3D Semantic Reconstruction in Nuclear Plant

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Introduction

In order to improve the life safety and decrease the labor cost for nuclear plant, it is necessary to facilitate planning and execution of remote handing as well as decommissioning operations. It means the KUKA robot arm should have the abilities that detect and recognize the nuclear stuff, understanding the unclear plant, perform object manipulation automatically.

KUKA Robot Arm

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Introduction

- This research provide a real-time dense semantic reconstruction in nuclear plant. It means unclear objects and scene can be reconstructed as dense 3D point clouds in real-time, and meanwhile every voxel of point cloud will be labeled to different classes like wall, ground, pipe, metal, robot and etc. All the recognized objects can be convert to CAD models to 3D pose tracking and object manipulation.

A frame of point cloud from RGBD camera

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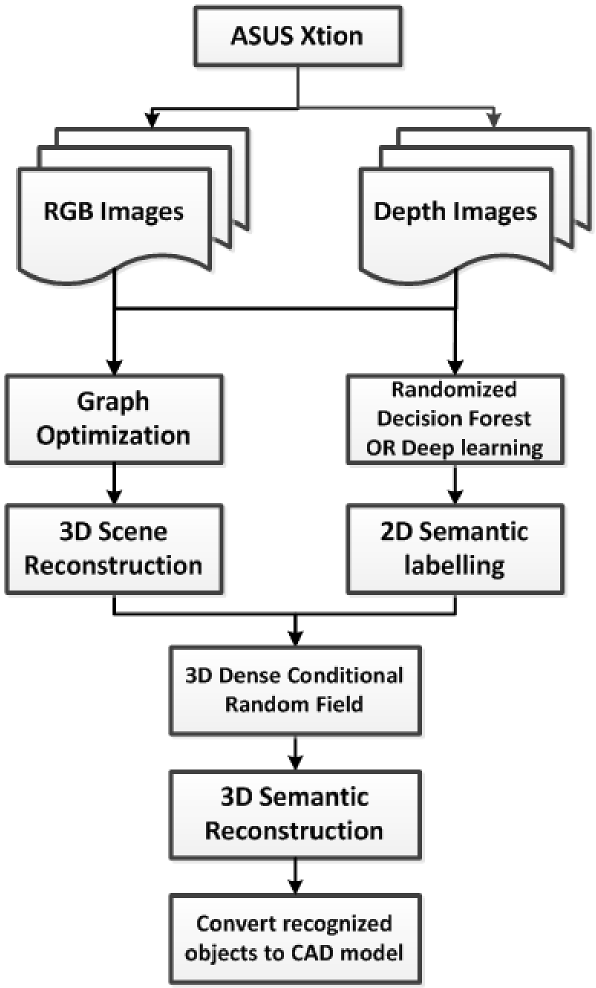
System Workflow

This work mainly includes two modules: 3D SLAM module and semantic labeling module.

1. The RGB and depth images can be obtained from Xtion or Kinect sensor.
2. Using RGB and depth data, 3D reconstruction can be performed based on graph optimization.
3. Meanwhile, every frame 2D image can be labeled by randomized decision forest. Then the result can be refined using dense conditional random field. Each point cloud can be assigned a class label.
4. Giving those semantic labels, the dense semantic reconstruction can be performed.
5. Finally, the recognized object can be converted to CAD model, which is used for 3D pose tracking and object manipulation.

