**SegDF: Segment-Based Dynamic Filter in 3D Point Cloud**

**Abstract**

Dynamic objects in lidar data frequently leave undesirable traces in 3D point clouds, degrading the quality of maps and the effectiveness of localization. We present a novel static reconstruction method, called SegDF, that focuses on filtering the potential-mobility elements contacted with the ground in urban environments. Our approach can not only reconstruct maps with low-semantic information, but also remove movable objects at a low cost. Given a pair of registered scans, we generate a curved-voxel map with the assistance of sensor intensities to cluster the scans into instances and populate semantics by geometric classification. To exclude instances that are non-static yet unstable due to inconsistent observations, we monitor volumetric states based on the occupancy change of curved voxels at object level. In addition, our method tightly couples instance segmentation with dynamic detection in order to refine imperfect clustering and enhance the removal precision. SegDF is validated on the KITTI dataset using SemanticKITTI as the ground truth, and it is demonstrated that the proposed can produce a high-quality static instance map.

**Ⅰ. INTRODUCTION**

Leveraging LiDAR odometry [1, 2, 3], location recognition [4, 5, 6], and simultaneous localization and mapping (SLAM) [7, 8, 9], recent advancements in 3D light detection and ranging mapping have been reported to counter an ambiguous environment. Most autonomous robotic systems always assume that all observations are accessible, however excluding dynamic items as outliers and relying solely on static objects might prevent confusion and increase resilience.

During the process of SLAM utilizing LiDAR in urban environments containing mobile items such as vehicles, pedestrians, etc. [14], we encounter non-static points with limited interpretability in raw scan data. The changes in maps between two registered scans correspond to the difference of point clouds, and existing algorithms [10, 11, 12, 13] also employ this principle to get rid of dynamic objects. However, the gap between maps is divided into two categories: a) moving objects and b) residuals caused by the restricted view. The former can be reflected as the ghost trail effect [10, 13] by sequential accumulations of scan data, whereas the latter may be misinterpreted as false dynamic points due to inconsistent observations in local maps. To address this problem, we present a segment-based dynamic filter that concentrates on processing a batch of measurements from a single-session SLAM. Our primary objective is to generate a static instance map of a particular length without regard to processing speed and to ensure that actual dynamic points are vigorously removed, even if some false negatives occur (i.e., wrongly erased points on natural static objects).

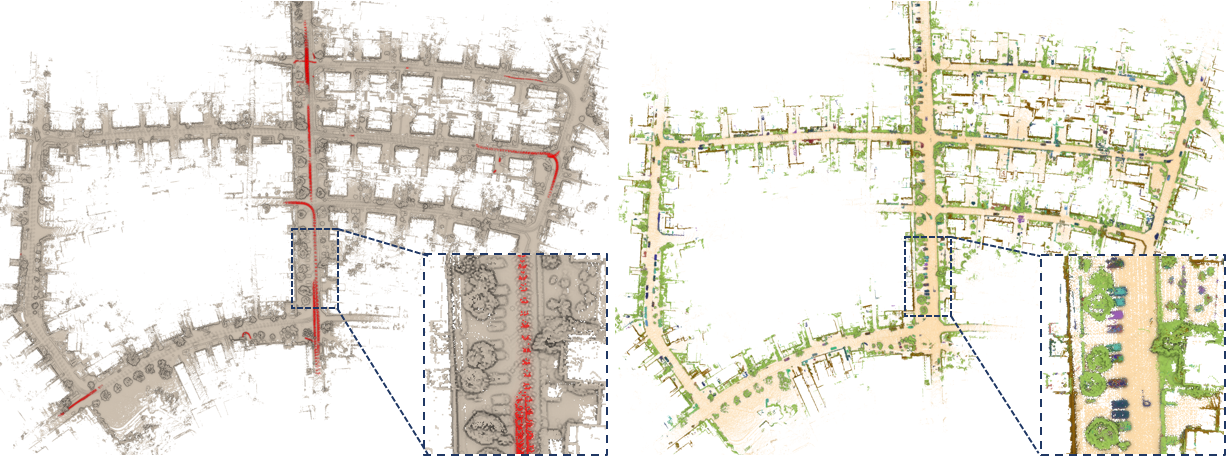
In this paper, the procedure is divided into two stages: a) instance segmentation assisted by intensity, and b) dynamic filtering at object level. Notably, all scan data used in the post-processing are derived from [3], and we deem the process flaws resulting from imprecise pose estimate neglectable. Firstly, we build the pre-processed point cloud into the coordinate system based on curved-voxel and perform clustering segmentation. Compare with [16], we additionally calibrate sensor intensity to refining the outcome and classifying instances by geometric verification. The assistance of intensity compensates for the lack of spatial clustering and groups the occlusion-caused distant, dispersed point clouds from the same object. Secondly, based on semantics in geometric distinguishing, we selectively conduct dynamic identification on possibly mobile objects (e.g., elements contacted with the ground and unknown instances). Furthermore, the two mechanisms are tightly coupled in object tracking to correct imperfect cluster and enhance the accuracy of dynamic removal. Therefore, the multi-frame data is integrated to compensate for the insufficient observation of objects in different screenings.

