PCR-Pro

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

機器人與多感知實驗室
Robotics & Multi-perception Lab

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381

3D Sparse and Different Scale Point Clouds Registration and Robust Estimation of Information Matrix For Pose Graph SLAM

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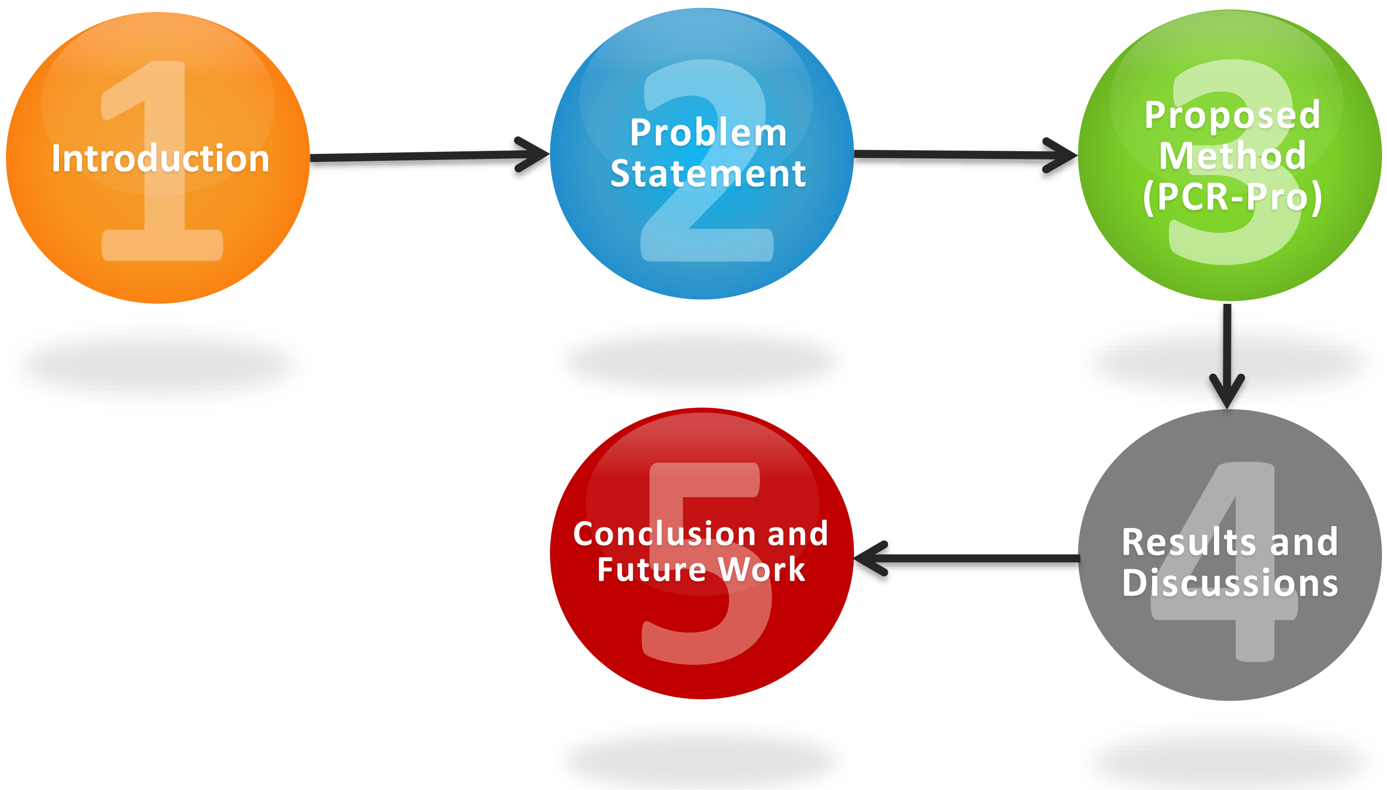
Presentation Plan



An Overview

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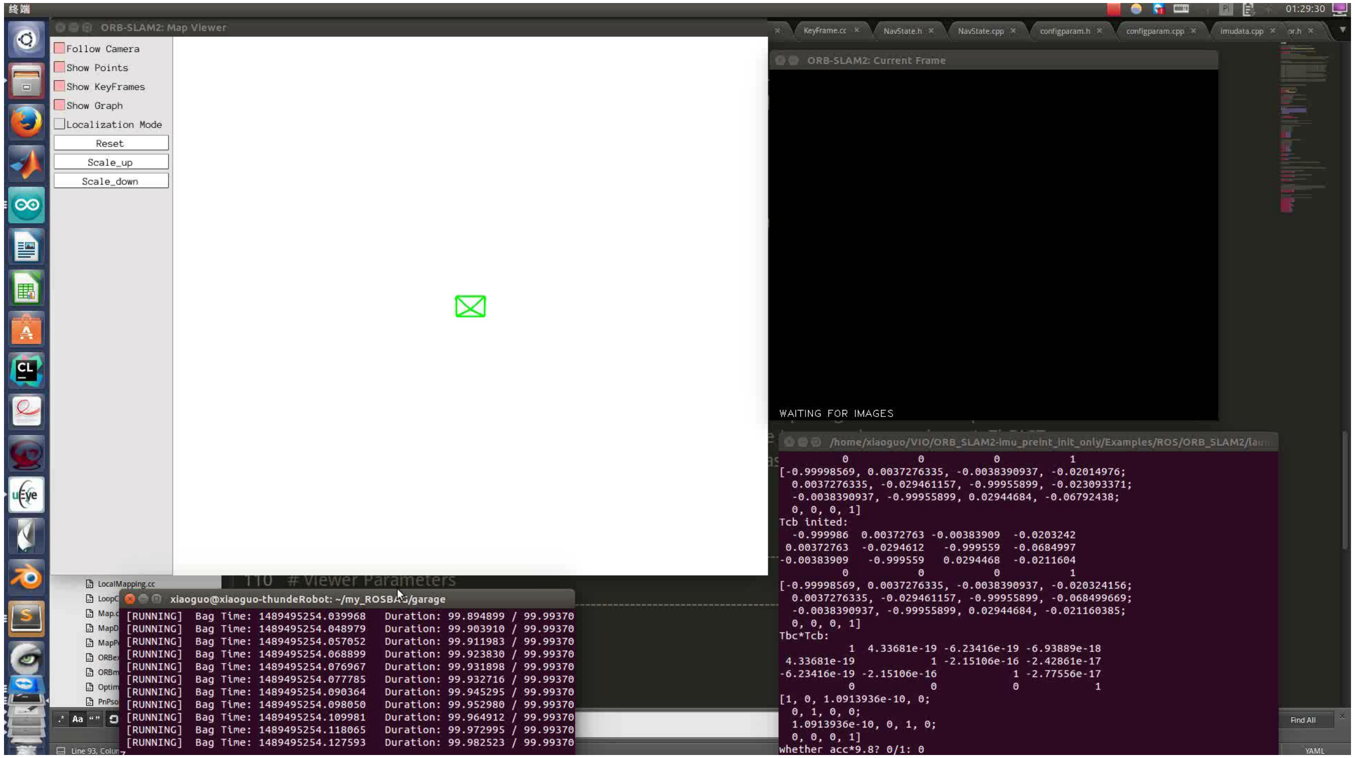
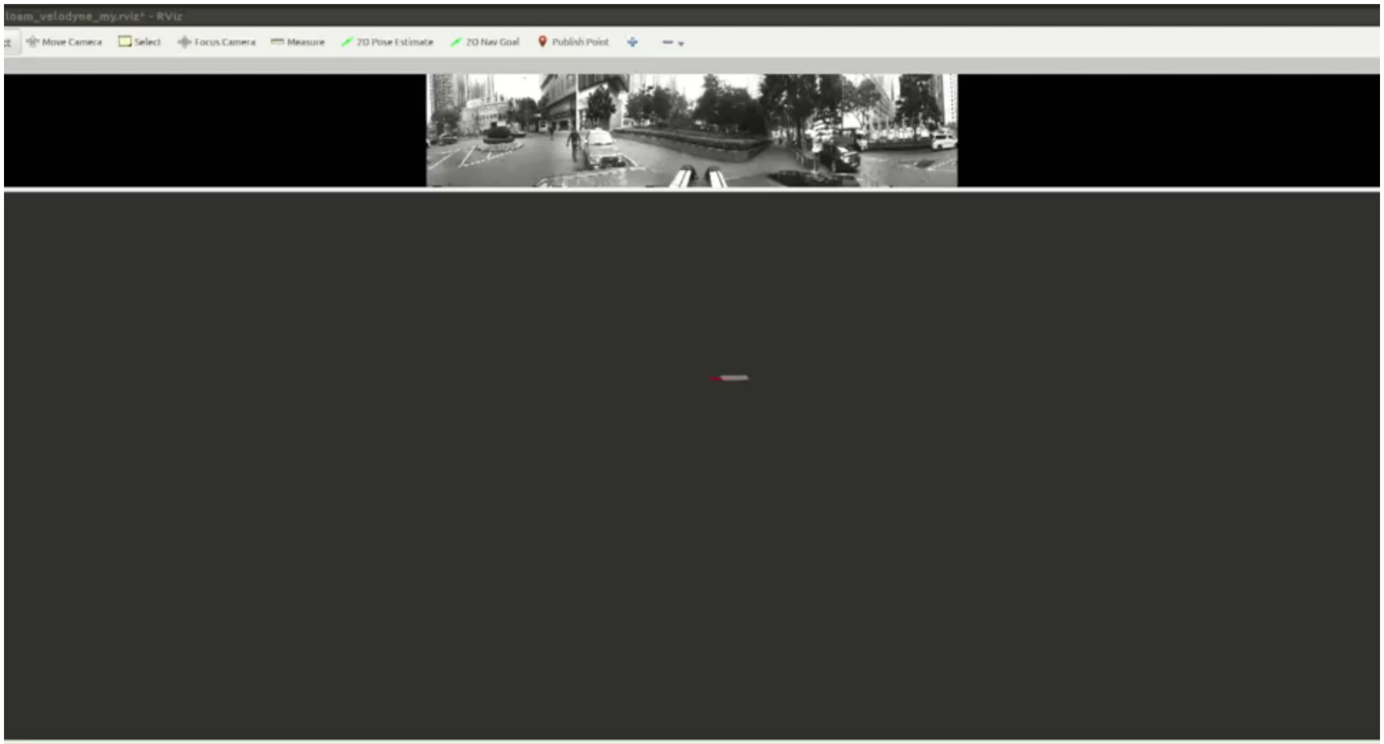
What can vSLAM deliver? [Liu2016a]



