ETH zürich

Improving Scalability of Bundle Adjustment

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Master Thesis

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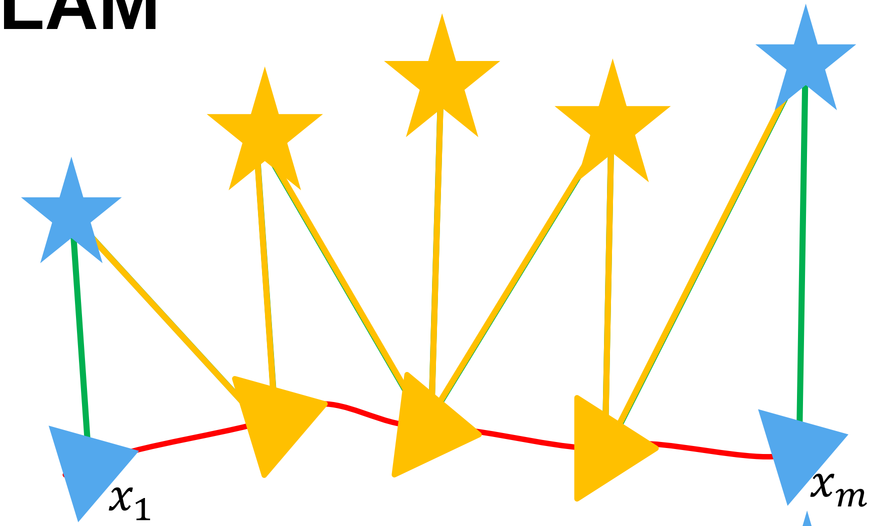
Agenda

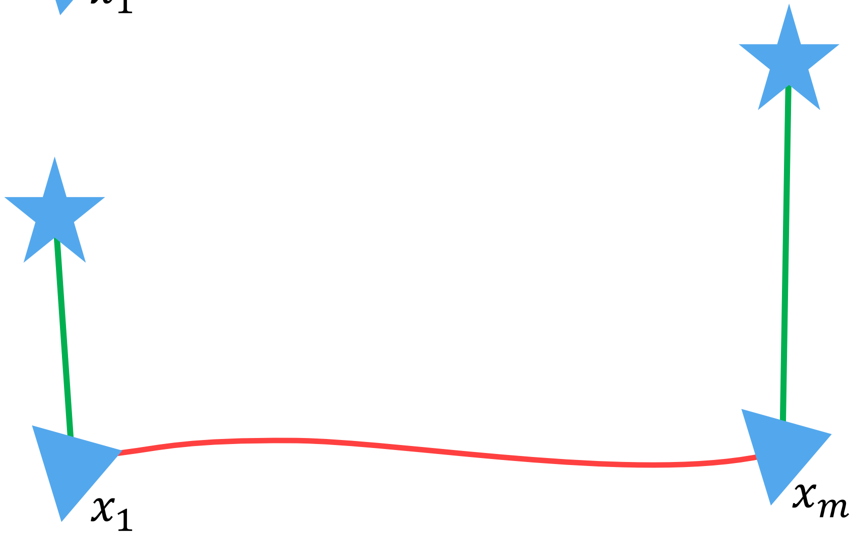
- Bundle Adjustment
  - Motivation
  - Keyframing
- CKLAM
  - Formulation
  - Sparsity
  - Results
- R-CKLAM
  - Formulation
  - Results