Above all, we propose a novel post-processing LiDAR reconstruction methodology, called SegDF, a segment-based dynamic filter in the 3D point cloud. Our contributions are threefold:

• An instance segmentation based on curved-voxel clustering assisted with intensity and geometric classification. (§III-B, §III-C)

• A dynamic object-level filter utilizing curved-voxel occupancy searching and instance tracking. (§III-D)

• An innovative approach for instance map initialization and a tight coupling framework for instance refining and dynamic removal. (§III-D)



**Ⅱ. RELATED WORK**

*A. Clustering segmentation*

According to [17], panoptic LiDAR segmentation is a combination of semantic segmentation for static stuffs and instance segmentation for countable objects. Despite the fact that many researches [18, 19] plunge right into deep learning solutions, point cloud clustering is a well-established research area that has the potential to contribute to the panoptic challenge.

**Clustering with Euclidean Distance**. Using the Euclidean distance to cluster points is a straightforward idea. A novel ground segmenting algorithm was proposed in [22], which clusters other non-ground points with voxelized Euclidean neighbors. In [23], researchers provided a probabilistic framework to incorporate Euclidean spatial and temporal information from consecutive frames. Though it considers the drawbacks of European clustering and combines the continuous frame information to improve the result, it is still based on the redundant point-to-point search.

**Clustering with Supervoxels or Superpoints**. Inspired by the concept of superpixels from traditional image processing [24], some researchers are interested in finding super voxels or super points [25, 26] in Euclidean space. However, unlike superpixels using color or texture due to the sensor type, it is challenging for point cloud to provide manual descriptor with extra information beyond Euclidean distance. In [16], the algorithm attains fine discriminations by considering three important aspects for clustering 3D lidar points: distance from the sensor, directional resolutions, and rarity of points to deal with sparse 3D point clouds. This method is similar to ours, but it still relies on searching in Euclidean space, and its results are highly resolution-dependent.

**Clustering on Range Image**. To improve the clustering rate, many researchers explored more clues to find better criteria for separating neighboring points from distinct clusters. In [27, 28], the angle formed by two adjacent laser beams is considered to construct the discriminator. To make the algorithm fast enough for real-time applications, authors of [27] worked on the 2D range image representation of the lidar point cloud. However, it is still a depth-dominated clustering method that is strongly impacted by the viewing angle or scan line density.