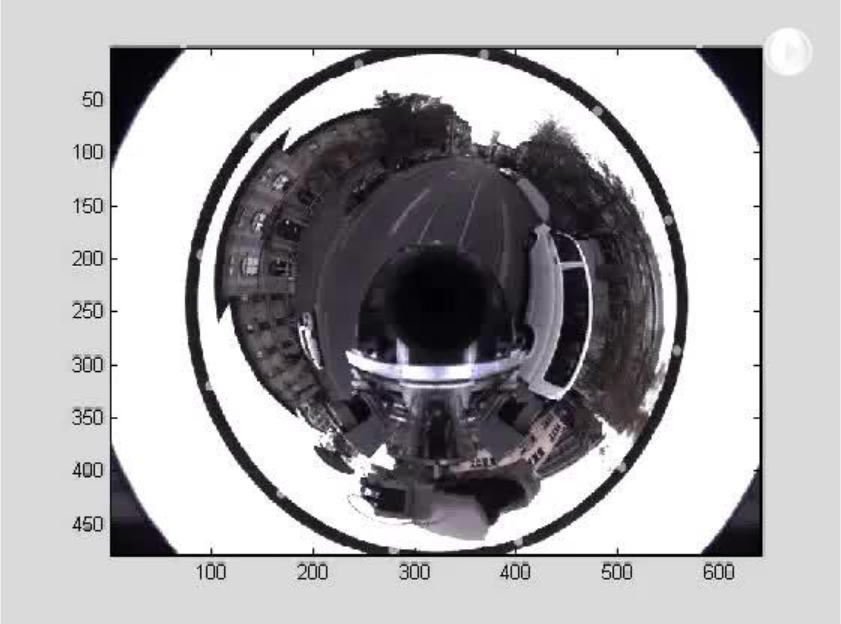
3D Mapping using moving vehicle inside a garage and pose graph SLAM

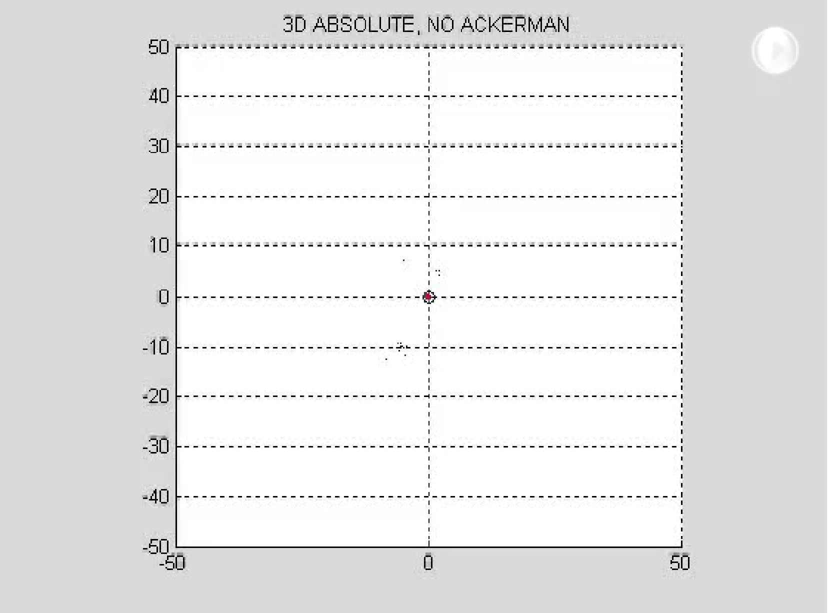
Other possible solutions? [Liu2017a]



Large scale mapping for autonomous cars

Large-scale applications [Scaramuzza,Liu2010]





Another example of visual SLAM using an omni-directional camera

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Collaborative vSLAM [Liu2016b]

TSLAM: Multi-robot SLAM using graph partition and visual scene recognition

Non Linear Pose Graph Optimization

- In graph-based SLAM, the state variables are the state of the robot and position of the landmarks.
- These parameters can be estimated with the sensors of the robot.
- The measurement of state variables depends only on the relative poses of the robots.

