URBAN ROBOTICS LAB

ICRA 2014 Workshop on Long Term Autonomy

Pose Graph-Based RGB-D SLAM in Low Dynamic Environments

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Overview

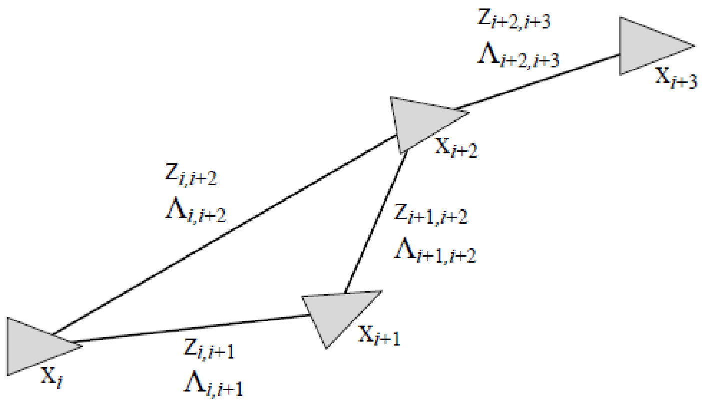
- A solution to the simultaneous localization and mapping (SLAM) problem in low dynamic environments by using a pose graph and an RGB-D (red-green-blue depth) sensor.
- The low dynamic environments refer to situations in which the positions of objects change over long intervals. The changes in the environments then causes false loop closing.
- First, nodes of the graph are grouped according to the grouping rules with noise covariances.
- And, false constraints of the pose graph are pruned by an error metric based on the grouped nodes.
- The performance of the method was validated in real experiments using a mobile robot system.

Background

- Originally, it was assumed that the SLAM technique can only be performed in static environments, but the real world is a dynamic environment.
- In recent years, SLAM has been developed for use in dynamic environments, but many of these methods rely on expensive laser range finder (LRF) sensors.
- In highly dynamic environments, since vision sensors can readily detect the moving object, visual SLAM delivers good performance [1].
- However, if the positions of objects change over long intervals, it is difficult to recognize these movements using vision sensors alone.
- This problem was defined in [2] (where they used an LRF sensor) and referred to as a low dynamic environment.

[1] A. Kawewong, N. Tongprasit, S. Tangruamsub, O. Hasegawa, "Online and Incremental Appearance-based SLAM in Highly Dynamic Environments," *The International Journal of Robotics Research*, vol. 30, no. 1, pp. 33–55, 2011.
[2] A. Walcott-Bryant, M. Kaess, H. Johannsson, J.J. Leonard, "Dynamic Pose Graph SLAM: Long-Term Mapping in Low Dynamic Environments," *Proc. IROS 2012*, pp. 1871–1878, 2012.

Pose graph SLAM



Graphical model of pose graph SLAM

- The nodes represent robot poses in the map, while the edges constrain the nodes based on the relative measurements between pairs of nodes.

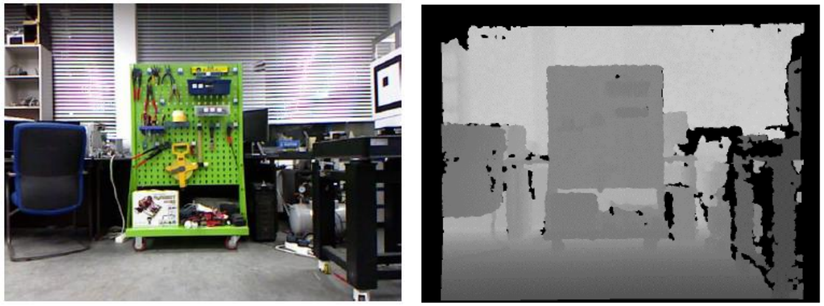
- The pose graph SLAM algorithm optimizes the full trajectory of a robot using the maximum-likelihood estimation (MLE) method, as follows:

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} \frac{1}{2} \sum_{\langle i,j \rangle \in \mathcal{C}} \mathbf{r}_{i,j}^T(\mathbf{x})\, \Lambda_{i,j} \mathbf{r}_{i,j}(\mathbf{x})$$

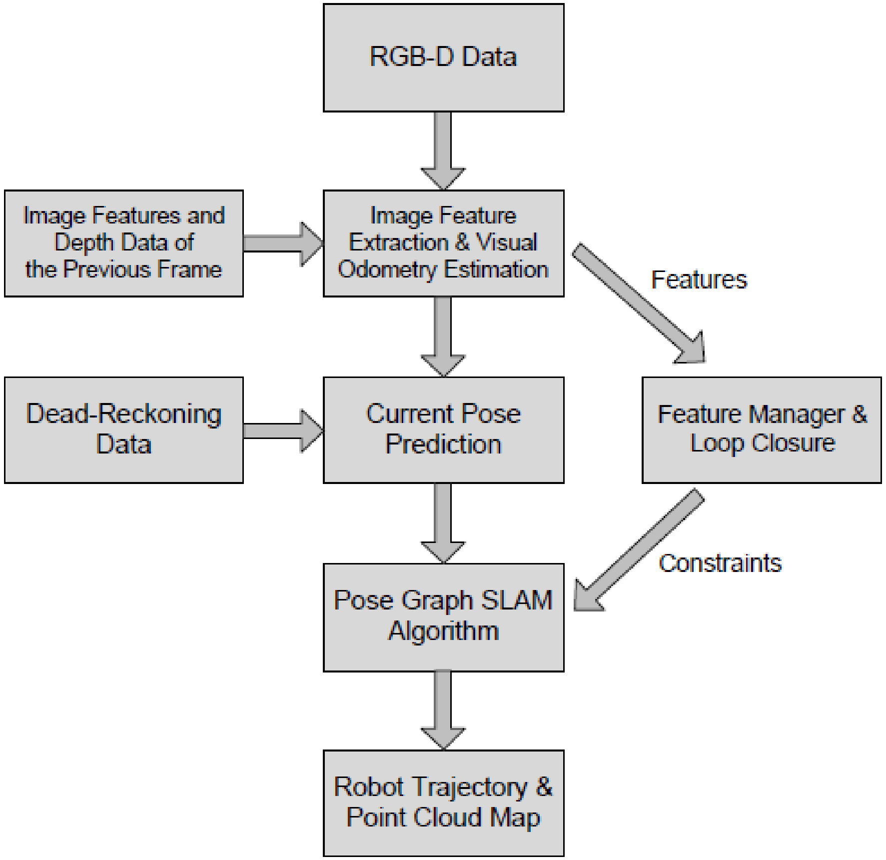
- A variety of graph SLAM algorithms, such as TORO, g2o, and iSAM, has been developed to improve the computational efficiency of this process.

RGB-D SLAM System

- The proposed SLAM method is implemented and validated using an RGB-D SLAM system.
- Image feature extraction and RANSAC with 3D positions of features.
- A feature manager detects loop closure.
- A pose graph is optimized by iSAM algorithm.