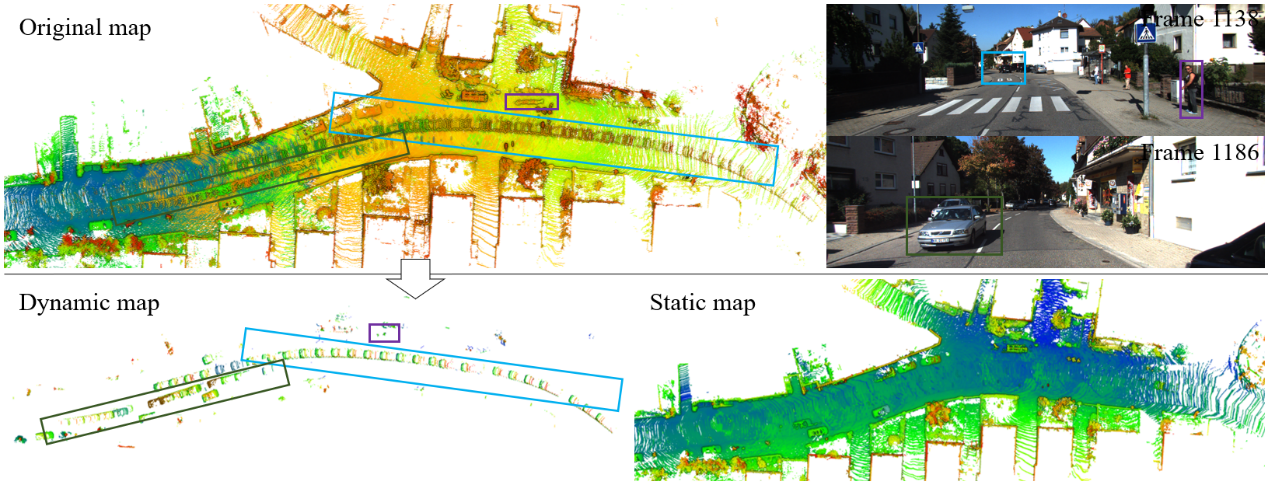
*B. Dynamic object removal*

Dynamic removal is closely related to static map construction. We exclude online approaches in this paper since we are primarily concerned with constructing a high-quality static map without regard to processing speed.

**Conventional approaches**. The remote-sensing community has carried out extensive studies on dynamic point removal as a method for establishing sterile environments, which is essential for constructing or comprehending the surroundings. However, expensive, dense terrestrial laser scanning (TLS) point cloud data with precisely aligned poses are required for use in time-intensive voxel ray casting-based algorithms [11, 29, 30].

**Visibility-based approaches**. Visibility-based approaches have been proposed [31, 32] to alleviate the computational burden. This sort of approach associates a query point (or a cluster) with a map point within nearly the same narrow field of vision (FOV) (e.g., cone-shaped [15]), concluding that the occluded points at subsequent sites should be static.

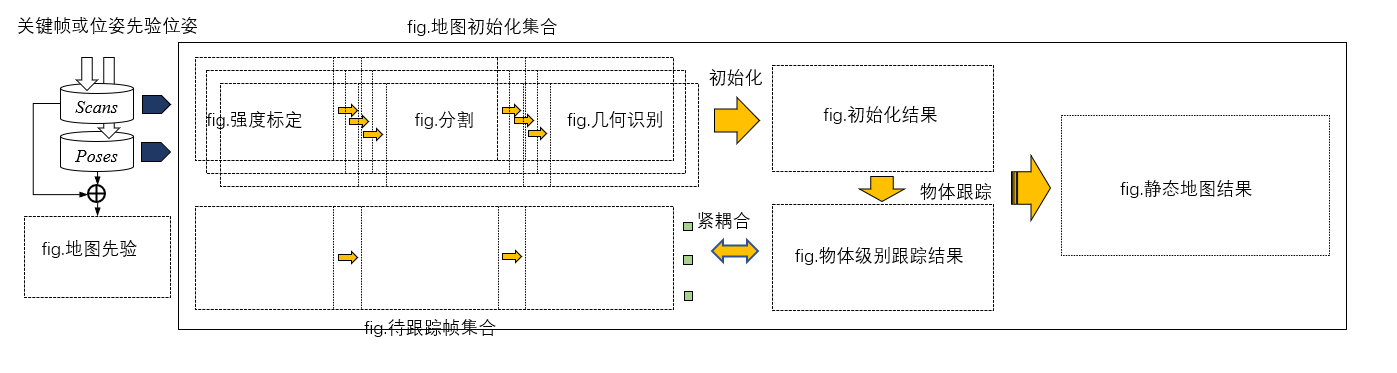
**Point cloud segmentation-based approaches**. Segment-based methods are also included in the list of related topics. Tools for segmenting point clouds have been developed [33]. Given accurate segment points and dynamic labels, it is simple to construct a map by omitting them [34, 35]. Nonetheless, segment-based algorithms rely largely on supervised labels and are susceptible to human mistake or unknown classes [36]. This point's semantic label must be combined as a prerequisite with the visibility-based process.



