2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 25-29, 2020, Las Vegas, NV, USA (Virtual)

Seed: A *Se*gmentation-Based *E*gocentric 3D Point Cloud *D*escriptor for Loop Closure Detection

Yunfeng Fan[1], Yichang He[1] and U-Xuan Tan[1]

***Abstract*— Place recognition is essential for SLAM system since it is critical for loop closure and can help to correct the accumulated drift and result in a globally consistent map. Unlike the visual slam which can use diverse feature detection methods to describe the scene, there are limited works reported to represent a place using single LiDAR scan. In this paper, we propose a segmentation-based egocentric descriptor termed *Seed* by using a single LiDAR scan to describe the scene. Through the segmentation approach, we first obtain different segmented objects, which can reduce the noise and resolution effect, making it more robust. Then, the topological information of the segmented objects is encoded into the descriptor. Unlike other reported approaches, the proposed method is rotation invariant and insensitive to translation variation. The feasibility of proposed method is evaluated through the KITTI dataset and the results show that the proposed method outperforms the state-of-the-art method in terms of accuracy.**

I. INTRODUCTION

To achieve accurate and robust 6 degree-of-freedom (DOF) Simultaneous Localization and Mapping (SLAM), LiDAR (Light Detection And Ranging) is mainly adopted due to its robustness to illumination changes (hence can work in day and night environment) and fine resolution to 360° perception of the environment, compared to visual sensors. However, once global positioning information is lacking, the SLAM system will drift, resulting in a globally inconsistent map.

Reliable loop detection (or place recognition) module is crucial for the SLAM system, it can reliably detect the loop by comparing the similarity of any two places captured by sensors. Benefiting from the mature technique of computer vision, different loop closure methods are designed for visual slam. For example, the similarity between different places captured by camera can be calculated by means of the state-of-art method, bag-of-words (e.g. [1], [2]), and it has shown great success in real-world applications.

However, the relevant research of LiDAR-based loop closure is not mature and rare. Current methods of place recognition for 3D LiDAR mainly consists of keypoint detection and matching [3], in either global [4] or local [5] manners. Those methods are mainly adopted from or inspired by computer vision methods. They can be generally classified into three categories, namely: signatures, histograms and segmentation-based approaches. According to [6], those existing LiDAR-based place recognition methods mainly address two issues:

[1]All the authors are with the Pillar of Engineering Product Development, Singapore University of Technology and Design, 487372, Singapore. Email: {yunfeng_fan, uxuan_tan}@sutd.edu.sg, yichange_he@mymail.sutd.edu.sg

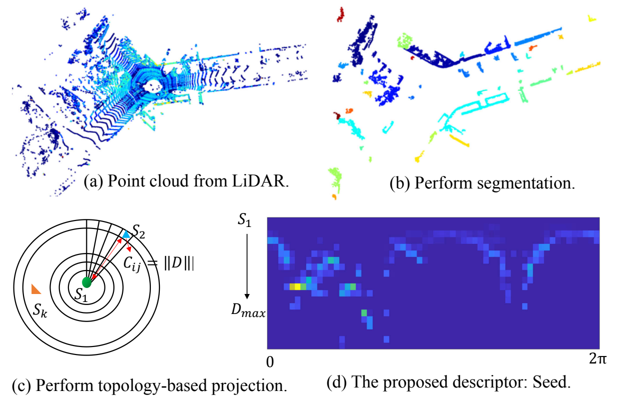

Fig. 1. The illustration of the proposed LiDAR-based descriptor (Seed) framework. The workflow is illustrated as (a) to (d). (a) The original point cloud of single LiDAR scan; (b) The segment result after processing the original point cloud; (c) One example to show how to design the descriptor. Based on the knowledge that the relative distance between segmented objects are both translation and rotation invariant, we select one segmented object as "primary" object (S_1 for example), then project the relative distance with respect to other objects into different cells, where C_{ij} denotes the relative distance between S_i and S_j. The following projection is similar to scan context; (d) Visualization of related descriptor.

