Object Scan Context: Object-centric Spatial Descriptor for Place Recognition within 3D Point Cloud Map

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Abstract—Place recognition technology endows a SLAM algorithm with the ability to eliminate accumulated errors and to relocalize itself. Existing methods on point cloud-based place recognition often leverage the matching of global descriptors which are lidar-centric. These methods have the following two major defects: place recognition cannot be performed when the distance between the two point clouds is far, and only the rotation angle can be calculated without the offset in the X and Y direction. To solve these two problems, we propose a novel global descriptor, which is built around the Main Object, in this way, descriptors are no longer dependent on the observation position. We analyze the theory that this method can solve the above two problems, and conduct a lot of experiments on KITTI Odometry and KITTI360, which show that our method has obvious advantages over state-of-the-art methods.

I. INTRODUCTION

Autonomous driving technology has become one of the key research contents of enterprises, universities, and research institutions all over the world. Among them, SLAM (Simultaneous Localization And Mapping) as a key part of environmental perception technology, has always been a top priority. An excellent SLAM algorithm is inseparable from loop closure detection and relocalization, which are both based on place recognition, which helps vehicles recognize places visited previously. Specially, place recognition algorithm should be able to calculate the similarity of any two scenes and the relative pose as accurate as possible.

Place recognition can be divided into point cloud-based method and image-based method according to the sensor type. In lidar-based SLAM, the usual practice is to convert each frame of point cloud into a global descriptor, and the matching between descriptors produces a similarity. In addition, some more advanced algorithms can calculate the approximate relative pose between point clouds, which can be used as a global mapping constraint or localization result after refined by ICP.

Scan Context series algorithms are popular place recognition methods based on 3D point cloud, among which there are SC [1], ISC [2], SSC [3], SC++ [4] and other algorithms. Their core idea is to create a descriptor called Scan Context for each frame of point cloud centered on the origin. Descriptors rotation matching calculates similarity and rotation angle. Specially, SSC also includes two-step semantic ICP, which can calculate 6D pose. Although this work has good loop closure-detection performance in many datasets, its defects are also obvious and fatal:

- Scan Context is lidar-centric, so it only represent the scene of the current observation position, which means that if the distance between the vehicles at two moments is not small enough, the corresponding descriptors will be dissimilar which will cause a loop misses or relocalize fails.
- Only the yaw angle can be calculated by rotation matching, and if provided as the initial pose to ICP, it is easy to fall into a local optimum. Some recent works, such as SSC, OverlapNet, SC++, etc., can calculate 6D pose, but unfortunately this calculation result is prone to errors in contactless place recognition.

In this paper, we propose a novel global descriptor named Object Scan Context (OSC) to focus on the environment around some salient static objects called the main object, rather than the environment around the vehicle itself. This idea is similar to how humans locate themselves through salient objects when exploring an unknown environment.

We refer to objects that are uniformly distributed across almost all environments as Main Objects, such as street lights and trash cans in the KITTI dataset. Besides, we also need to select those objects whose surrounding environment is sufficiently diverse as Main Objects. For example, tree trunks are usually surrounded by grass, so they are unsuitable
Fig. 2: The architecture of our approach. The whole framework consists of building Object Scan Context and calculating similarity score and relative pose between frames. First, we perform semantic segmentation and Euclidean clustering on raw points. After that, Main Objects are achieved (the colored points in the enlarged image are Main Objects, and the red circles indicate the scopes of Object Scan Contexts). Second, an accurate relative pose will appear by matching descriptors. It is worth mentioning that the pose is very accurate so that it can be directly applied to Pose Graph or act as a result of relocalization.

as Main Objects. After determining the semantics of Main Objects, the specific main objects in the point cloud can be obtained by the semantic segmentation and the clustering of the 3D point cloud.

Unlike Scan Context series algorithms, which is built around the vehicle, Object Scan Context is built around the main object, which means that this descriptor does not depend on the position of the lidar. During place recognition, the vehicles at two moments are not close which is extremely challenging for Scan Context series algorithms, but the environment around the main object will not change due to the change of the observation position, so the matching similarity will still be high. We only need to combine the yaw angle generated by the transformation of the two observation coordinate systems relative to the main object and the rotation matching to calculate the relative 3D pose of the two frames of point clouds, followed by a fast ICP to calculate the accurate 6D pose.