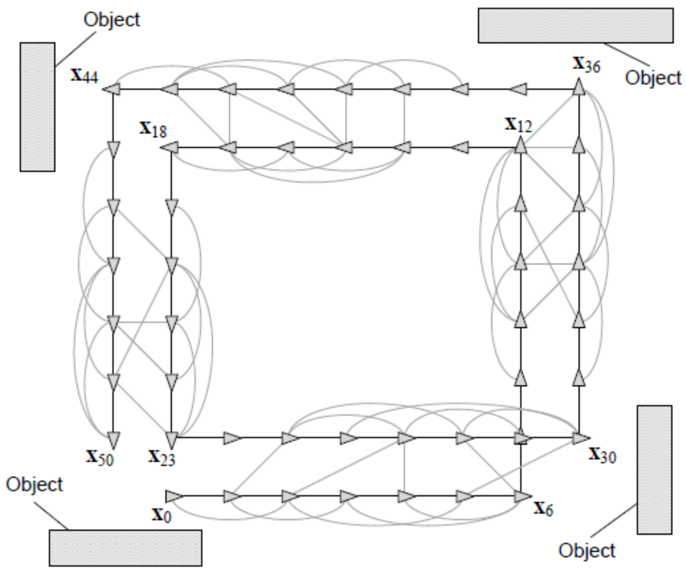


RGB-D sensor data. RGB 2D image and Per-pixel depth data.

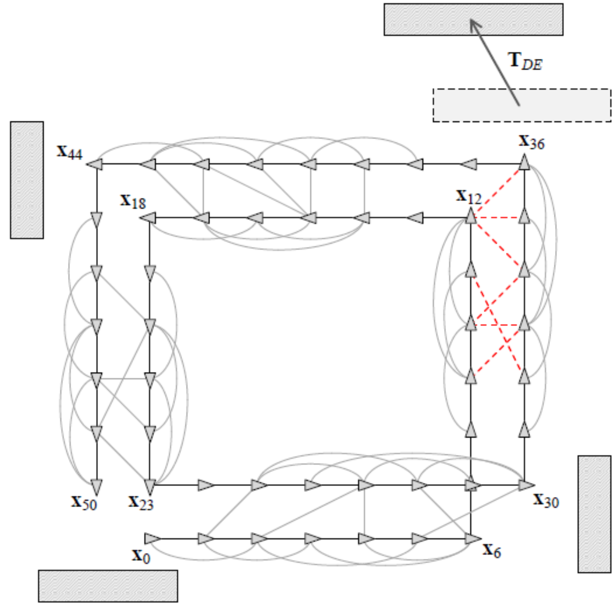


RGB-D SLAM system processing steps.

SLAM in Low Dynamic Environments

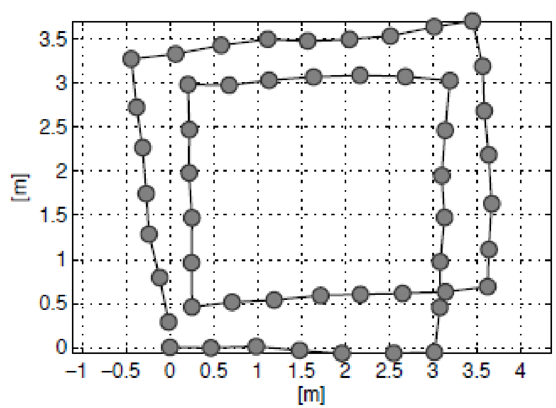


Example of pose-graph SLAM in a static environment.

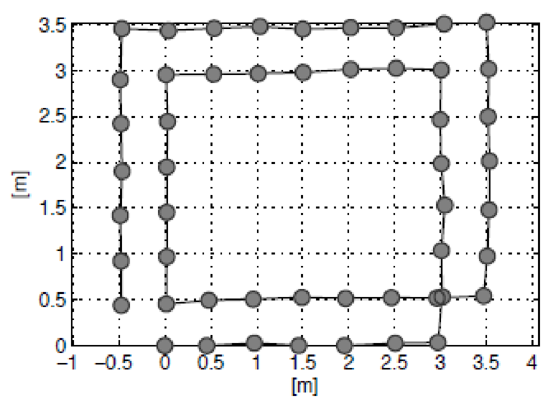


Example of pose graph SLAM in a low dynamic environment.

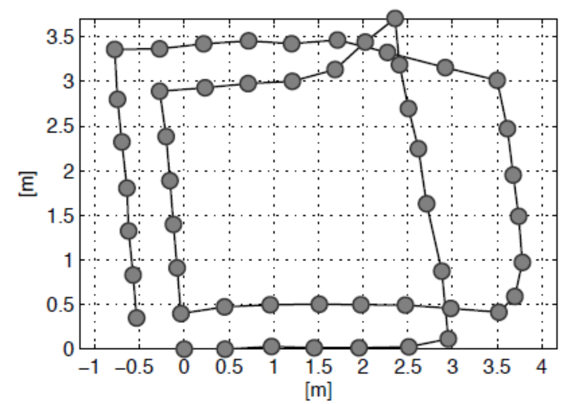
After the first visit to the object in the top right corner ($\mathbf{x}_6$ to $\mathbf{x}_{12}$) and before the second visit ($\mathbf{x}_{30}$ to $\mathbf{x}_{36}$), the object moves according to the transformation matrix $\mathbf{T}_{DE}$.



Odometry only.



Optimized trajectory in the static environment.

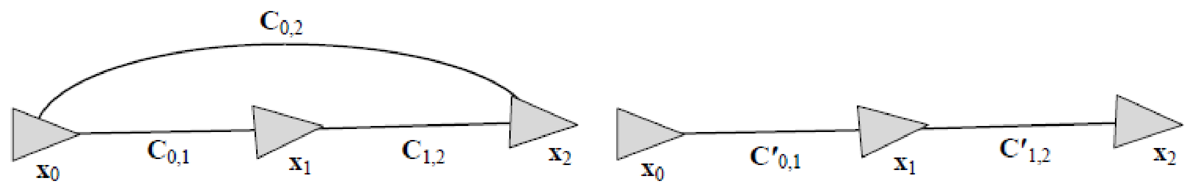


Distorted trajectory due to a low dynamic object.

Grouping Nodes

- Several false constraints emerge from the object movement because the robot has a vision sensor that points ahead and it observes the same object for a period.
- If two groups related to the moving object (the first and the second visiting groups to the low dynamic object) can be formed, the false constraints are established between the two visiting groups.
- Then, if it is revealed that the relationship between the two groups is incorrect, all of the constraints that connect the groups can be pruned concurrently.