1) Rotation Invariance: it means the descriptor should be rotation-invariant under the viewpoint changes. One example is revisiting the same place at opposite direction. In such case, the only difference is the robot or the sensor rotated 180°. The requirement is that the descriptor should look similar.
2) Noise handling: For the spatial descriptors, noise handling is another requirement. It will also be affected by the resolution of point cloud since it varies with relative distance from the LiDAR to the objects.

Although these two issues can be addressed by the histogram methods [7]–[9], the problem of histogram method is it cannot provide the internal structure of the scene (for example, height), which makes it less discernible for place recognition and may cause potential false positives. Scan context, on the other hand, can preserve internal structure of the scene by encoding the maximum-height information into each cell of the descriptor. However, it is not rotation invariant. In order to achieve rotation invariance, brute-force matching scheme is adopted. In addition, the translation change will also have effect on the descriptor.

In this paper, we propose a segmentation-based egocentric descriptor, named "Seed", for 3D LiDAR-based loop detection by using a single 3D scan. In this method, the

2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) | 978-1-7281-6212-6/20/$31.00 ©2020 IEEE | DOI: 10.1109/IROS45743.2020.9341517

original point cloud is firstly segmented and the subsequent processing is based on segmentation output as indicated in Fig. 1. The benefit of this process is that the segmented object is more descriptive than keypoint-based features. Moreover, the LiDAR resolution has less impact on the segmentation result. Then, the descriptor is designed based on the segmentation result and their topological structure, which can help achieve both translation and rotation invariance. The main contributions of this paper are as follows:

- A segmentation-based egocentric descriptor is proposed for 3D LiDAR place recognition. Unlike existing point cloud descriptors, the proposed method processes the segmentation result rather than the original point cloud, making it more robust (the segmented object is more descriptive than keypoint), distinct and discriminative.
- Given the information of the detected segmented objects, the proposed method can preserve the internal topology structure of the received 3D point cloud. Moreover, it is both *translation and rotation- invariant*.
- The proposed method is evaluated on the public dataset KITTI and compared with other state-of-the-art method.

The rest of this paper is organized as follows. In Section II, an overview of the related work is presented about place recognition for 3D point cloud. Section III illustrates the details of the proposed segmentation-based egocentric descriptor. The experiment evaluation is provided in Section IV to verify its ability for loop closure, followed by the conclusion with future work in Section V.

II. RELATED WORKS

Formation of point cloud descriptors can be boardly categorized into 3 different groups by the specific processing method applied to the point cloud. There are: signatures, histograms, and segmentation-based techniques. For signatures technique, an invariant reference is constructed to separate points within working region into bins. Based on measurement processing like normalization, counting, the information of each bin is extracted. Jan. et al. [10] defines voxelized 3D mesh by Haar wavelet response of the voxel. By doing so, the technique extended the SURF descriptor to 3D space. In [11], the Structure Indexing method is introduced. Based on 3D curve or a splash, the method encodes either the angels between consecutive segments of the curve or the surface orientation distribution along the circle as descriptor accordingly.

Histograms based techniques are more of recent interest. Featuring values of points or points subset are extracted and further encoded as descriptor. Rohling et al. [12] apply the point height and bins as 1D descriptor. While Granström et al. [13] bin invariant features like volume, nomial range, and range as histograms. Mentioned techniques applies global features while in [3], 3D Gestalt descriptor is calculated for selected keypoints. The selected points formulate voting matrix by finding the nearest neighbor. VFH [8] method also falls in this categorize. The techniques first find viewpoint direction and then counts the normal angles which formed by connecting points. The number of angles is then bin into histograms. CVFH [14] follows the idea and improves the robustness by dividing points cloud into smooth regions before calculating descriptor.

Segmentation technique is based on recognized shapes or objects. Douillard et al. [15] propose applying Symmetric Shape Distance defined in [16] for segment recognition. In [17], segments are used as landmarks for insertion in an Extended Kalman Filter. Fernandez-Moral et al. [18] propose recognition and accumulation of 3D planes in a graph for further matching with a interpretation tree. And a geometric consistency test is then conducted. The method is extended in [19], but both focus on enclosing small space.