Each point cloud will generate multiple Object Scan Contexts, and the pairwise matching of two point clouds produces a large number of matching results, so we propose a bubble filtering algorithm to select more robustly. Fig. [I] is a demonstration of our results. The main contributions are summarized as follows:

- We propose a novel independent global descriptor for 3D point cloud-based place recognition, which concentrates on Main Objects in the scene.
- We analyze the theory of OSC establishment and matching. It can solve the two major shortcomings of Scan Context, and the relative pose calculated from matching can be directly used as a global constraint to eliminate accumulated errors.
- We propose descriptor searching strategy, matching strategy, and matching result screening strategy, which can perform place recognition more robustly.
- A large number of experiments on the KITTI Odometry and KITTI360 show that our method is better than state-of-the-art place recognition method.

II. RELATED WORK

In this article, we only discuss place recognition methods based on 3D point clouds, more of which are original point clouds generated by lidar, and others are feature point clouds generated by cameras. According to whether and how the neural network is used, we divide place recognition methods into three categories: non-learning-based methods, learning-based descriptor established methods, and learning-based similarity calculated methods.

Non-learning-based methods: Scan Context [1] projects the 3D point cloud onto the X-Y plane and creates a global descriptor that can perform rotation matching by dividing Ring and Sector. Intensity Scan Context [2] is established with the same approach as Scan Context just replacing the intensity instead of the height as the feature of the grid. Scan Context++ [4] build two descriptors named Polar Context and Cart Context for a 3D point cloud. M2DP [5] is built from the projection of the 3D point cloud to multiple 2D planes, then uses SVD (singular value decomposition) to reduce the dimensions of the final descriptor. ISHOT [6] proposed a new local descriptor combining geometric and texture information called ISHOT, which is better than pure-geometric descriptor, but it still hasn’t solved the problems similar to Scan Context. LiDAR Iris [7] uses a binary feature map to generalize a point cloud, and then calculates the Hamming distance of the feature map as the similarity of the
two point clouds for place recognition. Lin et al. [8] proposed a loop detection method that can evaluate the similarity of keyframes from the 2D histogram of planes and lines in the frames.

**Learning-based descriptor established methods:** Semantic Scan Context [3] uses semantic information to replace the height of the point to construct the Scan Context, and cooperates with its proposed two-step ICP, which can improve the descriptor matching accuracy and generate a relative pose for point cloud registration. SA-LOAM [9] uses a semantic segmentation network to convert the original point cloud into a semantic point cloud, then generates a semantic graph to express the relative position of various semantics in the point cloud, and calculates the similarity of the pair of graphs by the network. SA-LOAM starts to pay attention to the invariance of the relative position between objects, but its descriptor is still closely dependent on the observation position, and it does not actually extract the object, so it can only allivae the two major flaws rather than completely solve them. PointNetVLAD [10] applies metric learning to generate a discriminative and compact global descriptor from an unordered input 3D point cloud and proposes a novel loss function that make descriptors more discriminative and generalizable. SphereVLAD [11] uses spherical projection and a neural network with four Spherical Convolution Layers, four WAG Pooling Layers and a Flatten Layer to generate an orientation-invariant place descriptor. GOSMatch [12] proposes a semantic-based graph descriptor, which pays attention to the transformation relationship between semantics and semantics in the scene, and gives a 6-DOF initial pose estimation.

**Learning-based similarity calculated methods:** OverlapNet [13] creates a multi-head neural network to calculate the yaw angle and similarity between any two point clouds, which is called the overlap in original article. OverlapNet-Transformer [14] adds a transformer attention mechanism to OverlapNet to improve its robustness and operational efficiency. SGPR [15] uses a semantic graph to represent the point cloud, and then learns the similarity between two semantic graphs. Furthermore, the authors prove the feasibility and robustness of their work and apply it to SA-LOAM [9]. LCDNet [16] proposes the novel LCDNet architecture for loop closure detection and point cloud registration, which consists a shared feature extractor, a place recognition head, and a novel differentiable relative pose head.