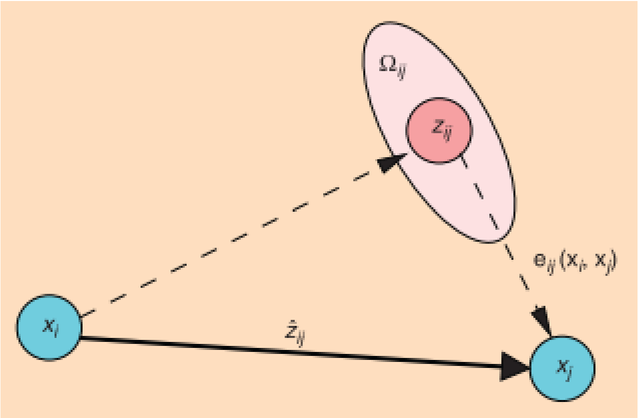


Fig:2 Aspects of an edge connecting the vertex $\mathbf{x}_i$ and the vertex $\mathbf{x}_j$

[1] Giorgio Grisetti, R Kummerle, Cyrill Stachniss, and Wolfram Burgard. A Tutorial on Graph-Based SLAM. IEEE Intell. Transp. Syst. Mag., 2(4):31–43, 2010
[2] Rainer Kummerle, Giorgio Grisetti, Hauke Strasdat, Kurt Konolige, and Wolfram Burgard. G2o: A general framework for graph optimization. In 2011 IEEE Int. Conf. Robot. Autom., pages 3607–3613. IEEE, May 2011.

Multi-Agent SLAM

For each node, we have;

- Key frame,
- Point cloud,
- Pose information.

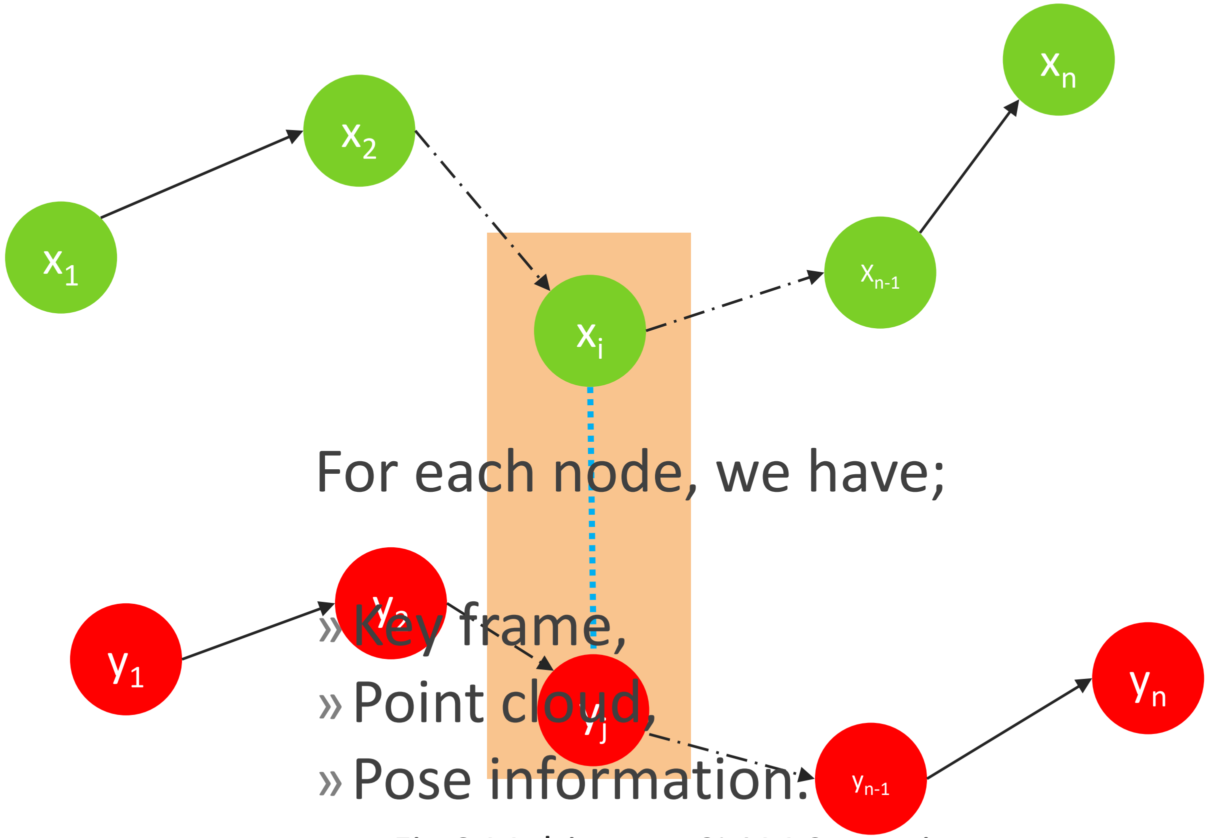
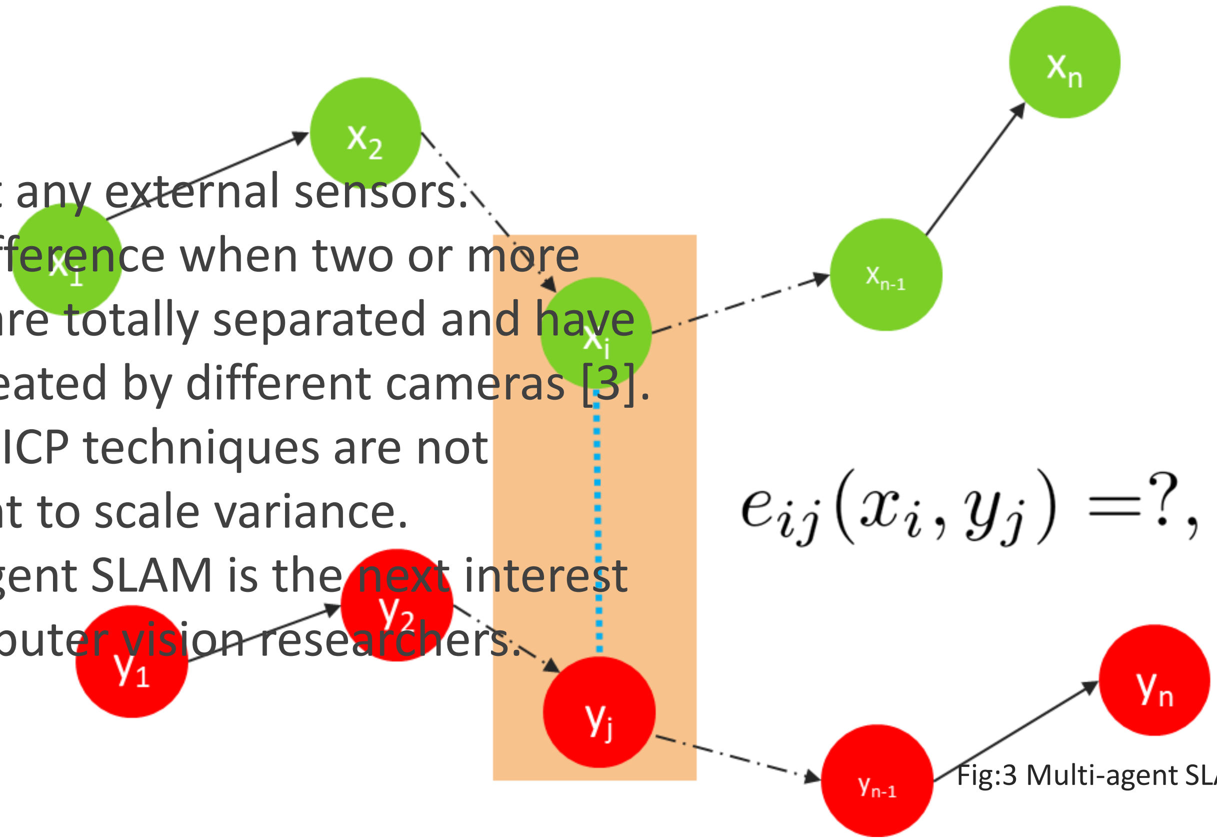