**Ⅲ. METHODOLOGY**

The proposed is a post-processing method to reconstruct a static instance map. Assuming that the process errors due to imperfect pose estimation are tolerable, we examine batch data of a certain length in [14] to enhance the quality of the static map.

框架图



*A. Problem definition*

Given a point cloud map generated from a set of raw lidar scans, we intend to remove dynamic objects in the map. Specifically, we consider the global unified map coordinate *M* and the local sensor query coordinate , where k is the frame index. We assume that the related SE(3) pose T (i.e., the transformation from to ) and the scan data in the local coordinate system are known. Additionally, we describe two groups in M, with D representing the dynamic group and S representing the static group. The mission thus corresponds to eliminating the dynamic objects in . The challenge stated above is phrased formally as

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| --- | --- |
|  | (1) |
|  | (2) |

where the is the transform in SE(3).

Our methods consist of two phases: *Seg*(...) (i.e., instance segmentation) and *Df*(..., ...). (i.e., dynamic filter). A static instance local map equates to the combination of static instances after dynamic removal between two registered scans, hence the procedure can be stated as

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| --- | --- |
|  | (3) |
|  | (4) |

*B. Intensity-assisted curved-voxel clustering*

Sharing the analogous philosophy to the existing approach [16, 22], We perform clustering for segmentation based on curved-voxel and solve difficult-to-cluster split sections by combining intensity information

**Ground extraction**. According to [13, 22], The majority of each frame's raw data consists of ground points, which may affect the segmentation of other instances; consequently, it is necessary to separate the ground before clustering. Moreover, the ground is utterly immobile, thus motion detection should not be conducted on it. We choose the method described in [37] to extract ground from the point cloud, resolving the uneven ground scene by multi-region plane fitting.

**Intensity calibration**. The sensor intensity reading indicates the surface reflectance structure surrounding the sensor. The intensity channel is noisy because it is influenced not only by target surface properties (e.g., surface roughness, surface reflectance), but also by acquisition geometry (e.g., distance) and instrument effects (e.g., transmitted energy) [31]. Calibration is important to limit the influence of other elements, yet, it is impossible to totally recover the true value of the object's substance through the mathematical model. In order to use the intensity in clustering efficiently, ensuring the continuity of the intensity in the adjacent space, we guide or restrict the operation of curved-voxel neighbor.

We solely evaluate the effect of distance , and incidence angle on raw intensity during the scanning period of a single keyframe. To satisfy the intensity we can suppose that is constant, hence the calibrated intensity can be formed as (fig关于邻域voxel内的方差)