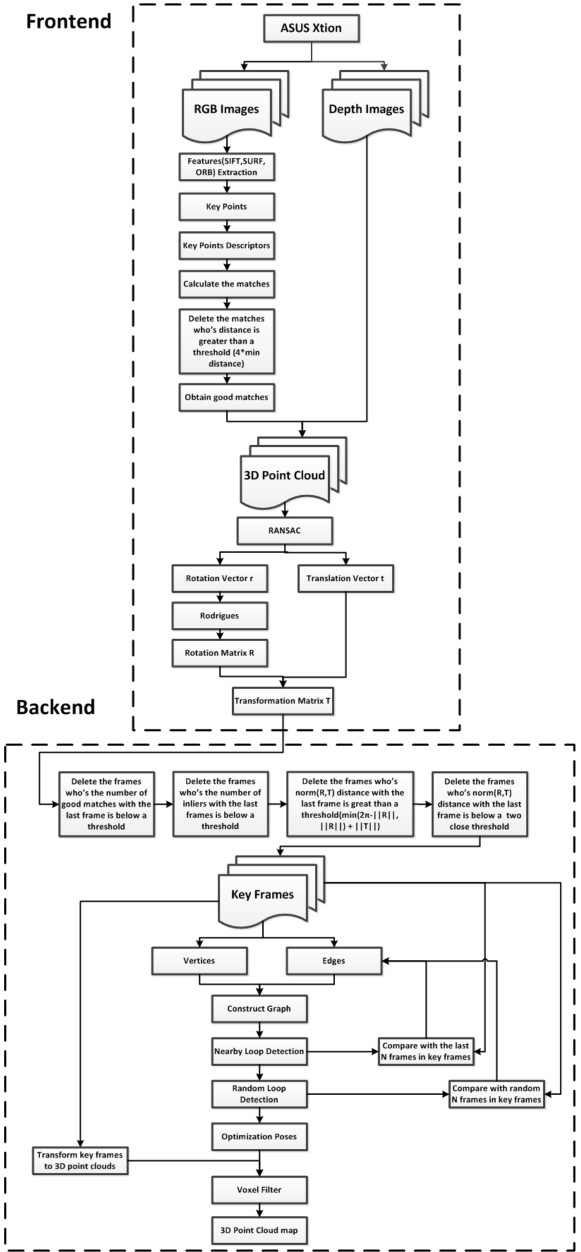


System workflow

Methodology

- 1. 3D SLAM/Reconstruction
- The graph optimization is used for 3D dense SLAM/Reconstruction.

- 1. Transform a pair of RGB and depth images to point cloud.
- 2. Extract features and find the corresponding points.
- 3. Compute the transformation matrix.
- 4. Select the key frames and construct a graph.
- 5. Perform the loop detection.
- 6. Optimize all the poses.
- 7. Combine all key frames together based visual odometry.



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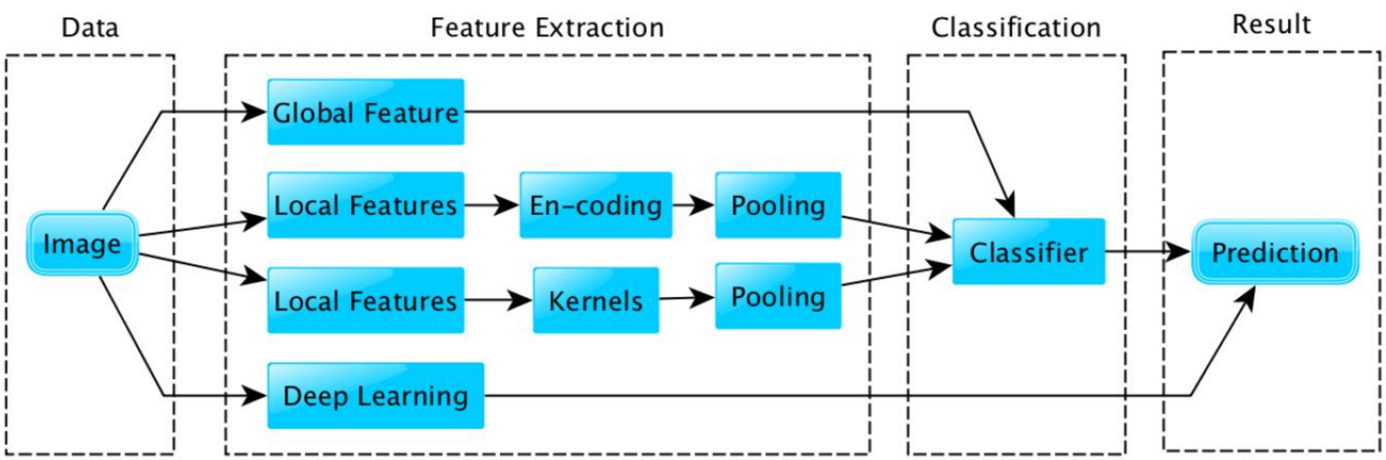
Methodology

- 2. Semantic labeling
- For semantic labelling, our solution is:

- 1. RGBD images are classified using the randomized decision forest.