Bundle Adjustment in SLAM

- $argmin_{x,f}(\sum C_{IMU} + \sum C_{visual})$



- Exclude redundant information



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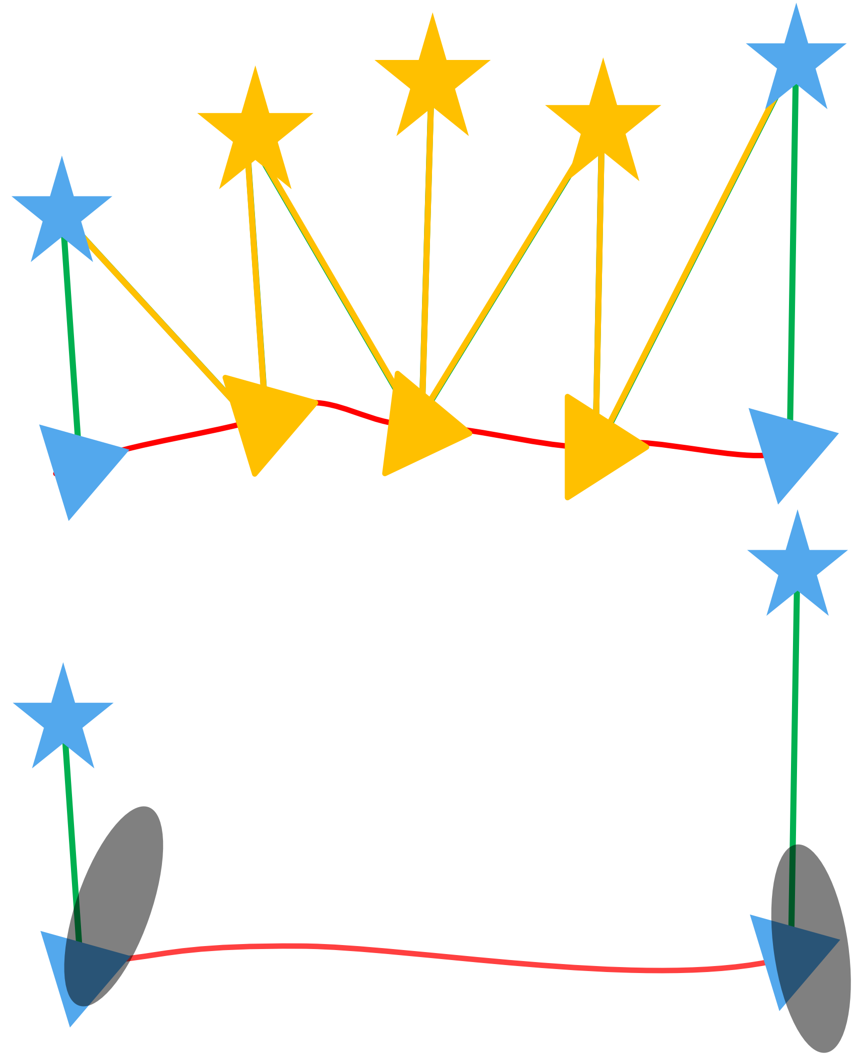
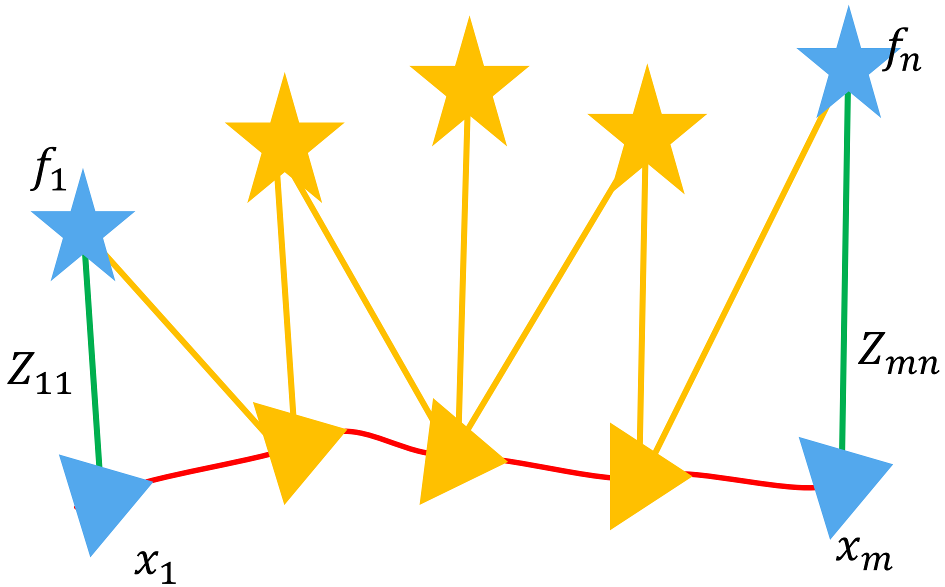
Constrained Keyframe-Based Localization and Mapping (CKLAM)

- Removal of Non-keyframes → Loss of information

- CKLAM → Preserve information as much as possible



CKLAM Formulation



- $C = C_P(x_1; \hat{x}_{1|1}) + C_0(x_1, f_1; Z_{11}) + C_0(x_m, f_n; Z_{mn}) + \sum_{i=0}^{3} C_M(x_{i+1}, x_i; u_i) + \sum_z C_o(x_i, f_j; z_{ij})$
- Quadratize cost $C_2 = f(a_2)$ and project on $C_1 = f(a_1)$

[1]