### III. METHODOLOGY

In this part, we formally introduce our method. Different from the state-of-the-art Scan Context series methods that build a local coordinate system with lidar as the center, we build a local coordinate system with the Main Object as the center and propose a variety of strategies to improve the matching speed and robustness of the descriptor. The framework is shown in Fig. 2.

#### A. Object Scan Context

**Get Main Objects.** When humans explore a new environment, they often only have the most typical objects in their minds and rely on these objects to determine their position. Following this inspiration, we use a 3D point cloud semantic segmentation network to extract the semantic information of the point cloud, which can also get by image semantic segmentation and projection from the semantic image to the 3D point cloud. Filter out points with specific semantics (usually static and immovable objects such as street lights), perform Euclidean clustering on them, obtain the point cloud clusters as Main Objects, and calculate the average coordinate of each point cloud cluster as the location of the Main Object.

**Build Object Scan Context.** The traditional Scan Context series methods rely heavily on the observation position of the vehicle, which means that if the descriptors are not close, the system will be unable to recognize the same scene due to the difference of the observation position. The proposed method traverses all the Main Objects in a point cloud and performs the following steps on them.

In the X-Y plane, we take the Main Object as the pole,
and take the connection direction of the lidar to Main Objects as the polar diameter to establish a polar coordinate system (set counterclockwise to be positive). Divide the circular area within 16 meters into \(N_s\) equal-width rings, which is called a Ring (we found through experiments that 16 meters are a suitable distance threshold). At the same time, divide the area into \(N_s\) equal-angle sector, which is called a Sector, thus \(N_s \times N_s\) grids is achieved. After projecting the 3D point cloud to the X-Y plane, we calculate the average height of the points in each grid as the feature of this grid. Regarding each Ring as a row and each Sector as a column, a matrix of \(N_s \times N_s\) is generated, which is the Object Scan Context, as Fig. 3 shown. Calculate the average value of each row of this matrix to get a row vector called SectorKey. Both of them will be used to improve the efficiency of the system in the future.

**B. Similarity Score and Relative Pose between Frames**

**Get Candidate KeyFrames.** From the steps of creating the descriptor above, it is obvious that when observing the same Main Object in different positions, the Object Scan Context has an offset, but the RingKey is exactly the same. In fact, we can regard RingKey as a descriptor with rotation invariance. Therefore, to speed up the efficiency of searching similar descriptors, we apply the KD-tree with RingKey as the node. Every time a keyframe is detected, all the RingKeys generated from this frame are inserted into the KD-tree.

Besides, each point cloud will generate multiple Object Scan Contexts. In order to make full use of all potential similar frames, we search several similar nodes to each descriptor in KD-tree, and insert its corresponding keyframe sequence number into a non-repeating set.

**Calculate Similarity Score.** With candidate frame pairs achieved, we have to distinguish whether a pair of frames are from the same scene, it is necessary to match descriptors from these two keyframes one by one. The following describes how to match the descriptors.

We use the cosine distance of the Sector to calculate the similarity of the two descriptors. If two descriptors are indeed generated by different observations of the same Main Object, then we only need to shift the current Object Scan Context to the left by \(\text{shift}\) units, and \(|| \cdot ||\) represents the 2-norm of a vector.

We use a search window with \(\text{shift}\) as the center and \(2k\) as the width to replace the entire range of \([0, N_s]\), which can greatly reduce the amount of calculation. Using \(I^n\) and \(I^n_c\) to indicate the candidate and the current Object Scan Context, where the subscript \(n\) is used to indicate that the descriptor is shifted to the left by \(n\) units. The following parameter optimization equation can be constructed to obtain the precise offset \(n\) and the similarity between the descriptor pair:

\[
    n = \arg \min_{n \in [\text{shift} - k, \text{shift} + k]} d(I^n, I^n_c) \quad (2)
\]