In this paper, we propose a segmentation-based egocentric 3D point cloud descriptor called *Seed* which can achieve both translation and rotation invariance by extracting the topological structure of the segment output. This differs from Scan Context [6] which processes the raw point cloud data and rotation-variant.

III. PROPOSED METHOD

In this section, we will describe the details of the proposed approach for loop detection using single 3D point cloud scan. The workflow of the proposed method is indicated in Fig. 2. It consists of three parts: 1) 3D point cloud preprocessing to obtain different segmented objects; 2) descriptor generation based on the topological information of the segmented objects; and 3) fast search for candidates if a loop exists. In the following, each module will be presented in detail.

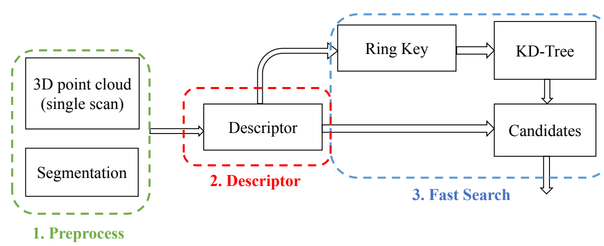

Fig. 2. The workflow of the proposed method.

A. Overview

The proposed approach starts from preprocessing the raw point cloud data. First, the raw point cloud data is downsampled for the consideration of computation complexity. After which, the segmentation is applied on those raw point cloud data to generate different segmented objects. The reason doing so is that the segmented object is more descriptive than raw points. In addition, the segmented object is more robust to resolution effect (this may caused by the relative distance between the object and LiDAR). Then, we extract the topological structure from the segmented objects and encode those information into a 2D image which is the final descriptor. To achieve fast search, we adopt the method proposed in scan context [6], which can accelerate the searching process and make it practical in real scenario.

B. Pre-processing

Once the raw measurement of the point cloud is received, down-sampling is first applied to reduce the number of point cloud and noise effect, which helps in accelerating the process. As mentioned in Introduction, the segmentation technique brings along the advantages of more descriptive shapes than keypoint-based features, since it has the ability to compress the point cloud into a set of distinct and discriminative elements for place recognition. This process can further reduce the processing time. Besides, it is also helpful for achieving rotation and translation- invariant property.

The segmentation approach used in this work is the “Cluster-All Method” [20]. To segment the point cloud into different clusters, the ground plane is first removed by clustering adjacent voxels based on vertical means and variances. With the ground-removed point cloud, Euclidean clustering is used for growing segments.

C. Rotation and Translation Invariant

In order to ensure the proposed descriptor invariant to arbitrary rotation and immune to translation variations, we encode the topological information into the descriptor.

For any two given sets of segmented object from a 3D point cloud scan captured at time instant t_k, S_i^k and S_j^k. Assume that at time instant t_{k+1}, we detect those two segment objects again, denoted as S_i^{k+1} and S_j^{k+1}. The relative rotation and translation between two scans are $\mathbf{R}$ and $\mathbf{t}$, respectively. Hence, it yields

$$\begin{aligned} S_j^{k+1} &= \mathbf{R}S_j^k + \mathbf{t} \\ S_i^{k+1} &= \mathbf{R}S_i^k + \mathbf{t} \end{aligned} \tag{1}$$

To ensure it invariant to both rotation and translation, we found that the relative distance

$$||S_j^{k+1} - S_i^{k+1}|| \quad = \quad ||S_j^k - S_i^k|| \tag{2}$$

is unrelated to both rotation $\mathbf{R}$ and $\mathbf{t}$. Hence, if the descriptor can effectively use this topological information, then the proposed descriptor can also maintain this property.

D. Descriptors

Suppose that there are N segmented objects from a single 3D scan. One of the them is denoted as S_i, where $i \in [1, \cdots, N]$. Its center is denoted as C_i. Since the relative distance among segmented objects remains unchanged regardless of the translation and rotation of the robot, we encode the relative distance into the descriptor as follows.