Fig:3 Multi-agent SLAM Scenario

Edge information

- Without any external sensors.
- Scale difference when two or more graphs are totally separated and have been created by different cameras [3].
- Current ICP techniques are not sufficient to scale variance.
- Multi-agent SLAM is the next interest for computer vision researchers.



$$e_{ij}(x_i, y_j) = ?, \Omega_{ij} = ?$$

Fig:3 Multi-agent SLAM Scenario

[3] Jakob Engel, Thomas Schops, and Daniel Cremers. LSD-SLAM: Large-Scale Direct monocular SLAM, volume 8690 LNCS, pages 834– 849. Springer International Publishing, Cham, 2014.

Overview of the proposed system

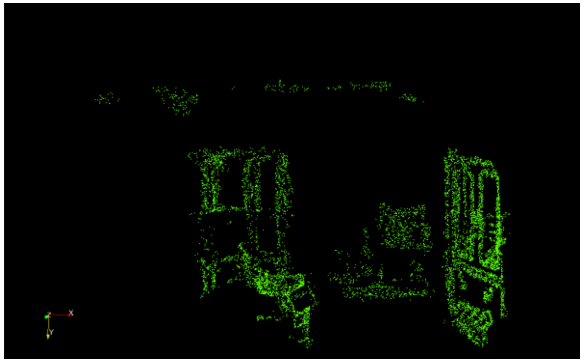


Fig 5: Source Point Cloud

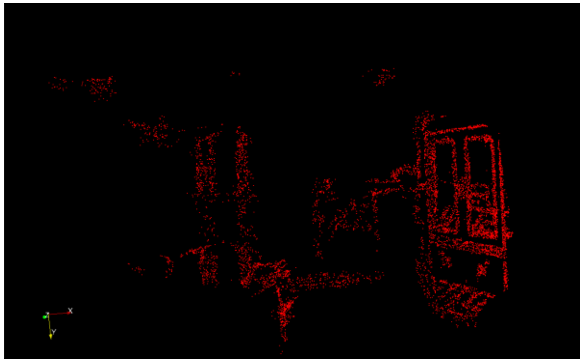


Fig 6: Target Point Cloud

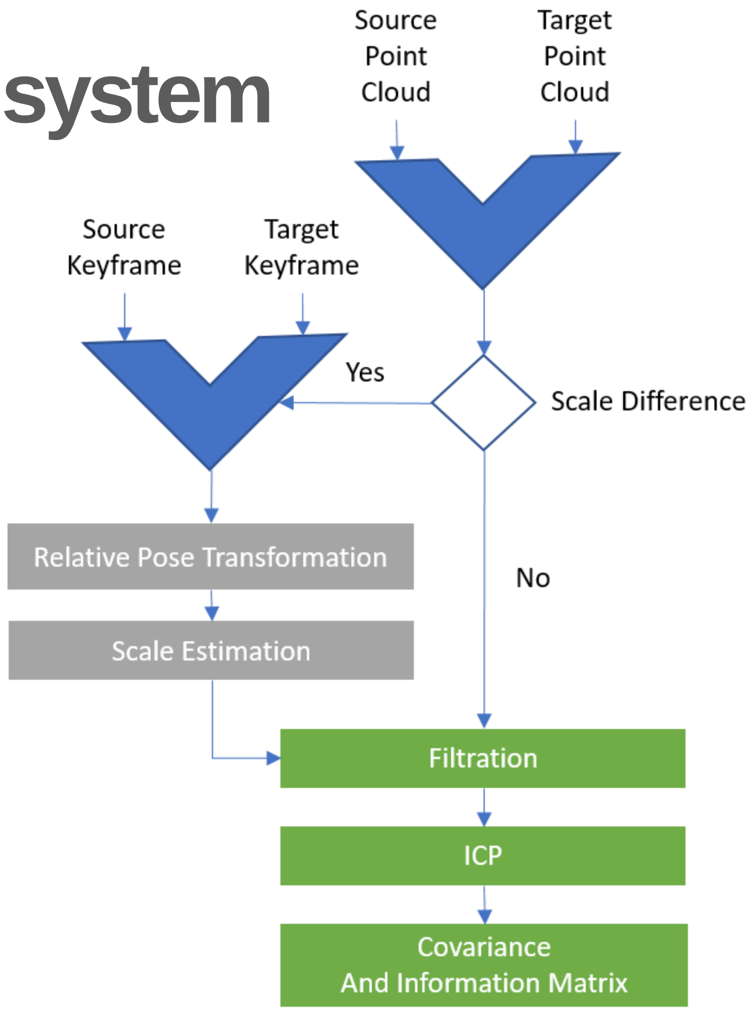


Fig 7: PCR-Pro Overview

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Overview of the proposed system