\[
    \text{similarity} = 1 - \min_{n \in [\text{shift} - k, \text{shift} + k]} d(I^n, I^n_c) \quad (3)
\]

where \(d\) represents an abstract distance between two descriptors, which can be derived from the cosine distance of the vector:

\[
    d(I^n, I^n_c) = \frac{1}{N_s} \sum_{j=1}^{N_s} (1 - \frac{c^n_j \cdot c^n_{jn}}{|c^n_j||c^n_{jn}|}) \quad (4)
\]

where \(\frac{c^n_j \cdot c^n_{jn}}{|c^n_j||c^n_{jn}|}\) indicates the cosine distance between the \(j\)th Sector of the candidate descriptor and the \(j\)th Sector of the current descriptor after performing the precise offset \(n\).

**Calculate Relative Pose.** The traditional Scan Context-based place recognition methods only rely on the ICP or neural network when calculating the relative pose. While ICP gets an inaccurate yaw angle as an initial value, it will consume a lot of time and even cause matching errors. In addition, the neural network relies on a large amount of training data. Thanks to the Object Scan Context being an independent descriptor that does not rely on the observation position, the calculation of the relative pose no longer requires ICP, only the observation position of the Main Object in the two point clouds and the precise offset \(n\) in the previous step are required.

As shown in Fig. 4 assuming that the observation position of the Main Object in the candidate frame is \((x_1, y_1)\), and the observation position in the current frame is \((x_2, y_2)\), the relative pose \((\Delta x, \Delta y, \Delta \theta)\) between them can be deduced as:

\[
    \begin{align*}
    \Delta x &= x_1 - x_2 \cos \Delta \theta + y_2 \sin \Delta \theta \\
    \Delta y &= y_1 - x_2 \sin \Delta \theta - y_2 \cos \Delta \theta \\
    \Delta \theta &= \arctan \frac{y_1 - y_2}{x_1 - x_2}
    \end{align*}
    \quad (5)
\]

where \(\gamma\) indicates the angle corresponding to the precise offset \(n\) in the precise step:

\[
    \gamma = 2\pi \times \frac{n}{N_s} \quad (6)
\]

**Matching Results Filter.** Assuming that the candidate frame and the current frame contain \(m\) and \(n\) Object Scan Contexts respectively. After the previous two steps, \(m \times n\) similarities and \(m \times n\) relative poses are achieved. In order to avoid occasional where a certain descriptor and multiple descriptors have high similarity, we use a screening algorithm to enhance the robustness of the result.
Fig. 4: An example of contactless loop closure. The relative pose \((\Delta x, \Delta y, \Delta \theta)\) between the current frame and previous frame can be determined by the rotation angle \(\gamma\) produced by the matching result \(n\) of Object Scan Context and the observation position \((x_1, y_1), (x_2, y_2)\) of the Main Object in two frames.

The idea of the algorithm is: after obtaining \(m \times n\) similarities, we select the maximum value and mark the two Main Objects that produce the maximum value, then leave the \((m - 1) \times (n - 1)\) similarities which are generated by unmarked Object Scan Contexts, and pick the maximum value again and repeat until all Main Objects are marked. The last step is to filter out the results that are less than the threshold.

It can be seen from the above algorithm that \(k\) results are finally selected from \(m \times n\) matching results, which means there are \(k\) relative poses. Usually, these poses are very close but to avoid unexpected situations, we have designed an outlier elimination algorithm. We regard the relative pose as a 3D point in a space, then perform Euclidean clustering on \(k\) points, and calculate the average value of the largest cluster as the final relative pose. If the number of points in the largest cluster is less than the threshold, which is related to \(k\), the result is considered invalid, which means the current frame and the candidate frame are not in the same scene.

### IV. EXPERIMENTS

#### A. Dataset and Implementation Details

We validate our method on KITTI Odometry [17] (00, 02, 05, 06, 07, 08) and KITTI360 [18] (00, 02, 04, 05, 06, 08, 09, 18). Various methods such as SGPR [15] and SSC [3] regard two frames of point clouds with a distance of less than 3m (greater than 20m) in the real world as positive (negative) samples. They do so understandably because none of them can handle contactless place recognition because their descriptors are all egocentric. However, our method can solve the problem of contactless place recognition, so we only use one threshold (10m in the experiments) to distinguish positive and negative samples. Because there are tens of thousands of positive samples and millions of negative samples, we randomly select 2,000 positive samples and 2,000 negative samples in a sequence.