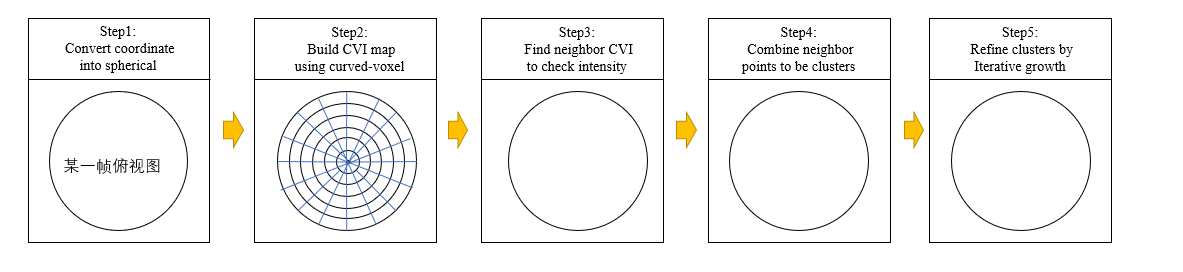
|  |  |
| --- | --- |
|  | (6) |

**Curved-voxel clustering assisted by intensity.** Referring to [16], we transform cartesian coordinates to spherical ones, X = [*ρ*, *θ*, *φ*]，which consists of the radial distance from the sensor , the polar angle, and the azimuth angle . We redefine curved-voxel assisted by intensity as *CVI*, a spatial unit comprised of three constituents: 1) spherical coordinates, 2) the average of intensity *AV*, which characterizes local reflectance, and 3) the covariance of intensity *COV*, which represents the credibility of the neighborhood. The fundamental components of is as follows:

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|  | (7) |

where , , and are unit size parameters for each spherical direction.

Intensity辅助聚类图



We describe our proposed segmentation method in Algorithm 1. We first implement a preliminary procedure to extract ground by [37] and calibrate intensity (line 1~2). Then we convert the coordinate of no-ground points into spherical ones (line 3) and build a hash table that maps each voxel index to the indices of points within the *CVI* (line 4). To maintain sparse representations of the hash table, only *CVI*s with at least one point are stored. After establishing the hash table, we visit each point to locate neighbor points in 27 (=) voxels with tiny COV surrounding the target CVI, where the AV difference must be less than the threshold, and then group them in to a cluster (line 5~11). After obtaining an initial list of clusters, we adopt a novel iterative algorithm to refine the clustering outcomes. All the clusters are visited to find the neighbor clusters through the neighbor voxel searching, after that, the sets are merged if the strength condition is achieved. The entire procedure is a mode of iterative growth based on cluster (line 12~18).

Compared with [16], in the iterative clustering growth mode, the combination of intensities can merge incompletely observed residual clouds in the region, hence strengthening the consistency of the same instance across multiple scan frames. (fig)

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| --- |
| Algorithm 1: **Curved-voxel clustering assisted by intensity** |
| **Input:** 3D point clouds from a scan data, and  curved-voxel size parameters , and , and  the threshold of average and covariance, *threAV* and *threCOV* |
| **Output:** |
| 1: **Extract ground:** use [37] to remove ground points in |
| 2: **Calibrate intensity:** in local region normal vector incident vector,  use the mathematical model (formula 6) |
| 3: Convert-to-Spherical ( |
| 4: hash-table Build-CVI (*X*, , , , *AV*, *COV*) |
| 5: **for** **do** |
| 6: **if** is already included in a cluster **then** |
| 7: **continue** |
| 8: **end if** |
| 9: Neighbor () Voxel-Searching **and** Satisfy (*threAV*) |
| 10: Initialize () Combine (Neighbor ()) |
| 11: **end for** |
| 12: **for** cluster **do** |
| 13:  **if** Noise-Remove () **then** |
| 14: **continue** |
| 15: **end if** |
| 13: **for** in **do** |
| 14: Neighbors () Voxel-Searching **and** Satisfy (*threAV*, *threCOV*) |
| 15: Neighbors () find cluster in Neighbors () |
| 16: Update () |
| 17: **end for** |
| 18: **return** |

C. Geometric classification

Intensity-assisted curved-voxel segmentation clusters the point cloud into multiple items, but instance segmentation should identify each object. We use geometric features [20, 21] to distinguish clusters to obtain low-level semantics using feature vector, as opposed to learning methods that mainly rely on supervised labels. The dimension of the geometric feature vector is 120, which consists of three parts:

1) Eigenvalue: This segment descriptor is merged into a 17-dimensional feature vector. In accordance with [38], we compute the linearity, planarity, scattering, omni-variance, anisotropy, eigen-entropy, change of curvature measures, and primary orientation. It utilizes the aggregated data of local characteristics to precisely describe the geometric distribution of objects. Because to its susceptibility to noise interference, it is frequently used to compare instances within the same category.