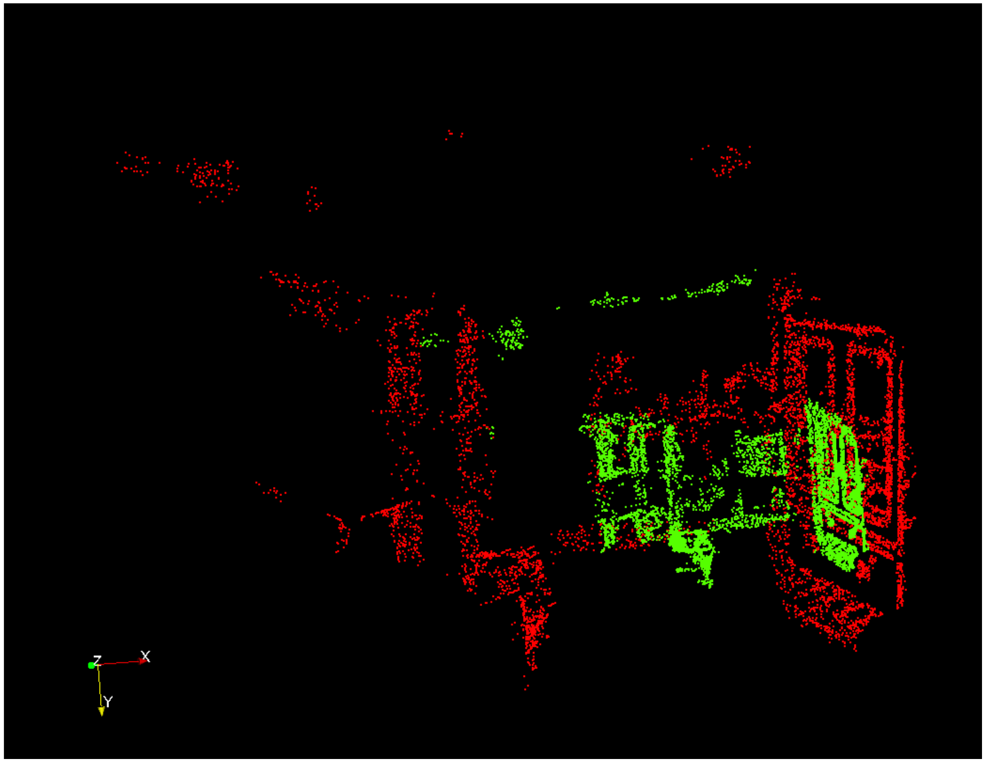
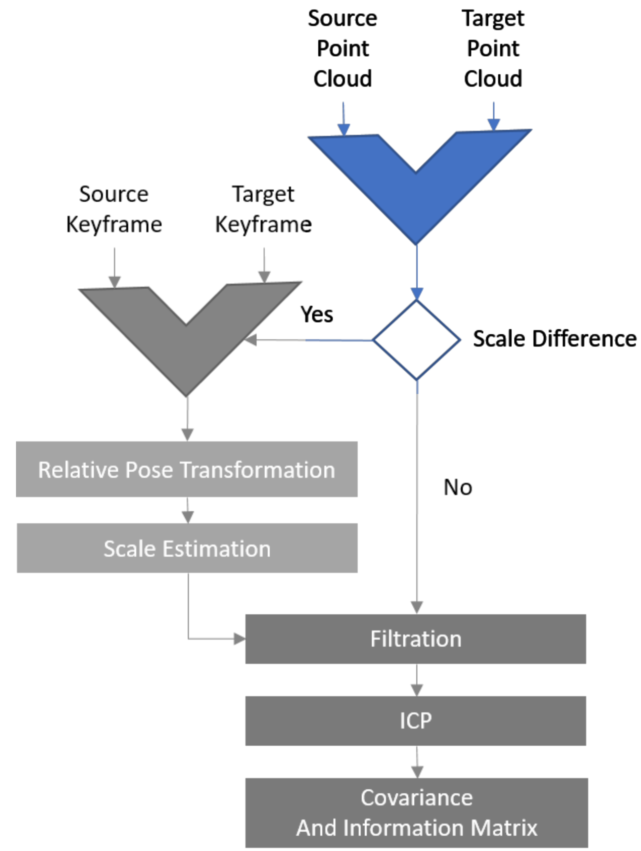
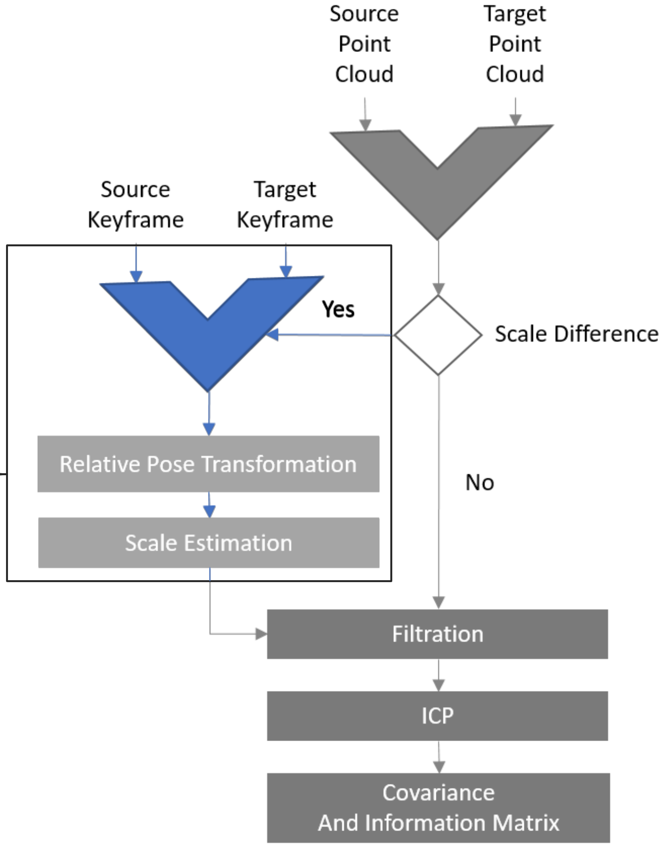


Fig 8: Scale Difference



Scale Estimation

if *scale difference* **then**
- **for** *each keyframe* **do**
  - compute SIFT features and use FlannBased descriptor to find matches
- calculate matches between keyframes;
- **for** *all matches* **do**
  - filter good matches
- **if** *good matches* **then**
  - by using opengv [6], create RANSAC object;
  - set threshold;
  - set max iteration;
  - compute central relative pose OT between keyframes
- **for** *all good matches* **do**
  - compute scale difference SC using kalman filter and relative pose OT
- Transform source point cloud using scale transformation SC;



[6] Laurent Kneip and Paul Furgale. OpenGV: A unified and generalized approach to real-time calibrated geometric vision. In 2014 IEEE Int. Conf. Robot. Autom., pages 1–8. IEEE, May 2014.[

Features Extraction and Matching

Fig 9: Source Keyframe

Fig 10: Target keyframe

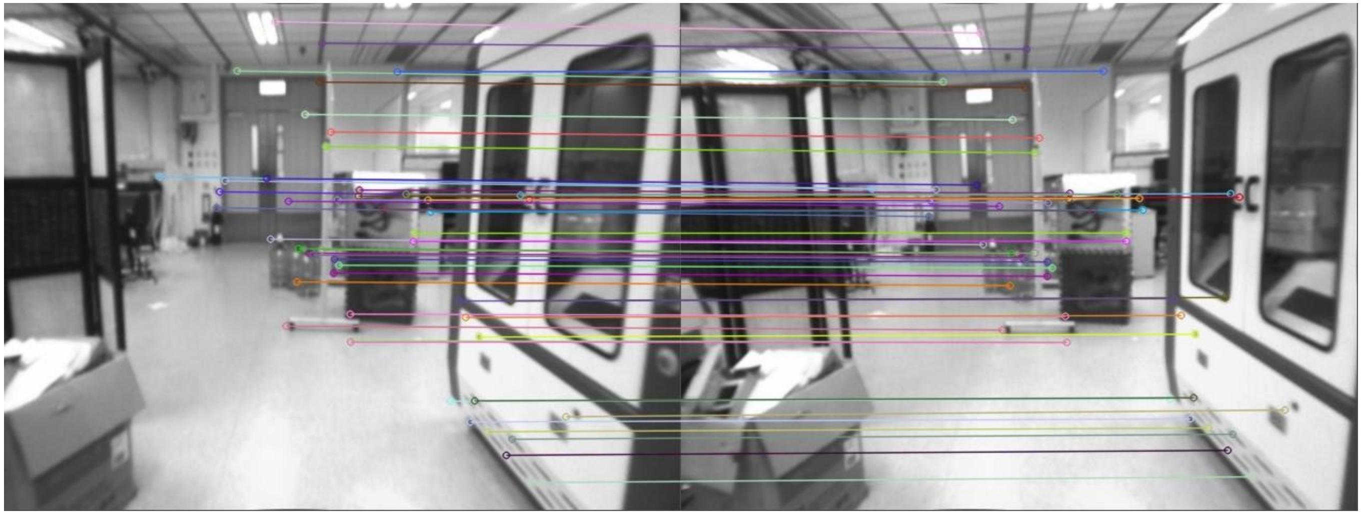


Fig 11: Feature Matches

Scale Estimation And Transformation

» Relative Post Transformation [6].
» Compute Scale Difference using Kalman Filter.
» Align the both point clouds.
» Further filtration of both point clouds.
» Apply Transformation[15].