Firstly, since the proposed descriptor is egocentric, we have to determine its center based on the given segmented objects. In this work, we select two segmented objects which have most data in their clusters. Then, we divide the corresponding point cloud data into two layers according to their height values. This is because dynamic objects usually occurs at the lower height. Removing dynamic objects will improve the robustness. After that, the mean μ and covariance Σ of the higher layer of these two segmented objects are computed. The mean μ is treated as the center. To determine the

Algorithm 1 Seed Algorithm

Input:
The set of point cloud data, P;
Parameters, like N_s, N_r, L_{max};
Output:
A $N_r \times N_s$ 2D matrix for point cloud P;

Downsample the point cloud P;
Do segmentation and obtain different segmented objects
Based on segmented objects, first extract two segmented objects with most data. Then, divide the corresponding point cloud data into two different layers according to their height values;
Compute the mean μ and covariance Σ with data in higher layer;
Treat mean μ as the center;
Perform the PCA on the covariance Σ then do voting, chose the one having more data located in this area as positive direction;
for each segmented object **do**
  Compute its relative distance with respect to center;
  Compute the angle between positive direction and the one from center to segmented object;
  Assign it to the corresponding bin of the $N_r \times N_s$ matrix;
end for
return I;

direction, we perform PCA (principle component analysis) on the covariance matrix Σ and the direction is obtained from its eigenvalues. However, the direction from PCA may be opposite for similar places. Hence, we use the remaining point cloud data to vote and chose the direction where more points vote as the dominant direction.

Secondly, once the center and direction are determined, we equally divide the segmented objects into azimuthal and radial bins in the coordinate formed by the determined center and direction, as illustrated in Fig. 1. Let N_s and N_r be the number of sectors and rings, hence, for each segmented object, it will be located in a specific bin. Then its relative distance to center is encoded into the descriptor. This means the final descriptor can be represented as a $N_r \times N_s$ matrix

$$I = (C_{ij}) \in \mathbb{R}^{N_r \times N_s} \tag{3}$$

where C_{ij} means the value of relative distance at the ith ring and jth sector in descriptor. The complete algorithm for constructing the descriptor is given at Algorithm 1.

E. Similarity Score

The main purpose of this work is to use the 2D image-like descriptor to roughly describe each single 3D point cloud scan. Once we have two different descriptors, their similarity is evaluated by means of normalized cross-correlation method, which is widely adopted in the field of computer vision (e.g., template matching, image tracking, etc.). The

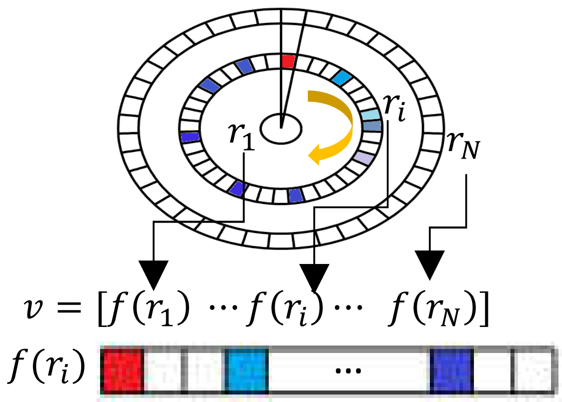

Fig. 3. The illustration about how to construct ring key from the descriptor.

similarity $S(I_i, I_j)$ of two 2D image-like descriptors is given as:

$$S(I_i, I_j) = \frac{\sum(I_i - \bar{I}_i)(I_j - \bar{I}_j)}{\sqrt{\sum(I_i - \bar{I}_i)^2 (I_j - \bar{I}_j)^2}} \tag{4}$$

where $\bar{I}_i$ is the mean of I_i. If the similarity between two descriptors is higher than a predefined threshold, a loop is thought to be detected.

F. Fast Search

The searching technique is similar to the one proposed in [6]. To accelerate the process of searching candidates, we formulate the ring key (as illustrated in Fig. 3). For each row of the descriptor (the circle r_i), we project it to a single real value by the function $f(\cdot)$, and denoted as

$$f(r_i) = \frac{||r_i||_0}{N_s} \tag{5}$$

where $||\cdot||_0$ is the L_0 norm.