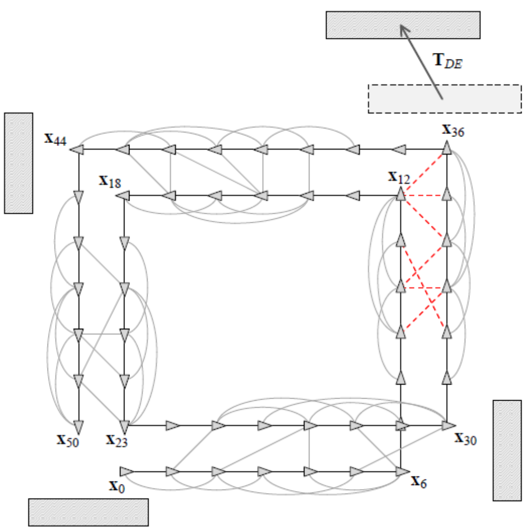
Grouping Nodes

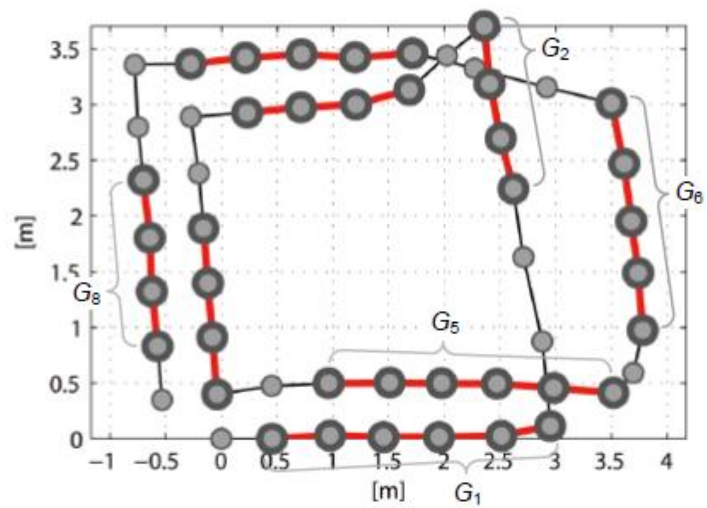


(a) (b)

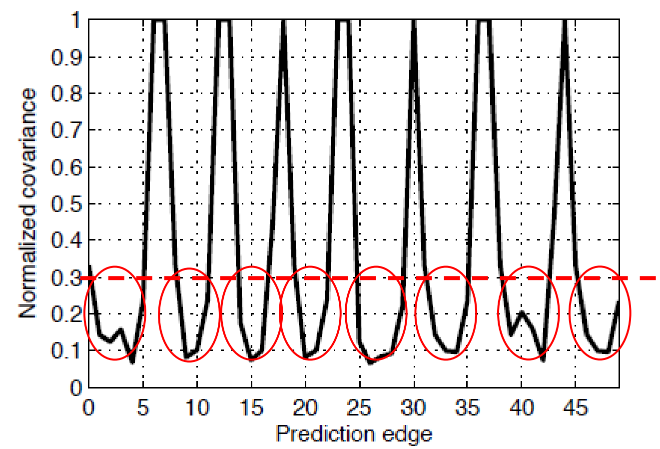
Example showing the merging of the covariances of edges. (a) Before merging $\mathbf{C}_{0,2}$ to $\mathbf{C}_{0,1}$ and $\mathbf{C}_{1,2}$. (b) After merging, $\mathbf{C}'_{0,1}$ and $\mathbf{C}'_{1,2}$ are updated.

$$\mathbf{C}'_{0,2} = \left[(\mathbf{C}_{0,1} + \mathbf{C}_{1,2})^{-1} + \mathbf{C}_{0,2}^{-1}\right]^{-1} \qquad \mathbf{C}'_{0,1} = \mathbf{C}'_{0,2}\frac{\mathbf{C}_{0,1}}{\mathbf{C}_{0,1} + \mathbf{C}_{1,2}} \qquad \mathbf{C}'_{1,2} = \mathbf{C}'_{0,2}\frac{\mathbf{C}_{1,2}}{\mathbf{C}_{0,1} + \mathbf{C}_{1,2}}$$





Result obtained after grouping the nodes. The red and bold lines represent the grouped nodes.



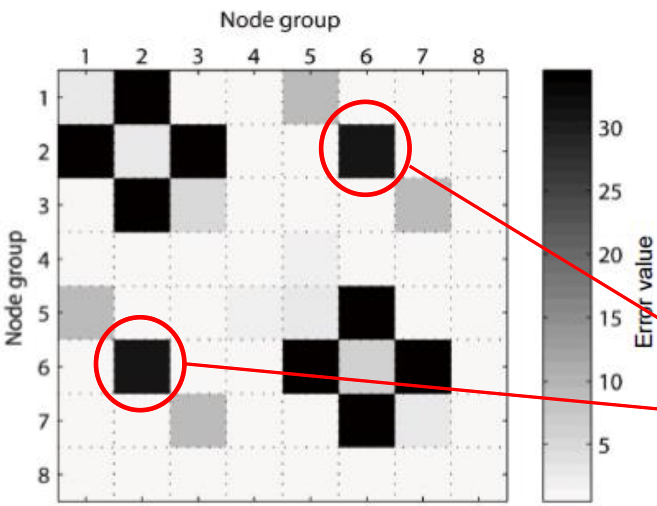
Normalized covariance values of the odometry edges.

Pruning Constraints

- A proposed error metric uses the grouped nodes to find the false constraints in an efficient manner.

- The error value $E_{k,l}$ is defined as the average Mahalanobis distances of the edges that connect the k-th and l-th node groups as

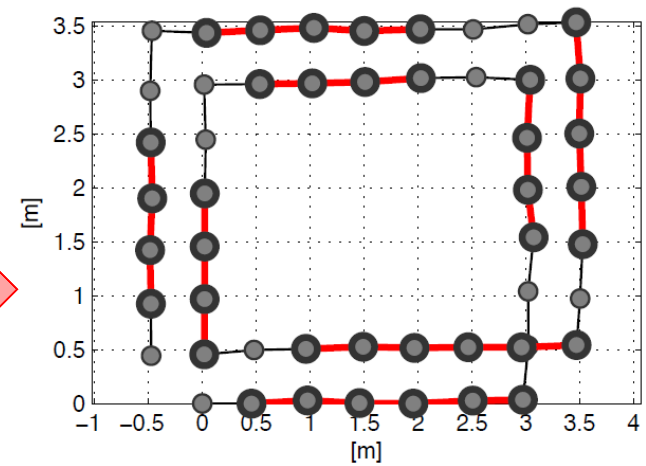
$$E_{k,l} = \frac{1}{N_{k,l}} \sum_{\langle i,j \rangle \in \mathcal{C}_{k,l}} \mathbf{r}_{i,j}^{T}(\mathbf{x})\, \Lambda_{i,j} \mathbf{r}_{i,j}(\mathbf{x})$$



Error metric based on the grouped nodes.