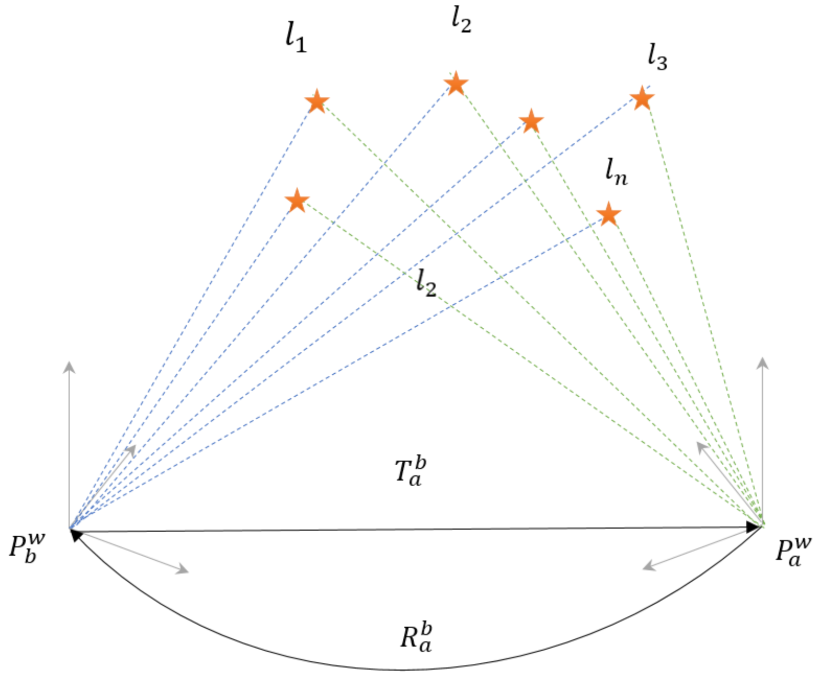


Fig 12: Relative Pose Transformation

[6] Laurent Kneip and Paul Furgale. OpenGV: A unified and generalized approach to real-time calibrated geometric vision. In 2014 IEEE Int. Conf. Robot. Autom., pages 1–8. IEEE, May 2014.
[15] Franc¸ois Pomerleau, St´ephane Magnenat, Francis Colas, Ming Liu, and Roland Siegwart. Tracking a depth camera: Parameter exploration for fast ICP. In 2011 IEEE/RSJ Int. Conf. Intell. Robot. Syst., pages 3824–3829. IEEE, September 2011

Point Cloud Registration

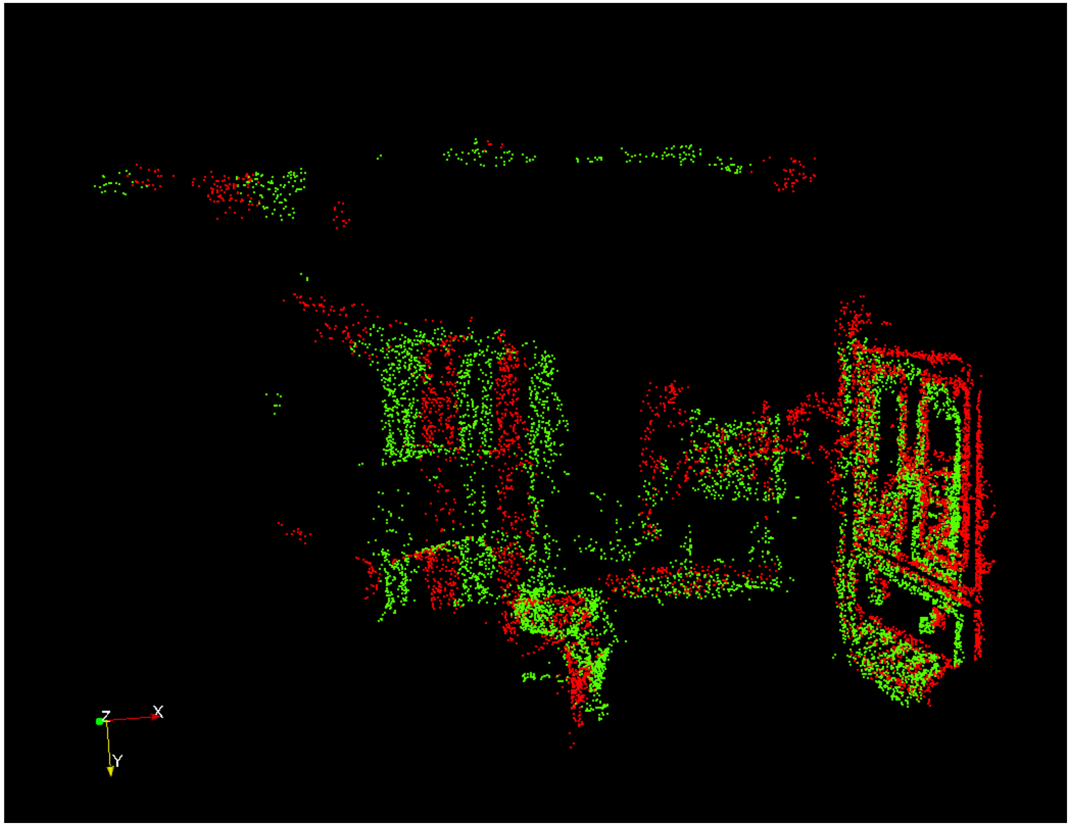


Fig 13: After Applying PCR-Pro

[15] Franc¸ois Pomerleau, St´ephane Magnenat, Francis Colas, Ming Liu, and Roland Siegwart. Tracking a depth camera: Parameter exploration for fast ICP. In 2011 IEEE/RSJ Int. Conf. Intell. Robot. Syst., pages 3824–3829. IEEE, September 2011
[18] Sai Manoj Prakhya, Liu Bingbing, Yan Rui, and Weisi Lin. A closedform estimate of 3D ICP covariance. In 2015 14th IAPR Int. Conf. Mach. Vis. Appl., number 3, pages 526–529. IEEE, May 2015.

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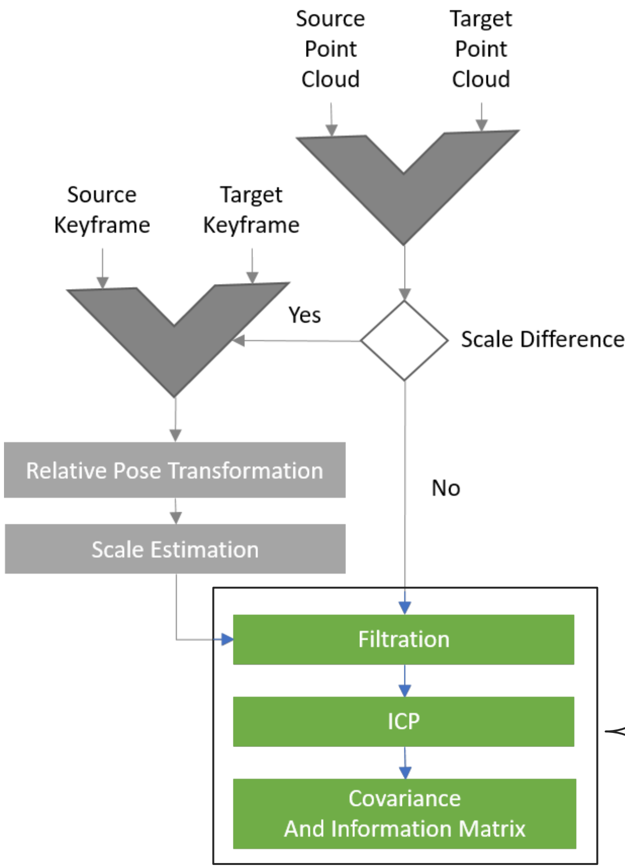
Covariance and Information Matrix



apply filter to crop lower area of source and target point clouds;
Estimate transformation T of filtered source and target point clouds using ICP [15];
Transform original source point cloud using rigid transformation RT will map on the target point cloud;
Now calculate of information matrix;
function 3D ICP Covariance [18] (Source Point Cloud, Target Point Cloud, Final transformation T)
    calculate the covariance using final transformation;
    return 6x6 covariance matrix;
Information Matrix = (covariance matrix)$^{-1}$