By concatenating the $f(r_i)$ from inner to outer circle, it forms the ring key, which is a vector v and is denoted as

$$v = (f(r_1), \cdots, f(r_(N_r))). \tag{6}$$

To construct the KD tree, the vector **v** is used as the key. For the query ring key, we retrieve its top N similar ring keys. To find the closest descriptor among those candidates, we calculate their similarity score according to eq. (4) and chose the one with highest similarity score. If the highest similarity score is larger than the given acceptance threshold, it is considered as a reliable loop.

IV. Experimental Evaluation

In this section, we evaluate the proposed method through KITTI dataset and against the state-of-the-art method. During the experiment, we compare our method with scan context. Although there are some other methods, for example: M2DP [4], Z-projection [8], and ESF [7], scan context shows better performance in terms of accuracy. If the readers are interested on the results for mentioned methods, please refer to [6].

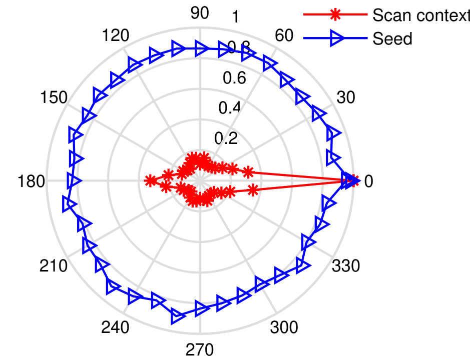

Fig. 4. Example to illustrate the rotation effect. The blue-triangulate and red-star curves are the similarity results under different rotated angles for proposed method and scan context, respectively.

TABLE I
The information about selected KITTI dataset sequences.

KITTI Seq	00	05	08
Distance (m)	3714	2223	3225
Environment	Urban	Urban	Urban + Country
Num of Nodes	4541	2761	4071
Route Direction	Same	Same	Reverse
Loops	790	493	332

Here, we only compare our method with scan context which is implemented in Matlab [1].

The proposed method is verified using the LiDAR sequence in KITTI [21], which is a popular dataset for autonomous driving and provides 64-ray LiDAR data (Velodyne HDL-64E). In the KITTI dataset, we selected sequences 00, 05, and 08, which contains most loops among others. In addition, the loops with different direction (same and opposite) are provided for different environments. The detailed characteristics of those sequence are summarized in Table I.

In this paper, the main parameters for both scan context and proposed method "Seed" are the same. We set $N_s = 60$, $N_r = 20$, and $L_{max} = 80$ m. In other words, each sector has $6°$ resolution and each ring has a 4 m gap. The number of candidates for KD tree searching is set as 50.

A. Rotation and Translation invariance

We first evaluate the rotation invariance of the proposed descriptor. To verify this ability, we select one LiDAR point cloud data and rotate it from $0°$ to $360°$ with $10°$ interval, then its similarity score is computed between the original scene and rotated scene. The result is shown in Fig. 4. It is clear that the scan context is sensitive to the rotation changes since the similarity score reduces significantly while the proposed approach is robust to the rotation changes. One example is shown in Fig. 5(a), where the original data is