A classic machine learning progress

- 2. Combine all the key frame 3D point cloud using the visual odometry.
- 3. The result is refined using 3D dense Conditional Random Field.

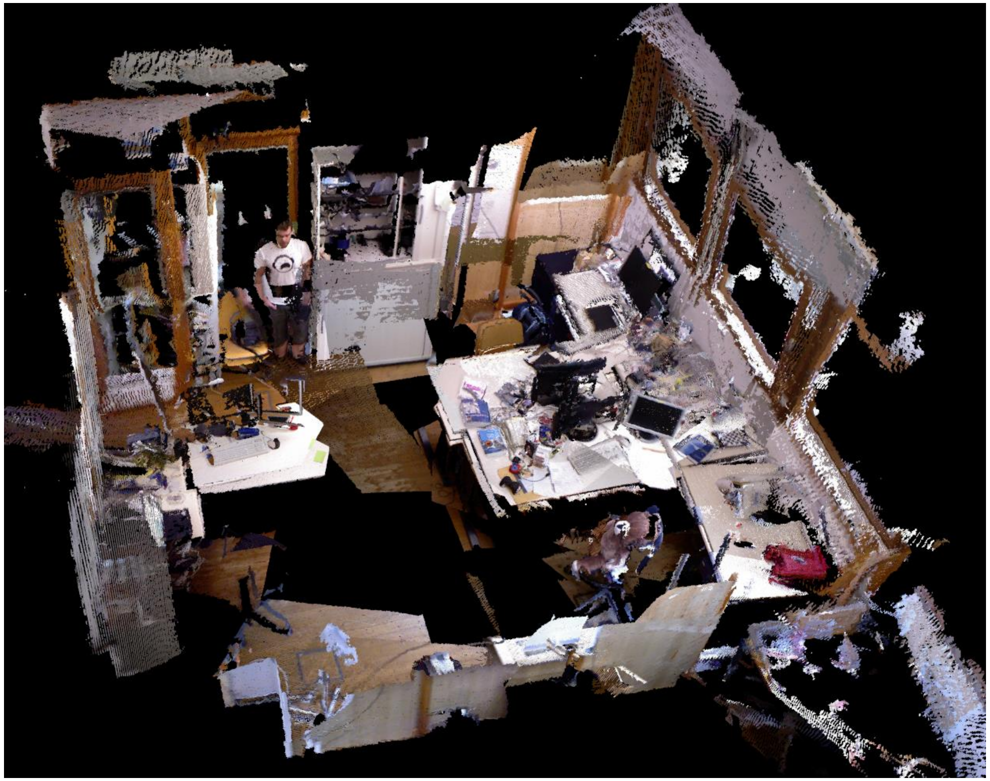
Experiment and Discussion

- Many 3D SLAM/Reconstruction tests are performed only in the office environment from TUM dataset and Birmingham STRANDS dataset, because of the dataset of Nuclear plant is still under way.

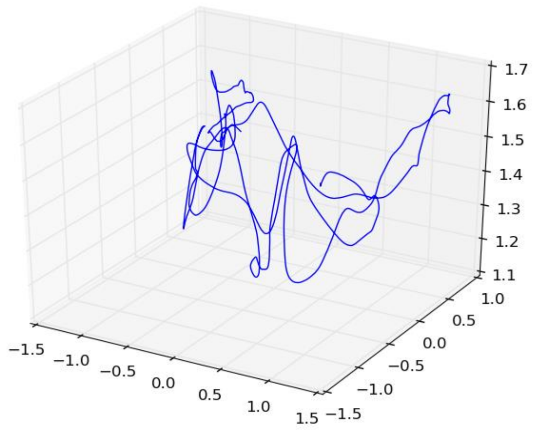
- In the Frantend of 3D SLAM, different features like SIFT, SURF, ORB and BRIEF are tested for feature detection and loop detection.
- The ICP and RANSAC are tested for motion estimation.
- In the Backend of 3D SLAM, different graph optimizations algorithms like TORO, GTSAM and G2O are tested.