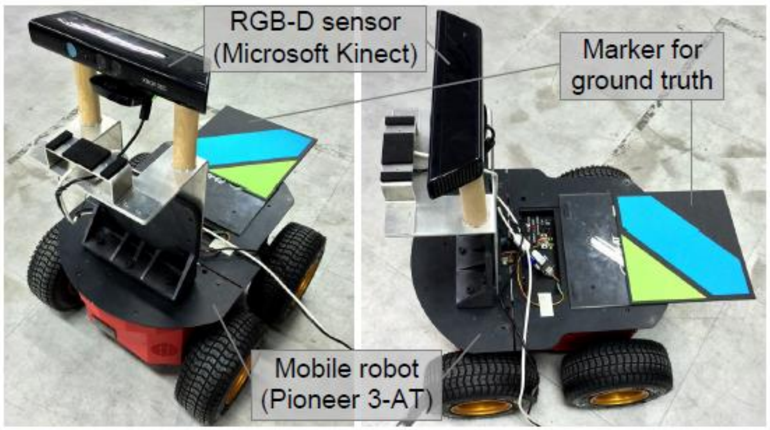
The error values $E_{k,l}$ when $|k-l| > 1$ are only considered for finding the false edges.

According to $E_{2,6}$, G_2 that has useless information of the past becomes an object of attention so that the measurement edges related to G_2 are removed.

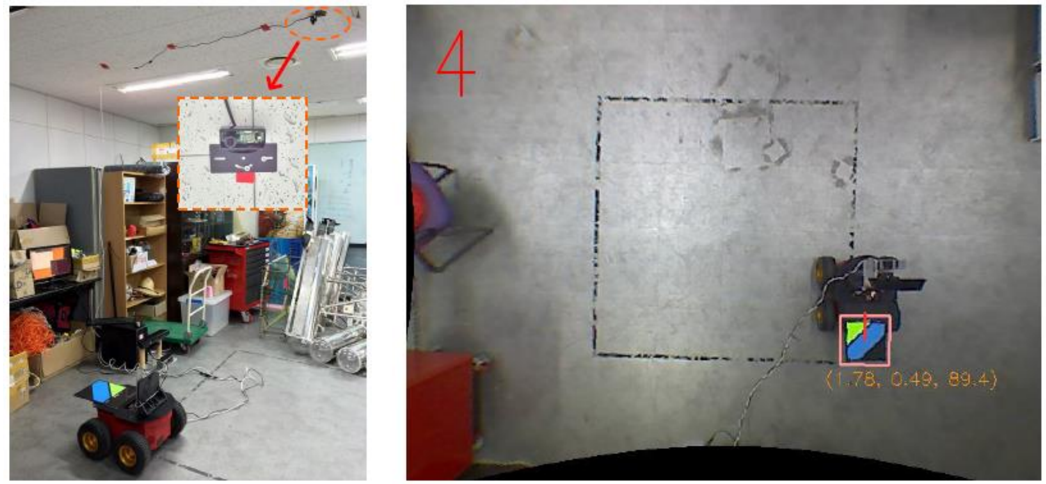


Optimized trajectory after pruning the false constraints.

Experimental Setup



Mobile robot system with a RGB-D sensor and a marker for measuring the ground truth position.



(a) (b)

Global vision system for obtaining the ground truth position. (a) Camera installed on the ceiling. (b) Global positioning result is displayed. A 3-DOF robot pose is obtained.

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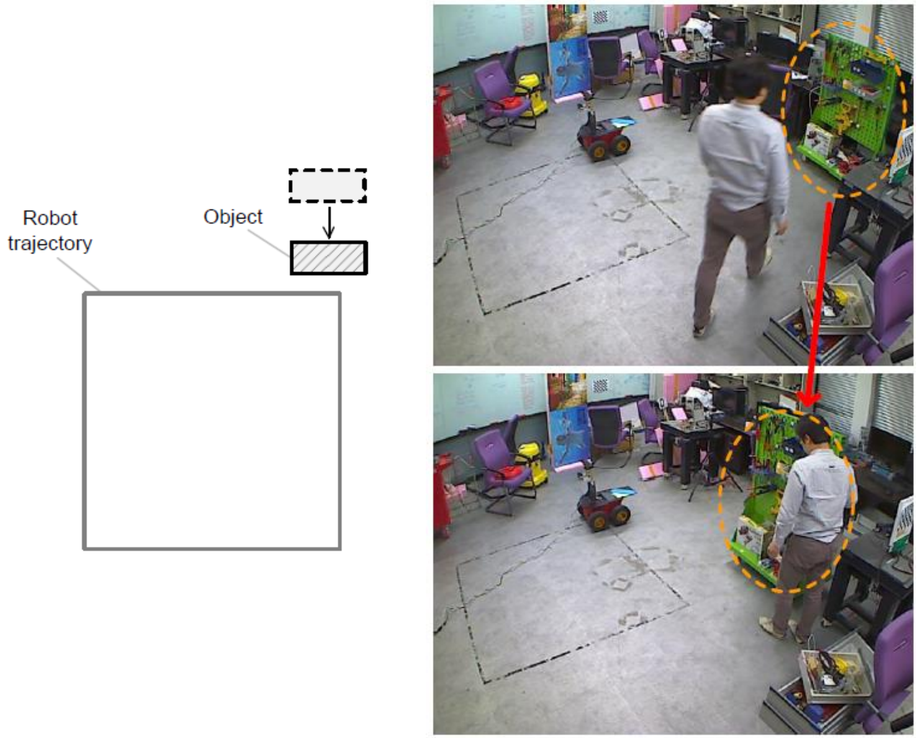
Experimental Setup

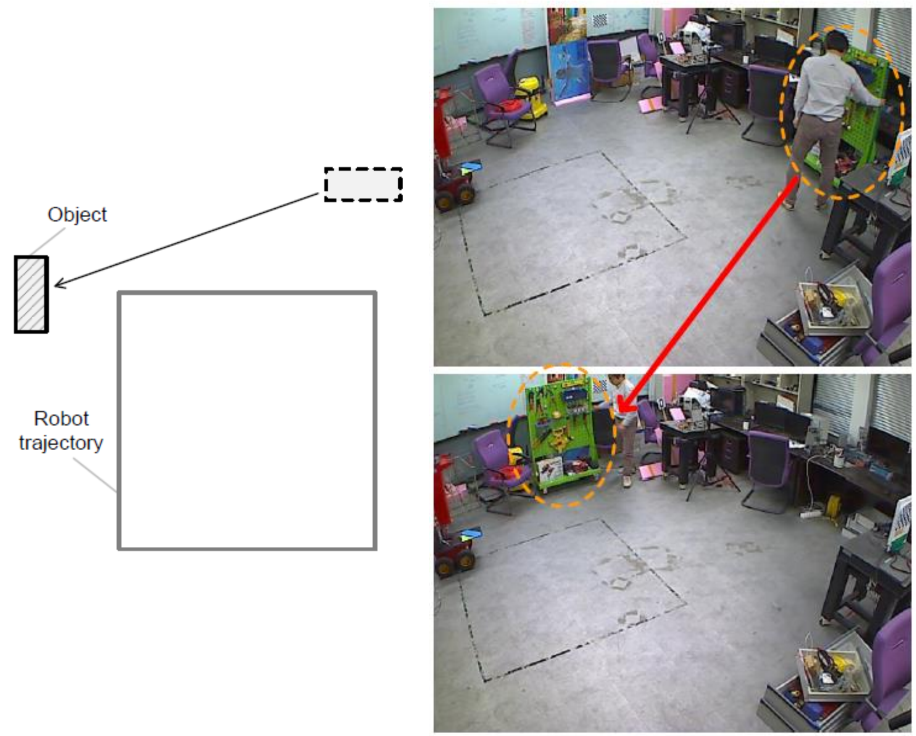
Experimental site used for low dynamic environments.

