







Object-based Loop Closure with Directional Histogram Descriptor

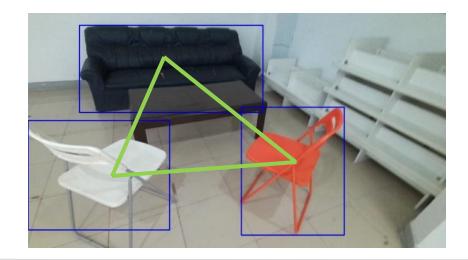
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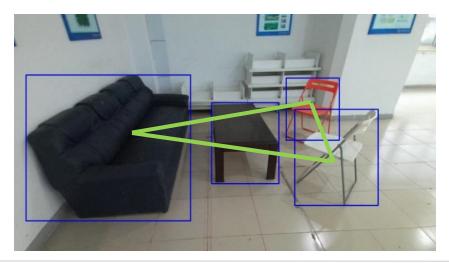
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Background



- Mobile robots will produce inevitable accumulated errors because of sensor noise
- Traditional feature-based loop closure methods are sensitive to environment changes and failed to detect loop under large viewpoint difference.
- Research problem: How to effectively detect the loop under large viewpoint difference?



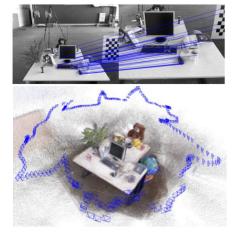




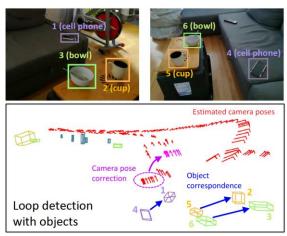
Related work



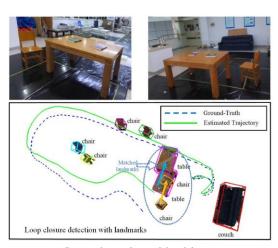
- Research problem: How to effectively detect the loop under large viewpoint difference?
 - > feature-based loop closure: accurate, but sensitive to environment changes
 - object-based loop closure: robust to viewpoint changes but not accurate
 - our idea: feature-based + object-based loop closure



ORB SLAM 2: Loop detection with ORB features (Mur-Artal at al. 2017)



Loop detection with objects (Li, et al, 2020)



Loop detection with objects (Lin, at al, 2021)

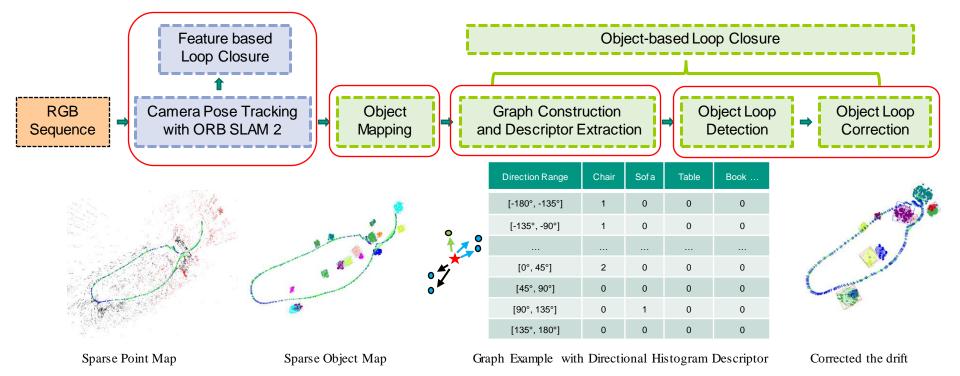


Method: overall framework

Assumptions:

- 1) Use only RGB images.
- 2) Objects are static and, on the ground.
- 3) Objects can be viewed in different viewpoint.

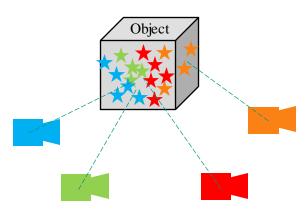






Method: object mapping

- How to detect objects in the environment?
- Object Representation: 3D bounding box with class, translation, rotation, dimension, feature points
- Object Detection: YOLOv5, collect the feature points that belongs to the object.
- Object Association: In every frame, check detected objects has a large 2D IoU (>0.5) with mapped objects, if so, merge them, if not, add a new object to the map.



Object detection example



Method: graph construction

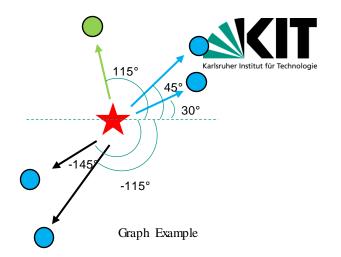
- How to represent the environment (not only the objects but also their relationship)?
- Graph (G) = {N, E},
 - Node (N): = {ID, Class, Centroid, Descriptor, Others},
 - Edge (E): = {distance_ij, yaw_ij}

Algorithm 2: directional histogram descriptor

Input: O: Object landmarks;

Output: V: directional histogram descriptor for O;

- 1. for o in objects do
- 2. neighbor ← find the closest 8 objects;
- 3. **for** n in neighbor of o **do**
- direction: a ← calculate the direction(n,o);
- 5. label: In ← record the object label;
- 6. histogram \leftarrow the histogram cell Vo(a,ln) +1;
- 7. end for
- **8.** add Vo to into V;
- end for