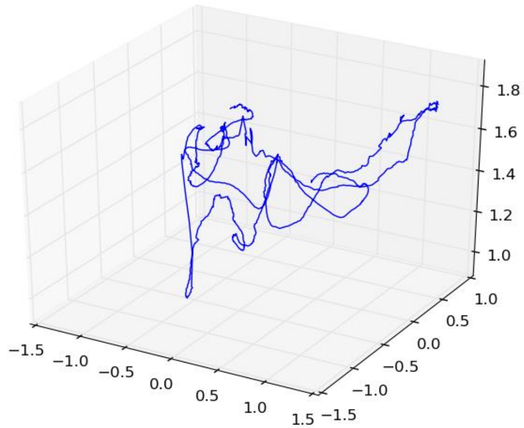
- The 3D reconstruction can not be evaluated directly. But it is reasonable to assume that the error in the 3D reconstruction is directly related to the error of the camera trajectory.
- The relative pose error (RPE) and absolute trajectory error(ATE) is used for the evaluation of the visual odometry drift and the global pose deviation.

Experiment and Discussion



The dense 3D reconstruction of office environment





The evaluated trajectory from RGBD SLAM and the ground truth trajectory from VICON

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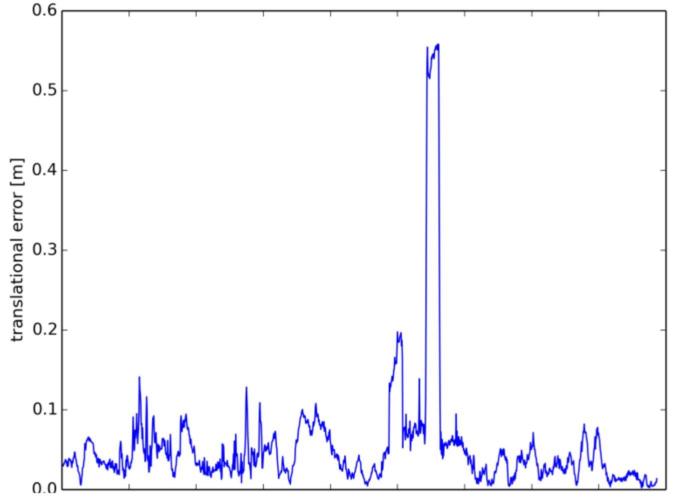
Experiment and Discussion

```
compared_pose_pairs 10000 pairs
translational_error.rmse 0.201289 m
translational_error.mean 0.143743 m
translational_error.median 0.093907 m
translational_error.std 0.140909 m
translational_error.min 0.000000 m
translational_error.max 0.747304 m
rotational_error.rmse 9.107426 deg
rotational_error.mean 7.458703 deg
rotational_error.median 0.098676 deg
rotational_error.std 5.226180 deg
rotational_error.min 0.000000 deg
rotational_error.max 20.845092 deg
```

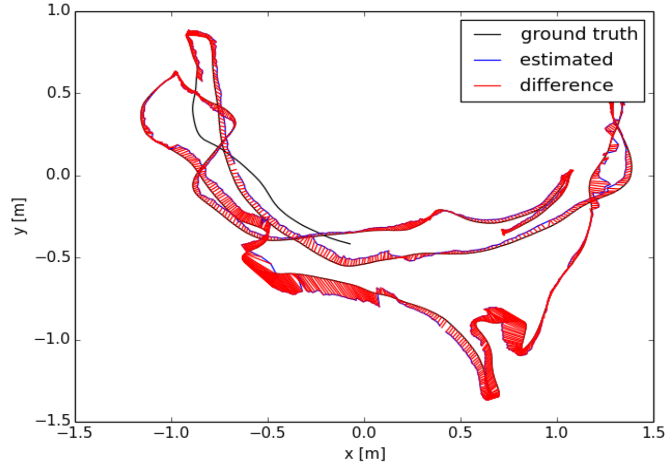
The RPE of the office environment



The RPE with time plot of the office environment

```
compared_pose_pairs 1332 pairs
absolute_translational_error.rmse 0.101165 m
absolute_translational_error.mean 0.072363 m
absolute_translational_error.median 0.048731 m
absolute_translational_error.std 0.070696 m
absolute_translational_error.min 0.005000 m
absolute_translational_error.max 0.436558 m
```

