3D Indoor Modeling Using RGB-D Camera

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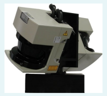
Motivation

➢Detailed 3D models of indoor space, from walls to floors to objects and their configurations, can provide extensive knowledge about the environments.

➢People used to use accurate, expensive laser scanners for 3D indoor modeling. Can we use a lower cost RGB-D sensor instead? RGB-D sensors like Kinect are much cheaper than laser scanners and can provide not only depth measurements, but also color information.

➢Current existing RGB-D methods are limited in their size since they store raw point cloud data. The memory requirement becomes prohibitive after a while.

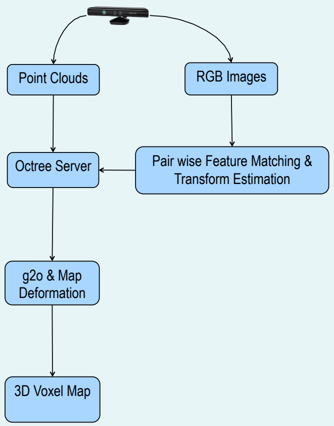


Objective

➢The objective of this project is to reconstruct indoor scenes using a Kinect by combining pose graph optimization with "as-rigid-as-possible" space deformation. We efficiently store the map in an octree structure and use the non-rigid deformation for octree map correction in a pose graph optimization framework.

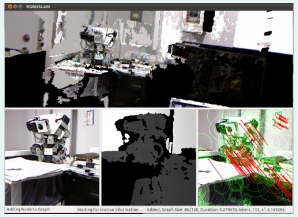
➢The algorithm should be robust to sensor noise in Kinect, memory efficient compared with other existing algorithms.

Overall Framework

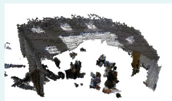


Overview of the Algorithm

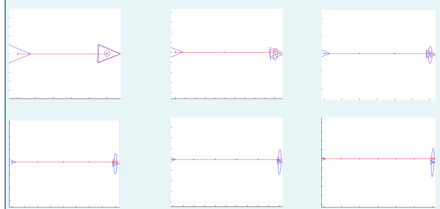
➢Incrementally register point cloud using pairwise SURF feature matching [1].



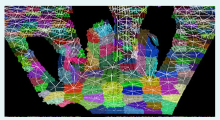
➢Store the map in an octree data structure.



➢Create a new submap when accumulated uncertainty is high or closing a loop.



➢Using supervoxel clustering to get supervoxels and use center of supervoxels as deformation graph nodes. Edges generated from supervoxel adjacency information.



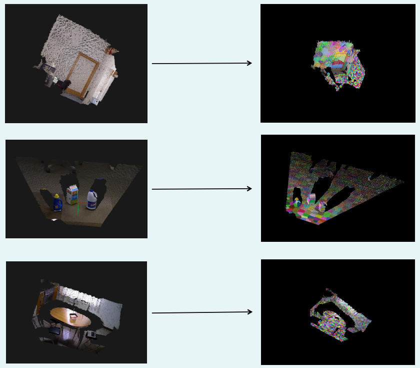
➢Get transformation associated with each node from Global Pose Graph Optimization (g2o) framework and use it as user edit constraints for map deformation.

➢Compute deformed position of supervoxel center by as-rigid-as-possible shape deformation (enforcing rigidity, smooth & user constraint).

Theory & Preliminary Result

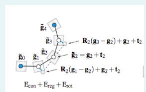
➢VCCS Supervoxel Clustering [2].

- ➢Construct an adjacency graph of occupied voxels.
- ➢Initialize supervoxels by uniform seeding and filter out seeds caused by noise.
- ➢Compute edge weight in adjacency graph.
- ➢Growing the seeds by running breadth-first-search of the adjacency graph.

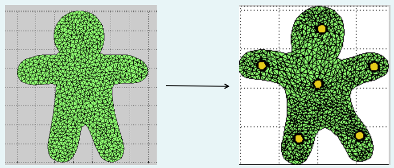


➢As-rigid-as-possible Map Deformation [3].

- ➢Construct deformation graph from uniform sampling of the model surface.
- ➢The influence of individual graph nodes on any 3D points is smoothly blended by a weighted sum of its position.

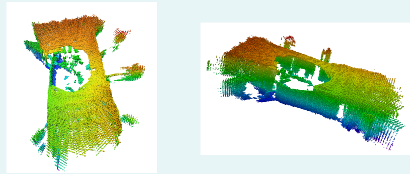


- ➢Associate affine transformation with each graph node.
- ➢Optimization (Rotation, Regularization, Constraints).

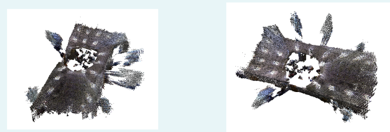


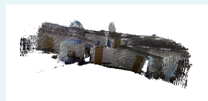
➢Voxel map obtained using only feature matching & visual odometry.

- ➢Smith Hall 2nd Floor Dataset



**Note that drift error accumulates after a while and the map becomes distorted.





**RGB-D SLAM result looks good overall. But surface lacks smoothness after pose graph optimization.

Further Work

➢Integrate code in each module into pipeline and make a working 3D indoor modeling system.

➢Collect more data sets for testing.

References

1. F. Endres, J. Hess, N. Engelhard, J. Sturm, D. Cremers and W. Burgard, "An evaluation of the RGB-D SLAM system", ICRA 2012
2. J. Papon, A. Abramov, M. Schoeler and F. Worgotter, "Voxel Cloud Connectivity Segmentation - Supervoxels for Point Clouds", CVPR 2013
3. R. Summer, J. Schmid and M. Pauly, "Embedded Deformation for Shape Manipulation", ACM SIGGRAPH 2007

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