2) Spatial scale: This descriptor consists of Minimum height, Maximum height, and scale in a 13-dimensional feature vector, naturally represents the instance's scale information and can discern global changes with precision.

3) Shape histograms: This 1x640-dimensional feature consists of 10 histograms encoding the shape functions D2, D3, and A3, as defined in [39]. The D2 shape function is a histogram of the distances between randomly selected point pairs, whereas the D3 form function encodes the region between chosen point triplets. The A3 shape function describes the angles between lines derived from triplets.

In comparison to the learning method, the categorization based on geometric characteristics is less robust. To meet the requirements of low semantic information, we classify the clustering conclusions into three categories: 1) vegetation (e.g., trees and grass), 2) buildings (e.g. walls and fences), and 3) potential-mobility objects. In order to intuitively distinguish the three categories for point clouds with limited information, we devised a hierarchical classification criterion. Similar to the appearance of the ground, buildings seem flat in most scans, and due of the low complexity of multi-plane, we extract this category using region growth and restrict it using the planarity and change of curvature. The representation of vegetation is quite complex, and it is difficult to recognize it based solely on spatial scale; therefore, we added thresholds of planarity, omni-variance, and anisotropy to restrict this class. Owing to the inconsistency of observations and the existence of noise in the sweep, the majority of objects related to the ground, such as vehicles, pedestrians, billboards, etc., are possibly in mobility. To enhance the accuracy of dynamic removal, we categorize the aforementioned instances as potential-mobility objects, indicating that they are potential of motion. (fig)

D. *Dynamic removal in object tracking*

To remove dynamic instances, we apply an object tracking-based strategy. Only potential-mobility elements are identified throughout this process. This concept effectively eliminates the issue of inconsistent observation of the same objects in successive scans, and the voxel search optimizes the processing speed of a single frame. In addition, to boost the accuracy of object tracking, we select a specific amount of frames to initialize the instance results and tightly couple the tracking and instance segmentation processes.

We discuss our proposed dynamic removal strategy in Algorithm 2. After obtaining and , we assemble them into the same curved-voxel map and perform an object-level registration (line 1). Then, for each instance with potential mobility in , we find its neighbor instance by curved-voxel searching and calculate the occupancy to check the observation consistency (line 5~8).

Registering the segmentation results from both frames in the same curved-voxel map, we utilize the amount of instance coverage and voxel occupancy changes to characterize the nature of motion. Notably, the above procedure is entirely based on curved-voxel tracking, which may not only lower the cost but also modify the instance in a flexible manner. According to this criterion, the motion properties of objects in can be divided into four categories:

*1) High Dynamic (HD) Objects:* Due to the unpredictability of observations in , interpreting high-mobility objects is exceedingly difficult. We divide it into two types: a) cannot be covered, meaning there is no voxel occupancy link; and b) may be covered, however the voxel occupancy is variable. Objects with high dynamic qualities, such as vehicles, pedestrians, etc., tend to have fast translation speeds. (line 9 ~ 12).

*2) High Static (HS) Objects:* Non-moving objects, such as parked vehicles, crates, etc., could be properly tracked in , provided they occupy one or more instances and satisfy a specific occupancy ratio. (line 13 ~ 18).

3) Object Split: We only conduct dynamic detection for objects with high mobility. However, due to the inconsistent observation of the two adjacent frames, different types of objects will establish contact after geometric recognition. To solve this problem, the proposed splits the object in the previous frame according to the observation occupancy (line 15).

4) Object Fusion: Faced with a one-to-many search, if the attributes of multiple objects searched are the same, they will be fused (line 18).