The ATE of the office environment



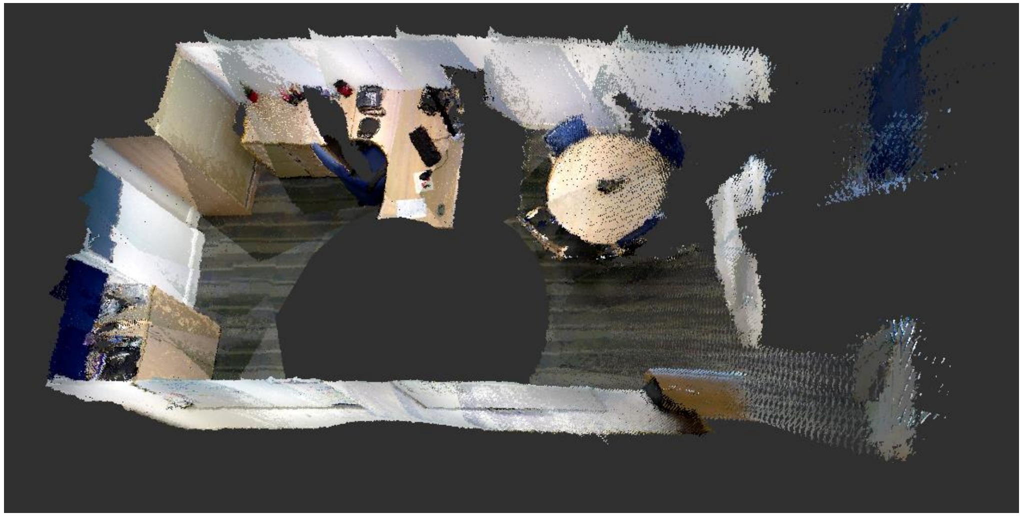
The ATE plot of the office environment

Experiment and Discussion

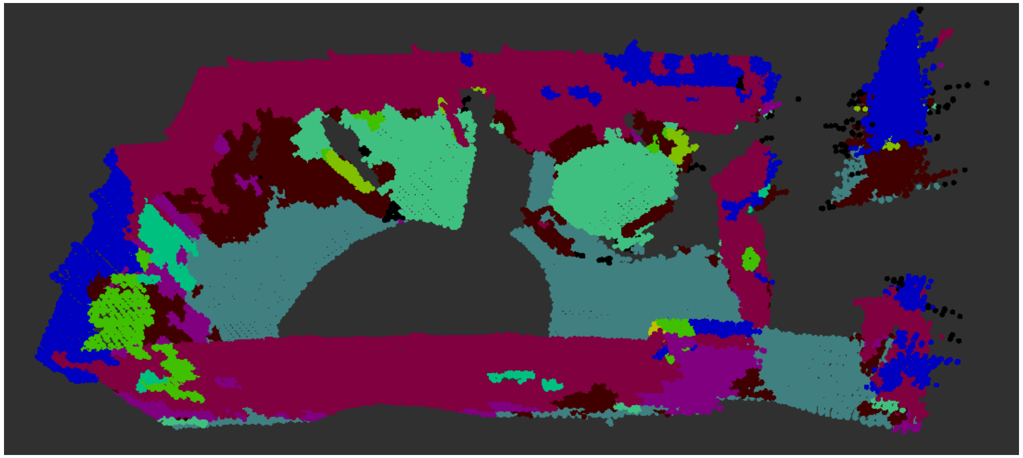
Classified by Randomized Decision Forest and refined by 3D Conditional Random Field, each voxel in the 3D reconstruction can be assigned a class label.

Each voxel is labeled by different color, like red is table, green is table, brown is cupboard and etc.

Millions of point clouds belong to the object can be converted to a whole CAD model based on emerging algorithm.



The original 3D reconstruction of an office includes table, chair, cupboard, wall and ground.



The labelled 3D reconstruction of an office. The table, chair, cupboard, wall and ground are labelled using different colour.

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Future Work

- The next step work will mainly focus on two areas:

- Build a nuclear environment dataset and perform 3D dense semantic reconstruction tests using this dataset. This dataset will include metal, wood, pipe plastics gloves and many nuclear stuff. With the help from Dr. Jeff, many 3D CAD models of real Sellafield nuclear plants will be provided very soon.

- The CNN model will be used for 2/3D object labelling to increase the accuracy and decrease the labelling time.

Many thanks for your attention