Experimental Setup

- Relocations of the tool cart during two experiments that produce low dynamic environments.



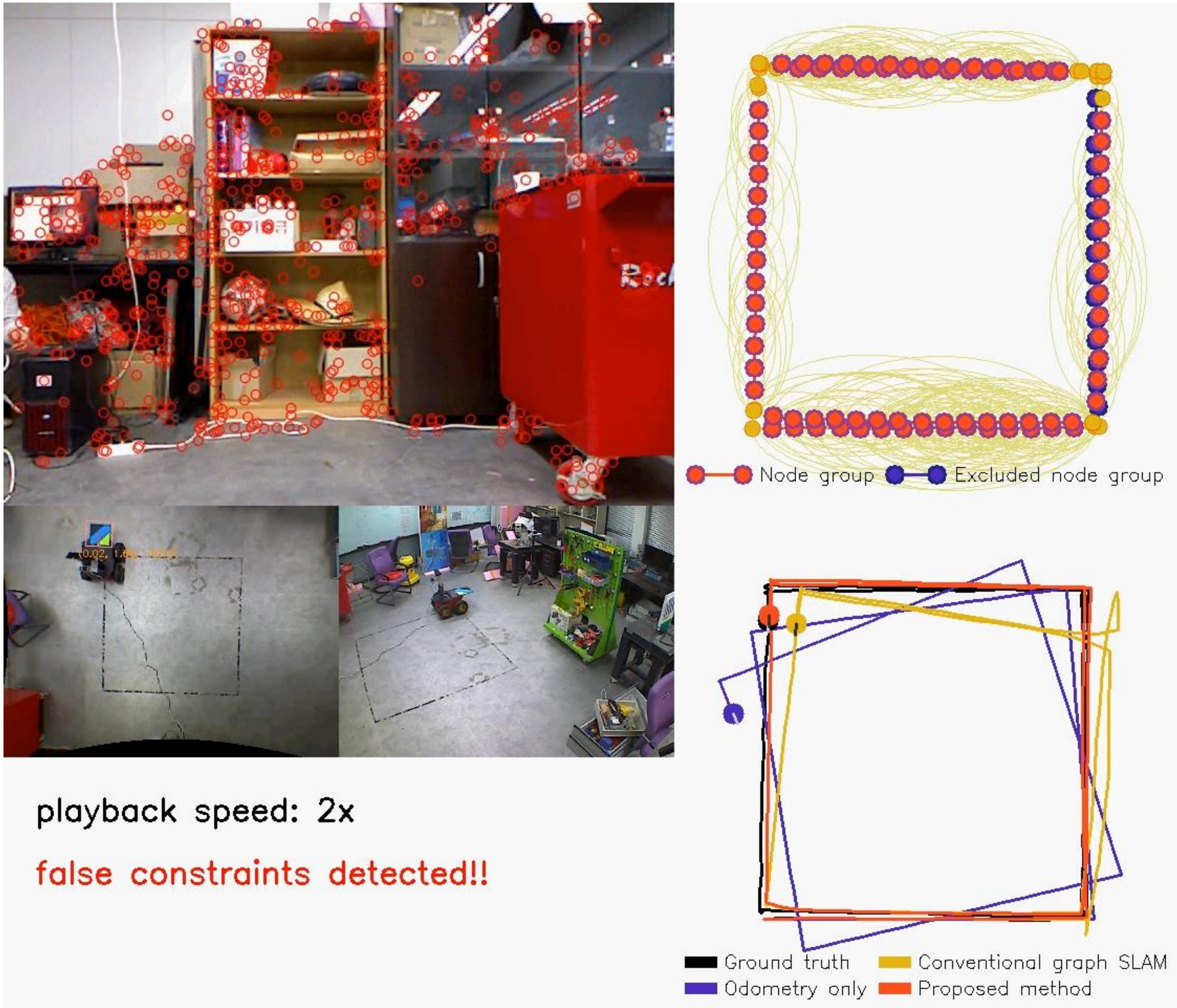
Experiment 1



Experiment 2

Experimental Results

- Experiment 1 (YouTube Link: http://youtu.be/RokKTSdKS7k)