[15] Franc¸ois Pomerleau, St´ephane Magnenat, Francis Colas, Ming Liu, and Roland Siegwart. Tracking a depth camera: Parameter exploration for fast ICP. In 2011 IEEE/RSJ Int. Conf. Intell. Robot. Syst., pages 3824–3829. IEEE, September 2011
[18] Sai Manoj Prakhya, Liu Bingbing, Yan Rui, and Weisi Lin. A closedform estimate of 3D ICP covariance. In 2015 14th IAPR Int. Conf. Mach. Vis. Appl., number 3, pages 526–529. IEEE, May 2015.

Covariance and Information Matrix

$$cov(x) \approx \left(\frac{\partial^2 J}{\partial x^2}\right)^{-1} \left(\frac{\partial^2 J}{\partial z \partial x}\right) cov(z) \left(\frac{\partial^2 J}{\partial z \partial x}\right)^{T} \left(\frac{\partial^2 J}{\partial x^2}\right)^{-1}, \quad (1)$$

where $\left(\frac{\partial^2 J}{\partial x^2}\right) = \sum_{i=1}^{n} \left(\frac{\partial^2 J_i}{\partial x^2}\right).$

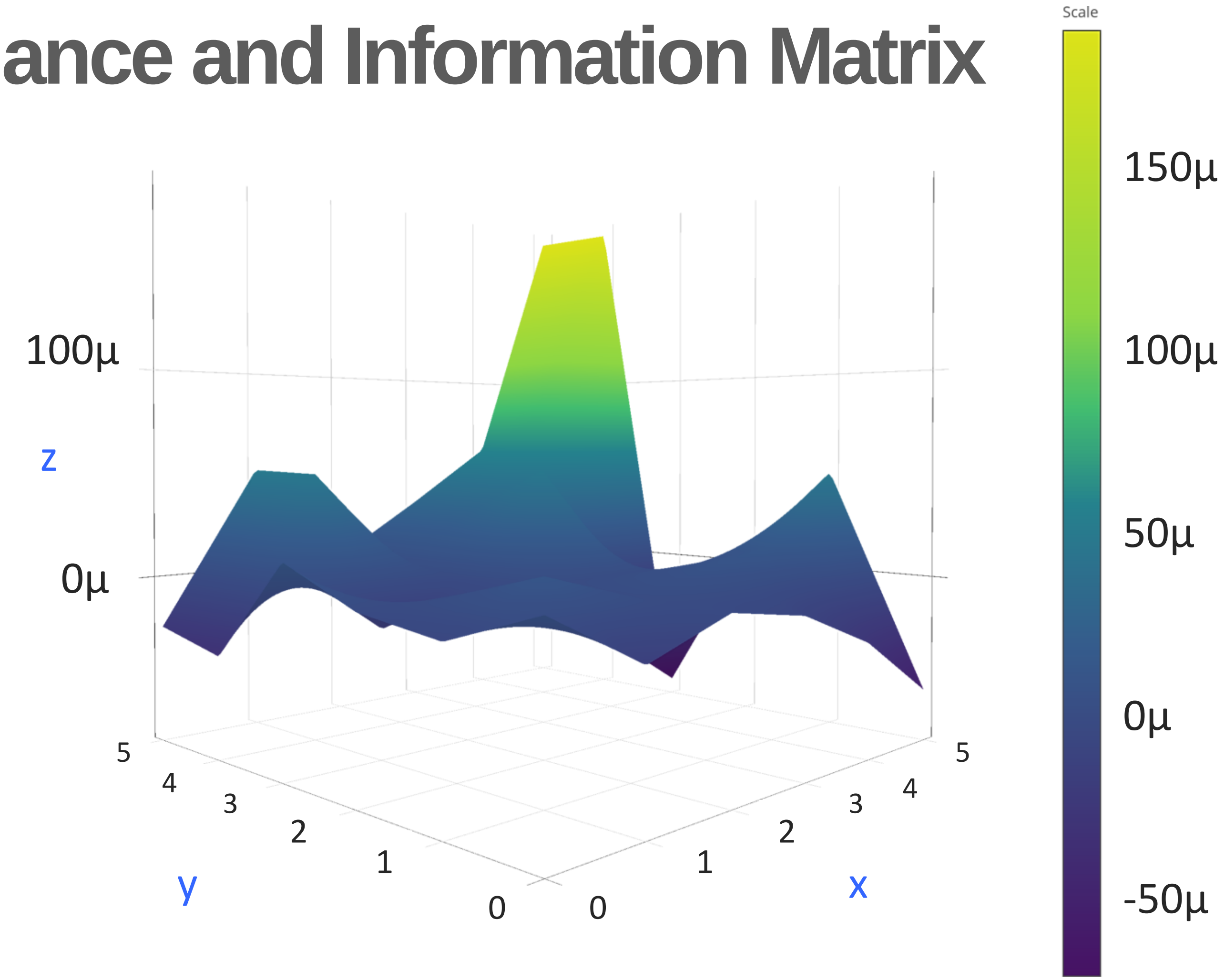
Objective Function:

$$J = \text{minimize} \sum_{i=1}^{n} F^2, \quad (2)$$

where $\mathrm{F} = \parallel G \parallel$, and $G = RP_i + T - Q_i.$

[3] Andrea Censi. An accurate closed-form estimate of ICP's covariance. In Proc. 2007 IEEE Int. Conf. Robot. Autom., pages 3167–3172. IEEE, April 2007
[18] Sai Manoj Prakhya, Liu Bingbing, Yan Rui, and Weisi Lin. A closedform estimate of 3D ICP covariance. In 2015 14th IAPR Int. Conf. Mach. Vis. Appl., number 3, pages 526–529. IEEE, May 2015.