这里需要一个类似于segmatch中的图进行上下比较，下图截图segmatch，将某个聚类物体分割、将多个聚类物体融合的图

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| Algorithm 2: **Dynamic removal in object tracking** |
| **Input**: } and , and |
| the threshold of occupancy *threOccu* |
| **Output**: in , and |
| after compensation |
| 1: **Registration**: Inverse (, and |
|  |
| 2: **for** cluster in **do** |
| 3: Convert-to-Spherical () |
| 4: Neighbor () Build-CVI () |
| 5: **for** **do** |
| 6: **if** find in hash-table () **then** |
| 7: Neighbors () check cluster |
| 8: **end if** |
| 9: **if** Size (Neighbors ()) = 0 **then** |
| 10: add into |
| 11: **else if** Size (Neighbors ()) > 0 **and** Satisfy (*threOccu*)**then** |
| 12: add into |
| 13: **else if** Size (Neighbors ()) > 0 **and** no-Satisfy (*threOccu*)**then** |
| 14: add into |
| 15: Split (Neighbors ()) |
| 16: **else if** Size (Neighbors ()) > 0 **and** Satisfy (*threOccu*)**then** |
| 17: add into |
| 18: Fuse (Neighbors ()) |
| 19: **end if** |
| 20: **end for** |
| 21: **return** and |

*Ⅳ. EXPERIMENTAL RESULTS*

*A. Dataset*

We use the KITTI odometry dataset [40] and the SemanticKITTI dataset [14] to evaluate our static map construction performance qualitatively and quantitatively. The SemanticKITTI contains scan-wise labeled data and the related LiDAR SLAM-based SE(3) poses are estimated by SuMa [41]. Furthermore, the SemanticKITTI offers point-wise annotations, points labeled with specific class (252, 253, 254, 255, 256, 257, and 259) are defined as ground-truth dynamic points to be erased. We notice that we did not include unlabeled points, whose label index is zero, since if we did, dynamic points would arise and the original map could no longer function as a static ground truth map.

To demonstrate the effectiveness of the proposed method in more environments, we conducted a qualitative test on the MulRan dataset [42] using LIO-SAM [3] to estimate the poses. By doing so, we aimed to prove the feasibility of the proposed method in various situations and consider less accurate pose estimation.

*B. Evaluation Criteria*

This paper refers to the static status as positive (P) and the dynamic status as negative (N). Then the estimates and are expressed as

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| and | (5) |

where TP, FP, TN, and FN represent true positive, false positive, true negative, and false negative point sets, respectively.

Using this equation, we can redefine the problem as reducing the number of FP and FN points within the static and dynamic estimates.

We used both SemanticKITTI’s static map and our original map voxel down-sampled with 0.05 m size cell. To quantitatively depict the results of dynamic filtering, the TP, FP, TN, and FN points are indicated in gray, orange, green, and red, respectively. If a true static point in the ground truth map is missing a nearest neighbor in the predicted static map, the point is annotated as FN.

*C. Parameter settings*

We used SemanticKITTI’s static map and our original map voxel down-sampled with a 0.05 m size cell.

**Our parameters**. We also used LiDAR SLAM-based scan poses for a fair comparison following the SemanticKITTI. By doing so, we aimed to consider less accurate pose estimation and prove the feasibility of the proposed method without using the original KITTI dataset’s ground truth poses. 重要参数设置补充

**Evaluation criteria**. We used SemanticKITTI’s static map and our original map voxel down-sampled with a 0.05 m size cell. For the proposed method’s estimated static points, we define TP if the estimated static points appear in the SemanticKITTI ground truth map and FP if they do not appear. Co-appearance is considered to have occurred when a nearest point distance is within 0:1 m. TP and FP samples are marked as green-blue and red respectively. If an actual static point in the ground truth map has no nearest neighbor in the predicted static map, then the point is marked as FN

此处有TP/FP/FN/FP的图片、局部动态剔除的图、真实环境parkinglot的图

Reference

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