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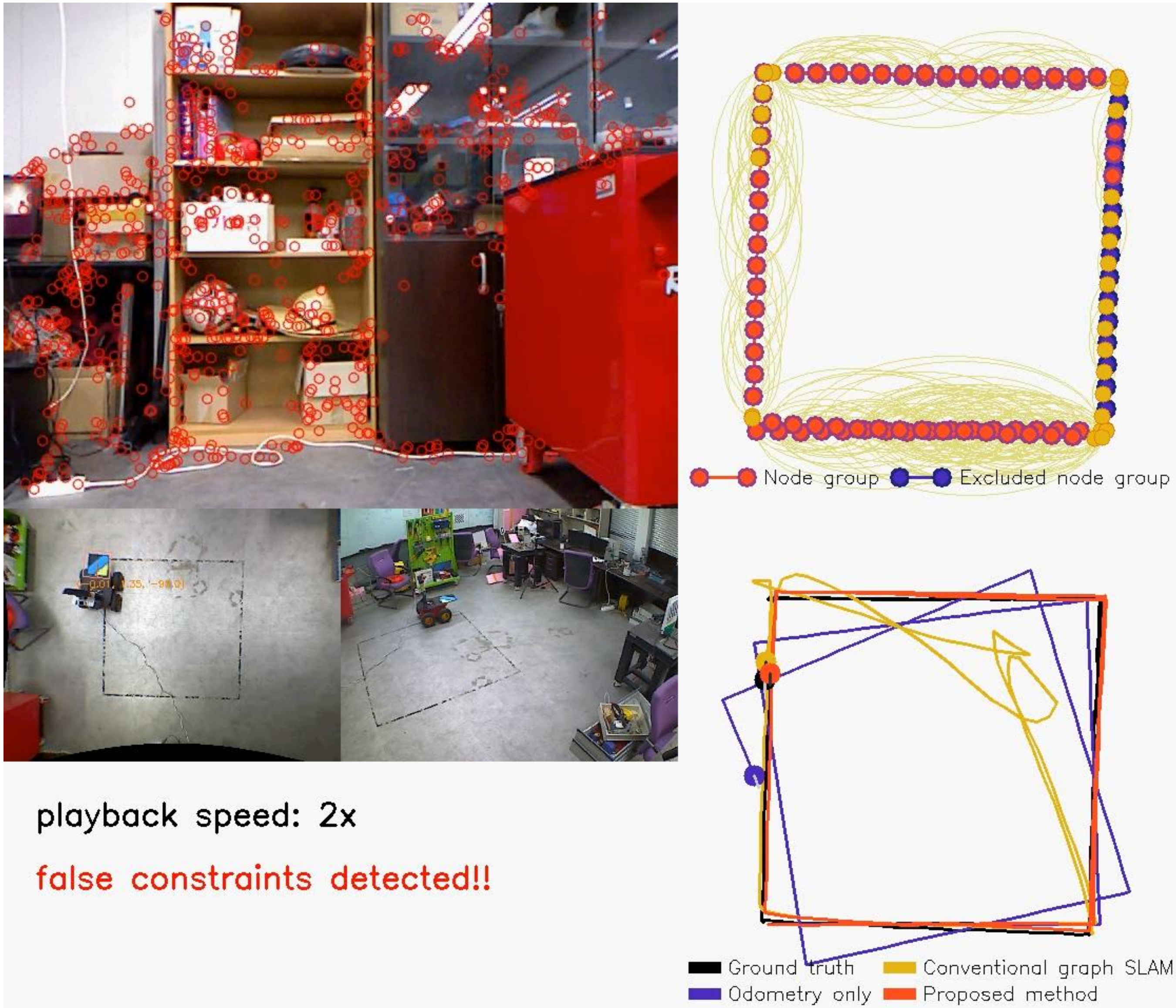
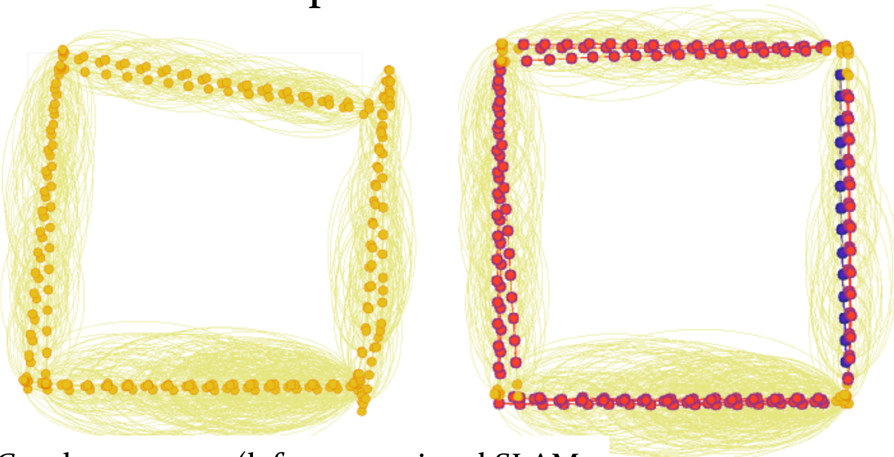
Experimental Results

- Experiment 2 (YouTube Link: http://youtu.be/72lmBUPLc84)

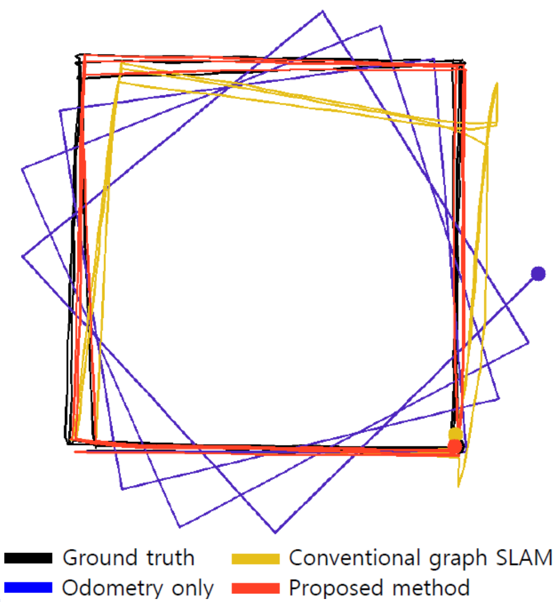


Experimental Results

Experiment 1

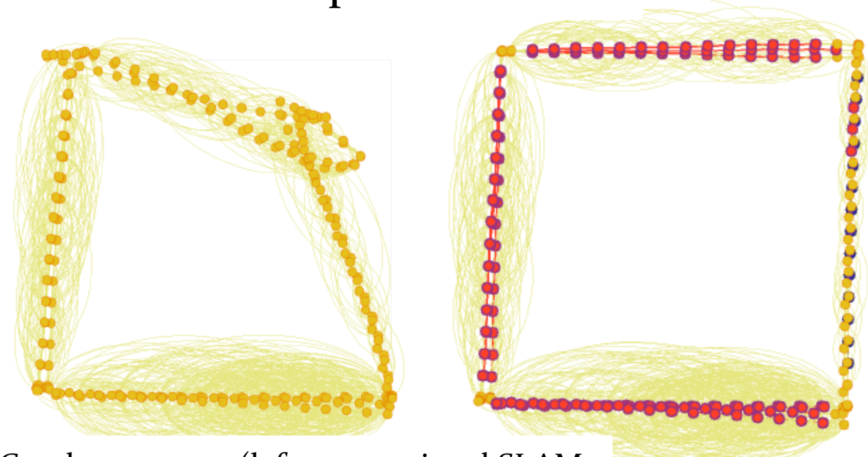


Graph structures (left: conventional SLAM, right: proposed method)