[1]`https://github.com/irapkaist/scancontext`

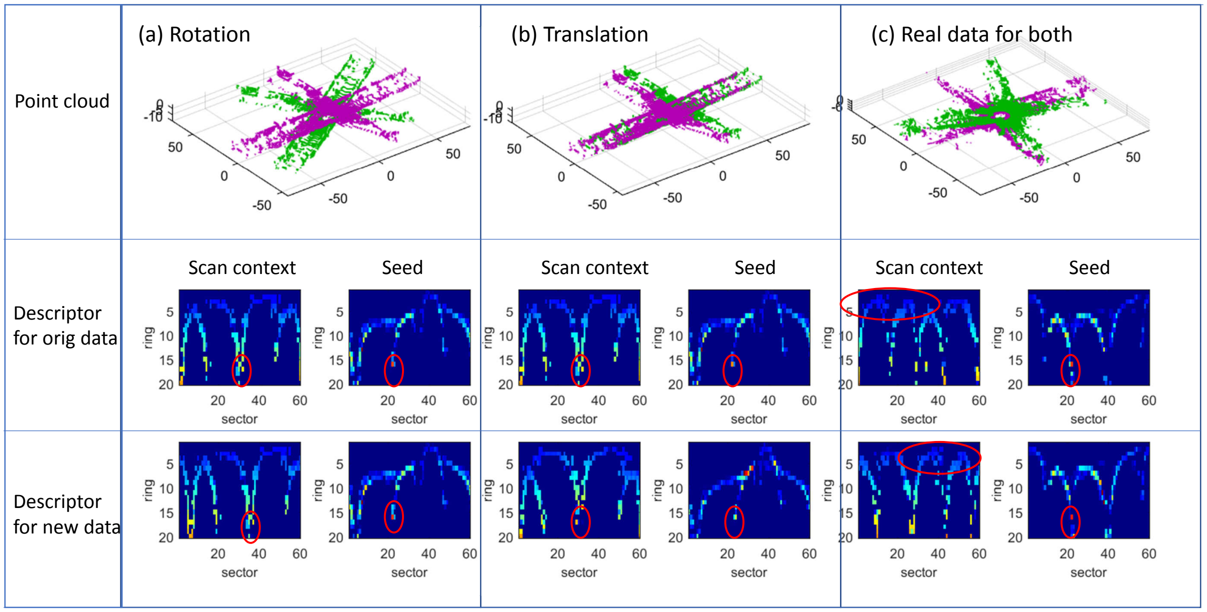

Fig. 5. Real experiment to show the performance of different descriptors under translation and rotation change. (a) One example to show rotation only, where the original point cloud is rotated by 30°; (b) one example to show translation only, where the original point cloud is transformed by 10 m along the x-axis; and (c) real data from KITTI dataset sequence 08 which including both translation and rotation.

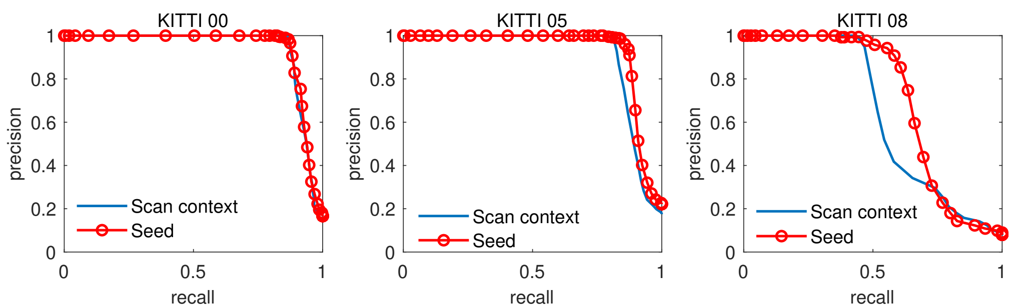

Fig. 6. Precision-Recall curves for different dataset sequences.

rotated by 30°. It can be found that the scan context is shifted along the y-axis while the seed is the same, which indicates the proposed method is robust to rotation changes.

In Fig. 5(b), we shows the effect of translation changes on the performances of different descriptors. In this experiment, the original point cloud is transformed by 10 m along the x-axis. It can be found that the scan context is shifted along x-axis while the proposed method keeps the same. This also indicates the proposed method is not sensitive to translation changes.

Lastly, we use the real data where the autonomous car revisits the same place at opposite direction (which also has a little translation difference) to test its ability under both translation and rotation effects. The data used here is from KITTI sequence 08. The descriptor results for scan context and Seed are shown in Fig. 5(c). It is obvious that the scan context has significantly shift while seed almost keeps the same. The similarity score for scan context is 0.1068 while it is 0.8648 for Seed. This shows that the proposed method is more robust to the translation and rotation variation.