For experiments on the KITTI Odometry we use labels from SemanticKITTI [19], and for experiments on KITTI360 we use RangeNet++ [20] and its pre-trained model to inference. In our experiments, we set \(N_r = 20, N_s = 60\), and all experiments are done on a laptop with AMD Ryzen 7th 5800H.

State-of-the-art methods usually use the ground truth to determine whether there is a loop closure. The pair of two point clouds is considered positive if the Euclidean distance between them is less than a threshold and the time interval is long enough, while the rest are negative. The reason why these methods use rigid distances to divide the positive and negative is that they rely on ICP to calculate the relative pose, and ICP is going to generate a wrong result between two point clouds with large Euclidean distance. On the contrary, our method is not limited by the Euclidean distance, so in addition to the commonly used evaluation methods, we also pay attention to the accuracy of the relative poses between the two point clouds that exceed the distance limit, which is not possible to be performed in other Scan Context-based methods.

We evaluate our method on the KITTI Odometry [17], which contains 11 sequences (from 00 to 10) obtained by Velodyne-HDL-64E which has 64 rings and ground-truth poses generated by GPS and RTK. We select sequences with loop-closure (00, 02, 05, 06, 07, 08) for the evaluation. Notably, sequence 00 has a contactless loop which is usually considered negative in state-of-the-art methods.

We choose RangeNet++ [20] to perform semantic segmentation on the 3D point cloud, which can divide points into 21 common types. We set the semantic of the Main Object to pole, the least number of points that forms a pole to 40, and \(N_r = 32, N_s = 90\). We use flann to build KD-tree and set the number of candidates to 10 and set the radius of the search window to 3. All experiments are conducted on the same system with an AMD R7-5800H CPU with 16GB RAM.

#### B. Place Recognition Performance

We compare our approach with the state-of-the-art methods, including Scan Context [1] (SC), Intensity Scan Context
Fig. 5: Precision-Recall curves on KITTI Odometry

Fig. 6: An example of contactless loop closure. The relative pose $c$ between the current frame and previous frame can be determined by the rotation angle $\gamma$ produced by the matching result $n$ of Object Scan Context and the observation position $\{(x_1, y_1), (x_2, y_2)\}$ of the Main Object in two frames.

C. Relative Pose Accuracy

There are not many place recognition methods mentioned above that can compute the complete relative pose. Among them, SC, ISC and OverlapNet can calculate the yaw angle. SSC can get the 6D pose because of its two-step fast ICP, and our method can calculate the 3D relative pose $(\Delta x, \Delta y, \Delta \theta)$. For the sake of fairness, the results of all the above methods are handled over to ICP for refinement, the same end conditions are set, and then they are compared with the ground-truth relative pose.

D. Robust Relocalization Performance

We not only test the effect of our method about the relocalization of the same sequence in KITTI but also on different sequences. Since Object Scan Context is centered on the Main Object and represents a small-scale environment around the Main Object, the point clouds collected at different periods can still be accurately matched, which is difficult for traditional methods.

Fig. 6 shows the relocalization performance between the 2610th frame in KITTI sequence 00 and the first frame in sequence 07. As shown, the environment has changed significantly, but our method still works.

V. CONCLUSIONS

In this paper, we propose a novel global descriptor called Object Scan Context for place recognition. Unlike most other place descriptors built around the lidar, OSC is centered on the Main Object, so the point cloud position interval is not objects in these two sequences.
required to be small enough for place recognition. Because the descriptor is established independently of the observation position, we can infer a relative pose comparable to the ICP result through spatial transformation.

In future work, we will try to extend the 3-DOF relative pose to 6-DOF, and continue to improve the accuracy so that this method can completely replace the role of ICP in SLAM.

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