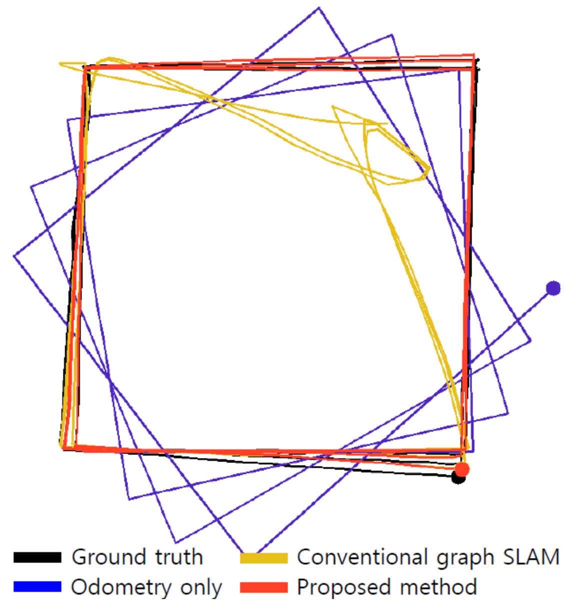


Robot trajectory

Experiment 2



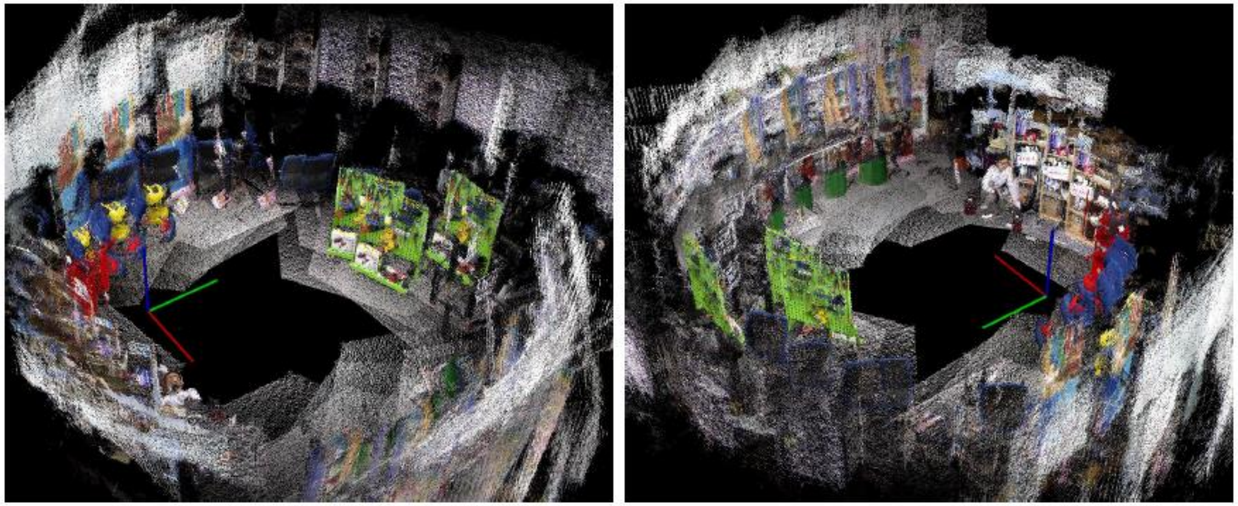
Graph structures (left: conventional SLAM, right: proposed method)



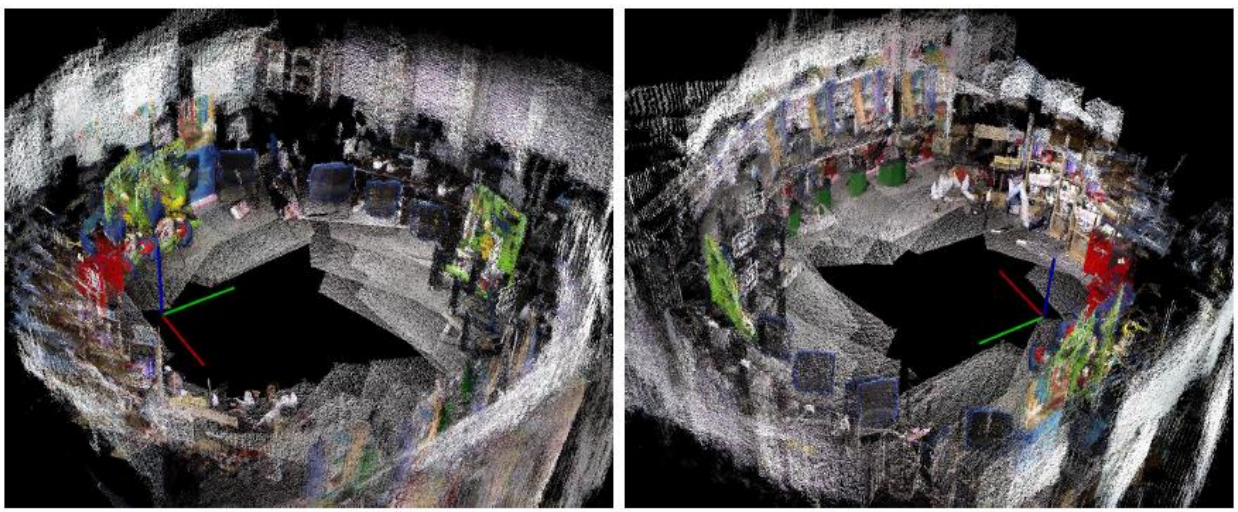
Robot trajectory

Experimental Results

- 3D maps (odometry only)



