sup>1</sup> and Brahim Tamadazte<sup>1</sup>

This paper presents a hybrid descriptor for 3D point matching and point cloud registration. It combines local geometric properties with learning-based feature propagation to describe the neighbourhood structure of each point. The architecture first extracts prior geometric information by computing the planarity, anisotropy and omnivariance of each point using Principal Component Analysis (PCA). This information is augmented by a descriptor based on normal vectors estimated by a triangle-based shape construction. The main contributions are summarised in the following:

- Estimating a single normal vector for each point by weighting the normals of triangles formed with their nearest neighbours.
- Using local PCA to compute a local reference frame (LRF) and local geometric features such as anisotropy, omnivariance and planarity that are used to create a robust feature vector by combining them with 3D spatial coordinates.
- Ensure rotation invariant descriptors by projecting the normals into the LRFs.
- Propagate descriptor information from local to global using KNN-based graphs and a *self-attention* mechanism.

The proposed descriptor is evaluated on ModelNet40 and MVP-RG datasets and shows a good performance, especially on noisy and low overlapping point clouds. We use the same process as SOTA methods [1], [2] by constructing a similarity matrix as a result of a projection between the features of the two point clouds. The set of correspondences is built by collecting the mutual best scores from this matrix and used to estimate the rigid transformation thanks to the FSR module of [3]. Table I shows that our descriptor outperforms all tested methods on noisy and partially overlapping point clouds as it ranks first in the four used metrics on, tying with RoCNet++ in translation. Both methods outperform the second best (RoCNet [2] and GeoTransformer [4]) by 50% in RMSE and by 67% in MAE. Table II highlights that our method can handle very challenging configurations with varying local densities, low-overlapping point clouds, and unrestricted rotations  $[0^\circ, 360^\circ]$ , outperforming the other methods in all metrics by at least a 55% relative gap.

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TABLE I  
PERFORMANCES ON NOISY AND PARTIALLY OVERLAPPING DATA.

| Method        | RMSE( <b>R</b> ) | MAE( <b>R</b> ) | RMSE( <b>t</b> ) | MAE( <b>t</b> ) |
|---------------|------------------|-----------------|------------------|-----------------|
| ICP [5]       | 33.067           | 25.564          | 0.294            | 0.250           |
| VRNet [6]     | 03.615           | 1.637           | 0.010            | 0.006           |
| GeoTransf [4] | 00.915           | 0.386           | 0.007            | 0.003           |
| RoCNet [2]    | 01.810           | 0.620           | 0.004            | 0.003           |
| RoCNet++ [3]  | 01.278           | 0.318           | <b>0.002</b>     | <b>0.001</b>    |
| <b>Ours</b>   | <b>00.774</b>    | <b>0.266</b>    | <b>0.002</b>     | <b>0.001</b>    |

TABLE II  
PERFORMANCES ON MULTI-VIEW PARTIAL VIRTUAL SCAN REGISTRATION (MVP-RG)

| Method      | $L_R$         | $L_t$        | $L_{RMSE}$   |
|-------------|---------------|--------------|--------------|
| IDAM [7]    | 24.35°        | 0.280        | 0.344        |
| RGM [8]     | 41.27°        | 0.425        | 0.583        |
| DCP [9]     | 30.37°        | 0.273        | 0.634        |
| RPMNet [10] | 22.20°        | 0.174        | 0.327        |
| GMCNet [11] | 16.57°        | 0.174        | 0.246        |
| <b>Ours</b> | <b>07.33°</b> | <b>0.043</b> | <b>0.099</b> |

## REFERENCES

- [1] C. Shi, X. Chen, K. Huang *et al.*, “Keypoint matching for point cloud registration using multiplex dynamic graph attention networks,” *IEEE Rob. and Auto. Let.*, vol. 6, pp. 8221–8228, 2021.
- [2] K. Slimani, B. Tamadazte, and C. Achard, “Rocnet: 3d robust registration of point-clouds using deep learning,” *arXiv preprint arXiv:2303.07963*, 2023.
- [3] K. Slimani, C. Achard, and B. Tamadazte, “Rocnet++: Triangle-based descriptor for accurate and robust point cloud registration,” *Pattern Recogn.*, vol. 147, p. 110108, 2024.
- [4] Z. Qin, H. Yu, C. Wang *et al.*, “Geometric transformer for fast and robust point cloud registration,” in *IEEE/CV Conf. Comput. Vision Pattern Recognit.*, 2022, pp. 11 143–11 152.
- [5] P. J. Besl and N. D. McKay, “Method for registration of 3-d shapes,” in *Sensor fusion IV: control paradigms and data structures*, vol. 1611, 1992, pp. 586–606.
- [6] Z. Zhang, J. Sun, Y. Dai *et al.*, “Vrnet: Learning the rectified virtual corresponding points for 3d point cloud registration,” *IEEE Trans. on Cir. and Sys. for Video Tech.*, vol. 32, pp. 4997–5010, 2022.
- [7] J. Li, C. Zhang, Z. Xu, H. Zhou, and C. Zhang, “Iterative distance-aware similarity matrix convolution with mutual-supervised point elimination for efficient point cloud registration,” in *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXIV 16*. Springer, 2020, pp. 378–394.
- [8] K. Fu, S. Liu, X. Luo, and M. Wang, “Robust point cloud registration framework based on deep graph matching,” in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2021, pp. 8893–8902.
- [9] Y. Wang and J. M. Solomon, “Deep closest point: Learning representations for point cloud registration,” in *IEEE Int. Conf. on Comput. Vision*, 2019.
- [10] Z. J. Yew and G. H. Lee, “Rpm-net: Robust point matching using learned features,” in *IEEE/CVF Conf. Comput. Vision Pattern Recognit.*, 2020, pp. 11 824–11 833.
- [11] L. Pan, Z. Cai, and Z. Liu, “Robust partial-to-partial point cloud registration in a full range,” *IEEE Rob. and Auto. Lett.*, 2024.