Covariance and Information Matrix



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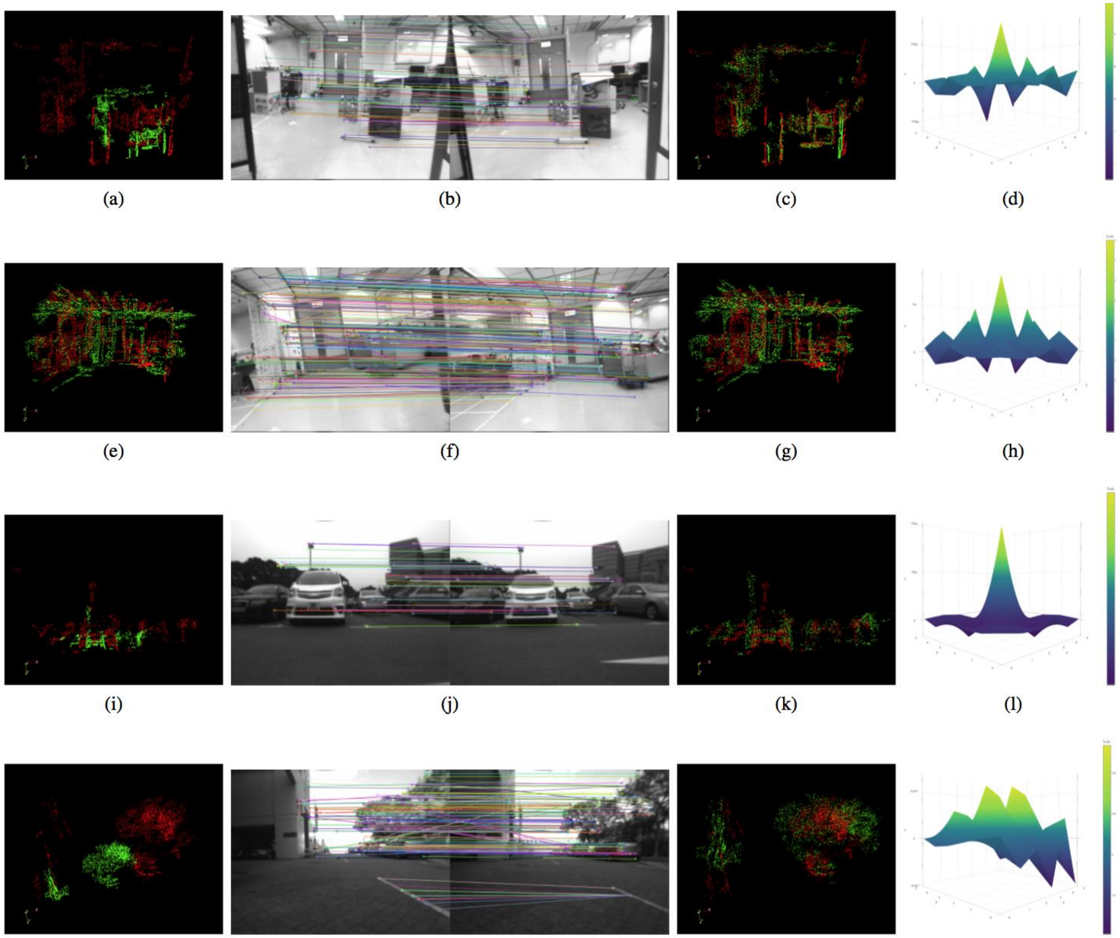
Testing and Results

Indoor and outdoor scenarios;

- » Keyframe matching
- » Point cloud registration
- » Estimated covariance



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)
(m) (n) (o) (p)

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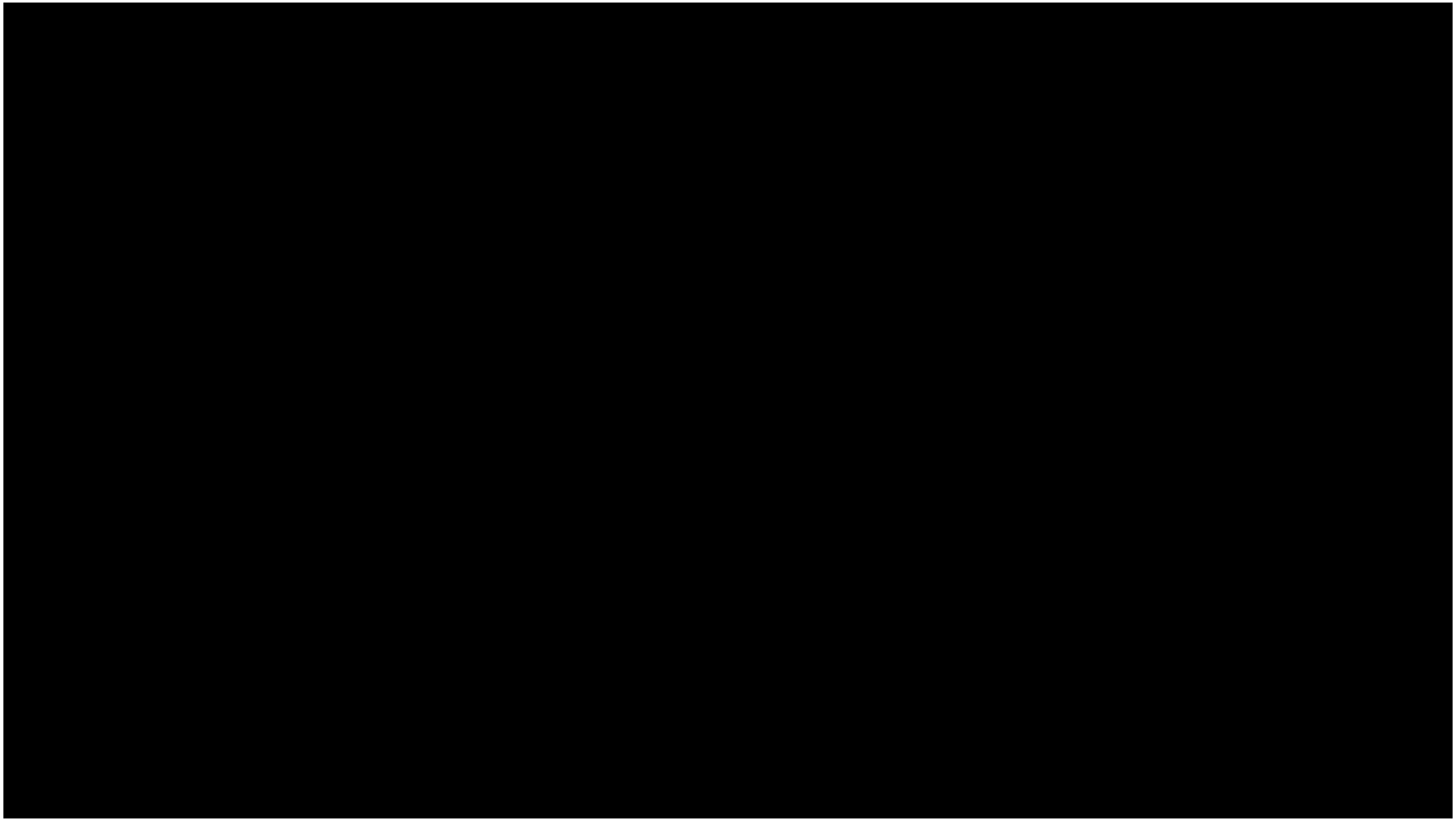
Testing and Results



Available at YouTube: https://www.youtube.com/watch?v=jVjiV6BOH10

Conclusion and Future Work

- PCR-Pro is a robust method to find an accurate transformation between point-clouds with variant scales.
- The covariance is very small as system converges to a global minimum.
- We developed a way of using direct SLAM approaches for multi-agent SLAM systems.
- Real time multi-agent SLAM systems in large-scale can be envisaged and will be presented next year.

For Collaborations:

» Multi-Agent SLAM Systems
» Autonomous Cars / Boats
» Startups

» Lisee Technologies – lisee.io

LISEE

» DaLocation – dalocation.com

DALOCATION

Wechat: **MUsmanMBhutta**

» Slides will be available at **usmanmaqbool.github.io**
» Cell: **+852-6843-2892**

Any Question

Thank you