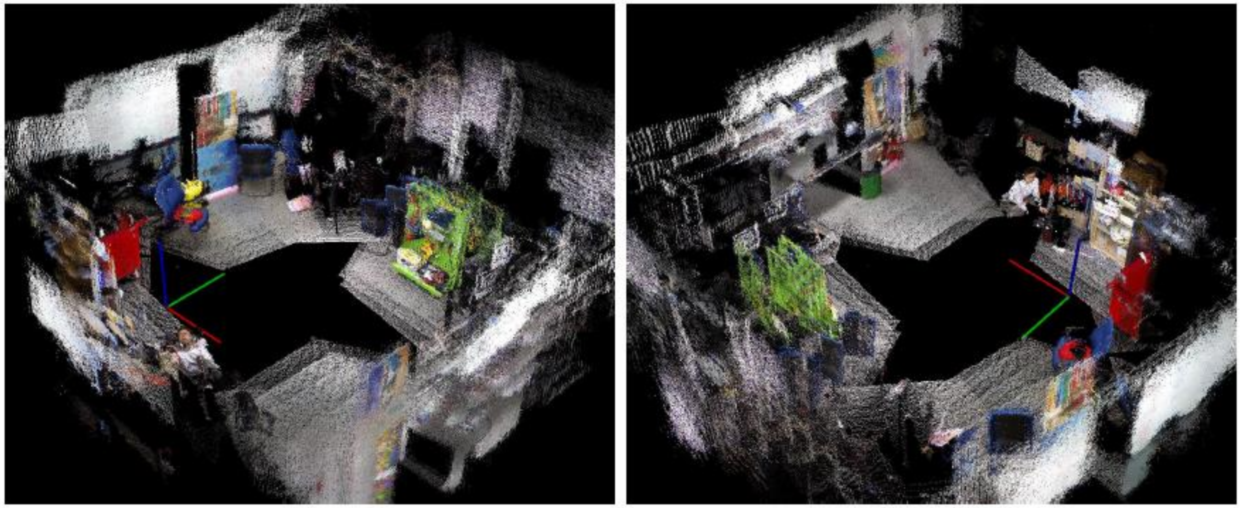
Experiment 1



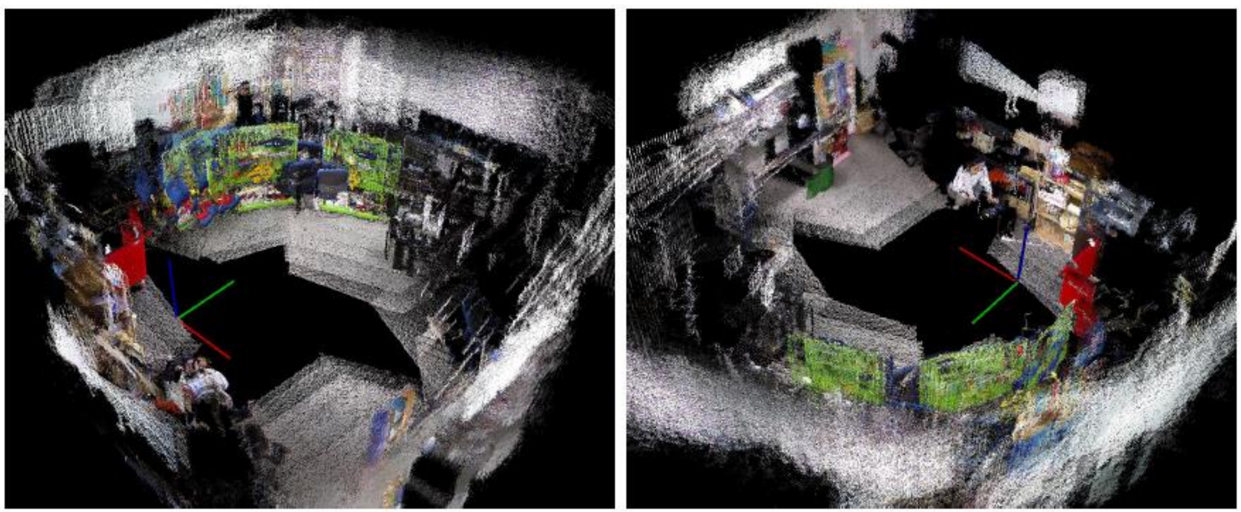
Experiment 2

Experimental Results

- 3D maps (conventional SLAM)



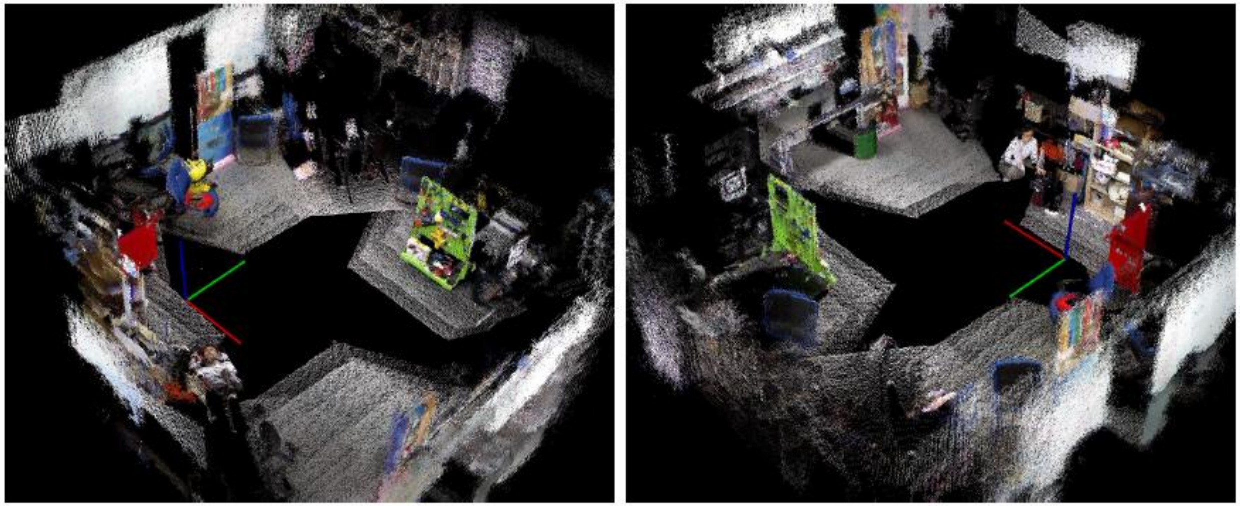
Experiment 1



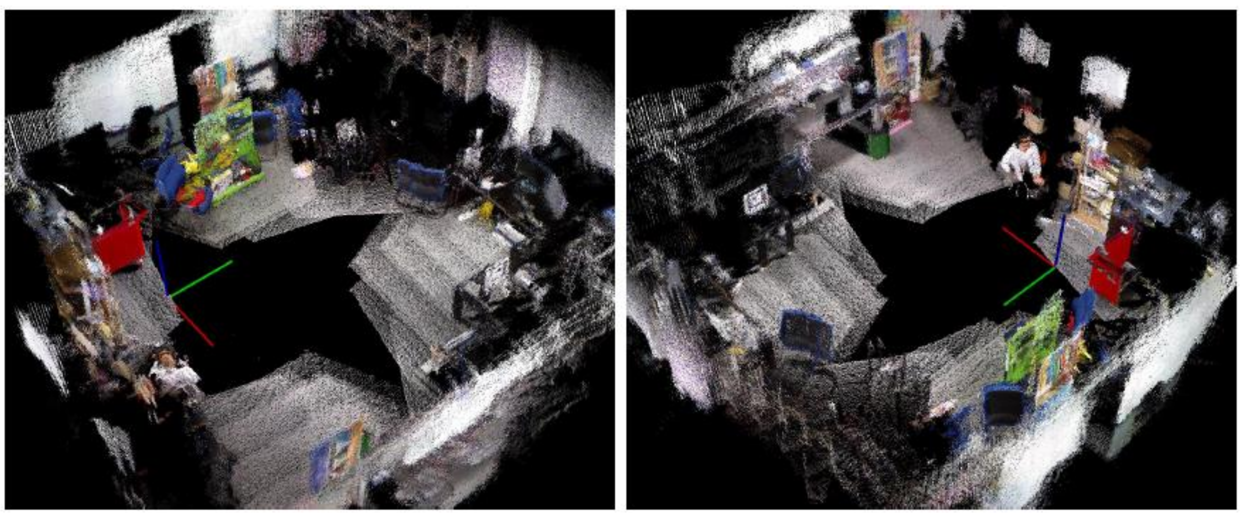
Experiment 2

Experimental Results

- 3D maps (proposed method)



Experiment 1



Experiment 2

Conclusions

- The proposed RGB-D SLAM method handles low dynamic situations using a pose-graph structure.
- Nodes are grouped based on their covariance values and false constraints are pruned based on an error metric.
- The validity of the proposed method was demonstrated by real experiments in low dynamic environments.
- The corrected trajectories of a robot and 3D maps that contained the final appearance of the dynamic object were obtained successfully.
- It is expected that this method will help to improve the performance of graph SLAM in various dynamic environments.