The main reason that the proposed method outperforms scan context comes from the usage topological information of segmented objects, which results in the translation and rotation invariance of the descriptor. Besides, the selection of egocentre and direction is also more robust than scan context.

B. Precision-Recall curves

To evaluate the loop detection performance of the proposed method, we also tested our method on three KITTI dataset sequence, which are 00, 05, 08 by means of precision-recall curve. They contain lots of loops occurred either in same direction or in opposite direction.

During experiment, we run the proposed method “Seed” on those data sequences and compared the performance with the method scan context. The result is shown in Fig. 6. Overall, the proposed method outperforms scan context for all tested sequences in terms of the precision-recall performance. The improvement of the performance mainly benefits from the segmentation process. It can reduce the noise effect and extract more descriptive segment objects rather than the raw point cloud data.

TABLE II

THE RECALL RESULT AT 100% PRECISION ON KITTI DATASETS.

KITTI Seq	00	05	08
Scan context	0.8481	0.7842	0.4225
Seed	0.8306	0.8574	0.5070

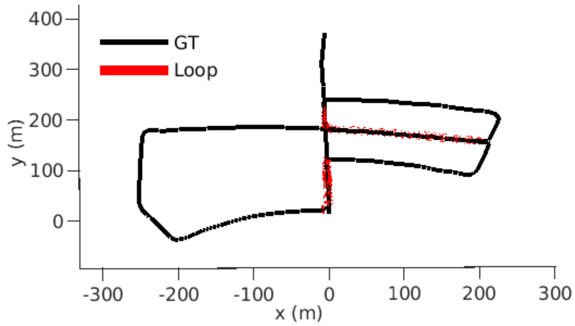

Fig. 7. The results of loop detection based on proposed method, tested on KITTI Seq 05.

In addition, the recall values at 100% precision of these two methods are also listed in Table II. It also shows that the proposed method has better performance.

C. Example of Loop Detection

Finally, we also give an example to illustrate the loop detection performance of the proposed method. In this experiment, we evaluate the proposed method on the KITTI sequence 05. The total length of the autonomous car traversed is around 2223 m in the urban environment and the result is shown in Fig. 7. It is obvious that the proposed method can effectively detect the loop. This will be helpful for the loop detection of LiDAR-based slam.

V. CONCLUSIONS AND FUTURE WORKS

In this work, we presented a segmentation-based egocentric descriptor for 3D point cloud scan, to increase the reliability of detecting loop closure. The proposed method can achieve both translation and rotation invariant by utilizing the inner topological structure of segmented objects, compared to other existing methods. However, the limitation of this work is that the performance will degrade significantly if the environment has less segmentation information.

Therefore, the future work will use multi-view images of the LiDAR scan and the segmentation result to formulate a more general and robust descriptor, which can work even in segment-less environment. Besides, we are planning to integrate the loop detection module into LiDAR-based slam system to improve the performance.

REFERENCES

[1] R. Mur-Artal and J. D. Tardós, "ORB-SLAM2: An Open-Source SLAM System for Monocular, Stereo, and RGB-D Cameras," *IEEE Transactions on Robotics*, vol. 33, no. 5, pp. 1255–1262, Oct. 2017.

[2] T. Qin, P. Li, and S. Shen, "VINS-Mono: A Robust and Versatile Monocular Visual-Inertial State Estimator," *IEEE Transactions on Robotics*, vol. 34, no. 4, pp. 1004–1020, Aug. 2018.

[3] M. Bosse and R. Zlot, "Place recognition using keypoint voting in large 3D lidar datasets," in *2013 IEEE International Conference on Robotics and Automation*, May 2013, pp. 2677–2684, iSSN: 1050-4729.

[4] L. He, X. Wang, and H. Zhang, "M2DP: A novel 3D point cloud descriptor and its application in loop closure detection," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. Daejeon, South Korea: IEEE, Oct. 2016, pp. 231–237.

[5] B. Steder, M. Ruhnke, S. Grzonka, and W. Burgard, "Place Recognition in 3D Scans Using a Combination of Bag of Words and Point Feature based Relative Pose Estimation," p. 7.