Yaw Angle Range	Chair	Sofa	Table	Book
[-180°, -135°]	1	0	0	0
[-135°, -90°]	1	0	0	0
	•••	•••	• • •	•••
[0°, 45°]	2	0	0	0
[45°, 90°]	0	0	0	0
[90°, 135°]	0	1	0	0
[135°, 180°]	0	0	0	0

Directional Histogram Descriptor



Method: loop detection



- How to detect loop with object information?
- General check: same class and ID difference > 3

$$\eta(a,b) = |ID_a - ID_b| \ (a \in L_a, b \in L_b)$$

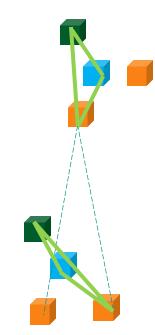
■ Graph check: the similarity score of their directional histogram descriptor > 0.8

Score(A, B) =
$$\frac{\sum_{d=1}^{n_d} A_d \times B_d}{\sqrt{\sum_{d=1}^{n_d} (A_d)^2} \times \sqrt{\sum_{d=1}^{n_d} (B_d)^2}}$$

Geometry check: at least 3 objects are matched, and their scale factor < 0.01</p>

$$s_{12} = |dis_{a_1,a_2}| / |dis_{b_1,b_2}|$$
 $\delta = \sqrt{(s_{12} - \overline{s})^2 + (s_{23} - \overline{s})^2 + (s_{13} - \overline{s})^2}$

Duplicated check:



Geometry verification example



Method: loop correction



- How to correct the drift after the object loop is detected?
- General idea: compute a similarity transformation that satisfy:

$$O_a = sR*O_b+t$$

- However, use only object information may cause errors, because the object detection is not so accurate, instead, we take the associated map points and compute a scaled ICP.
- The scale ratio is computed by:

$$s = \frac{1}{n} \sum \frac{|dis_{a_1,a_2}|}{|dis_{b_1,b_2}|} + \dots + \frac{|dis_{a_n,a_1}|}{|dis_{b_n,b_1}|}.$$

 Then, we scale the associated map points and compute the rigid transform (R, t) by minimizing the sum of squared error

$$(R^*, t^*) = \underset{R,t}{\operatorname{argmin}} \sum_{k=1}^{s_p} \|p_{a,k} - sR * p_{b,k} - t\|^2$$



Experiments

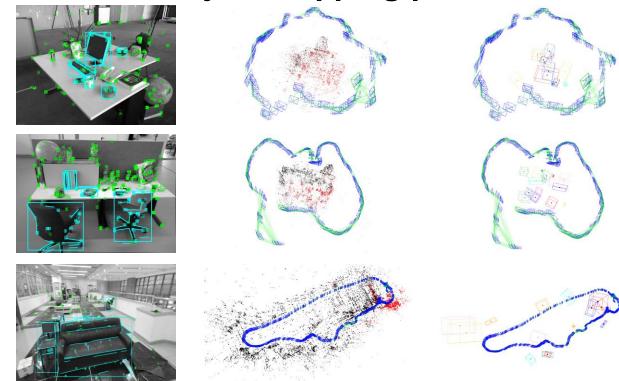


- Datasets:
 - TUM RGB-D Dataset
 - USTC RGB-D Dataset
- Metrics:
 - Object mapping performance
 - Loop detection performance
 - Localization performance



Experiments – object mapping performance



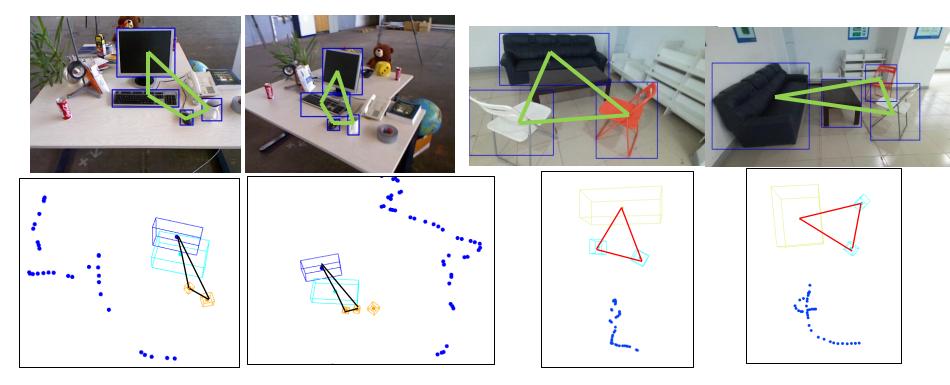




feature point map

Experiments – loop detection performance





ustc_07 sequence



Experiments – offline video









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Experiments – localization result

Sequence	ORB SLAM without loop closure (m)	ORB SLAM with feature-based loop closure (m)	Ours (object and feature-based loop)
fr2_desk	0.012499	0.007723	0.008851
fr3_long_office	0.034488	0.012362	0.013587
ustc_01	1.515137	1.515137	0.268989
ustc_02	0.733596	0.733596	0.191738
ustc_03	4.399249	4.399249	0.742086
ustc_07	0.733087	0.733087	0.498279









Conclusion



- We present a monocular SLAM system that can build a semantic map with feature points and object landmarks.
- An object-based loop closure method based on semantic graph matching is proposed, which is robust to the change of viewpoint.
- We propose a loop correction method to align the matched objects, which can effectively correct the drift error.

- Future work
- Object detection method with other sensors
- Field experiments in logistic environment



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