[6] G. Kim and A. Kim, "Scan Context: Egocentric Spatial Descriptor for Place Recognition Within 3D Point Cloud Map," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. Madrid: IEEE, Oct. 2018, pp. 4802–4809.

[7] W. Wohlkinger and M. Vincze, "Ensemble of shape functions for 3D object classification," in *2011 IEEE International Conference on Robotics and Biomimetics*, Dec. 2011, pp. 2987–2992, iSSN: null.

[8] N. Muhammad and S. Lacroix, "Loop closure detection using small-sized signatures from 3D LIDAR data," in *2011 IEEE International Symposium on Safety, Security, and Rescue Robotics*, Nov. 2011, pp. 333–338, iSSN: 2374-3247.

[9] M. Himstedt, J. Frost, S. Hellbach, H.-J. Böhme, and E. Maehle, "Large scale place recognition in 2D LIDAR scans using Geometrical Landmark Relations," in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sep. 2014, pp. 5030–5035, iSSN: 2153-0866.

[10] J. Knopp, M. Prasad, G. Willems, R. Timofte, and L. Van Gool, "Hough Transform and 3D SURF for Robust Three Dimensional Classification," in *Computer Vision – ECCV 2010*, K. Daniilidis, P. Maragos, and N. Paragios, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 589–602.

[11] F. Stein and G. Medioni, "Structural indexing: efficient 3-D object recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2, pp. 125–145, Feb. 1992.

[12] T. Röhling, J. Mack, and D. Schulz, "A fast histogram-based similarity measure for detecting loop closures in 3-D LIDAR data," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sep. 2015, pp. 736–741, iSSN: null.

[13] K. Granström, T. B. Schön, J. I. Nieto, and F. T. Ramos, "Learning to close loops from range data," *The International Journal of Robotics Research*, vol. 30, no. 14, pp. 1728–1754, Dec. 2011.

[14] M. Cummins and P. Newman, "FAB-MAP: Probabilistic Localization and Mapping in the Space of Appearance," *The International Journal of Robotics Research*, vol. 27, no. 6, pp. 647–665, Jun. 2008.

[15] B. Douillard, A. Quadros, P. Morton, J. P. Underwood, M. De Deuge, S. Hugosson, M. Hallstrom, and T. Bailey, "Scan segments matching for pairwise 3D alignment," in *2012 IEEE International Conference on Robotics and Automation*. St Paul, MN, USA: IEEE, May 2012, pp. 3033–3040.

[16] B. Douillard, J. Underwood, V. Vlaskine, A. Quadros, and S. Singh, "A pipeline for the segmentation and classification of 3D point clouds," in *In ISER*, 2010.

[17] J. Nieto, T. Bailey, and E. Nebot, "Scan-SLAM: Combining EKF-SLAM and Scan Correlation," in *Field and Service Robotics*, P. Corke and S. Sukkariah, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 167–178.

[18] E. Fernández-Moral, W. Mayol-Cuevas, V. Arévalo, and J. González-Jiménez, "Fast place recognition with plane-based maps," in *2013 IEEE International Conference on Robotics and Automation*, May 2013, pp. 2719–2724, iSSN: 1050-4729.

[19] E. Fernández-Moral, P. Rives, V. Arévalo, and J. González-Jiménez, "Scene structure registration for localization and mapping," *Robotics and Autonomous Systems*, vol. 75, pp. 649–660, Jan. 2016.

[20] B. Douillard, J. Underwood, N. Kuntz, V. Vlaskine, A. Quadros, P. Morton, and A. Frenkel, "On the segmentation of 3D LIDAR point clouds," in *2011 IEEE International Conference on Robotics and Automation*, May 2011, pp. 2798–2805, iSSN: 1050-4729.

[21] A. Geiger, P. Lenz, C. Stiller, and R. Urtasun, "Vision meets robotics: The KITTI dataset," *The International Journal of Robotics Research*, vol. 32, no. 11, pp. 1231–1237, Sep. 2013.