CKLAM Objective Simplified

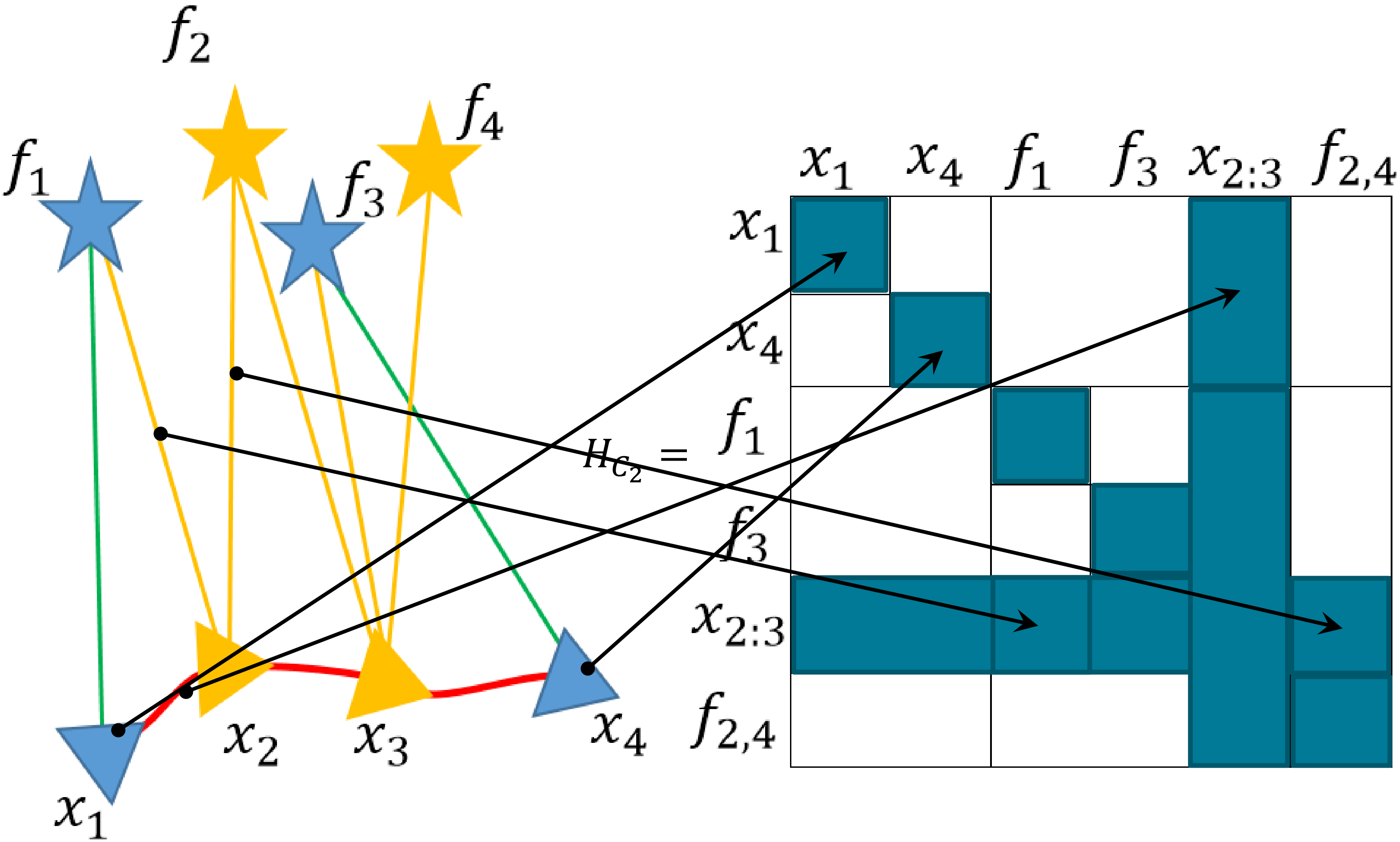
- Have $C_2 = f(a_1, a_2)$ need $C_{new} = f_{new}(a_1)$
  - Such that $argmin_{a_1,a_2}(C_2) \approx argmin_{a_1}(C_{new})$

- Quadratization
  - $C_2 = \frac{1}{2}\begin{bmatrix} a_1 \\ a_2 \end{bmatrix}^T H \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + g^T \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \alpha$

- $C_{NEW} = a_1^T H_{new} a_1 + g_{new}$

  where $H_{new} = (H_{11} - H_{12} H_{22}^{-1} H_{21})$ and $g_{new} = (g_1 - H_{11} H_{22}^{-1} g_2)$

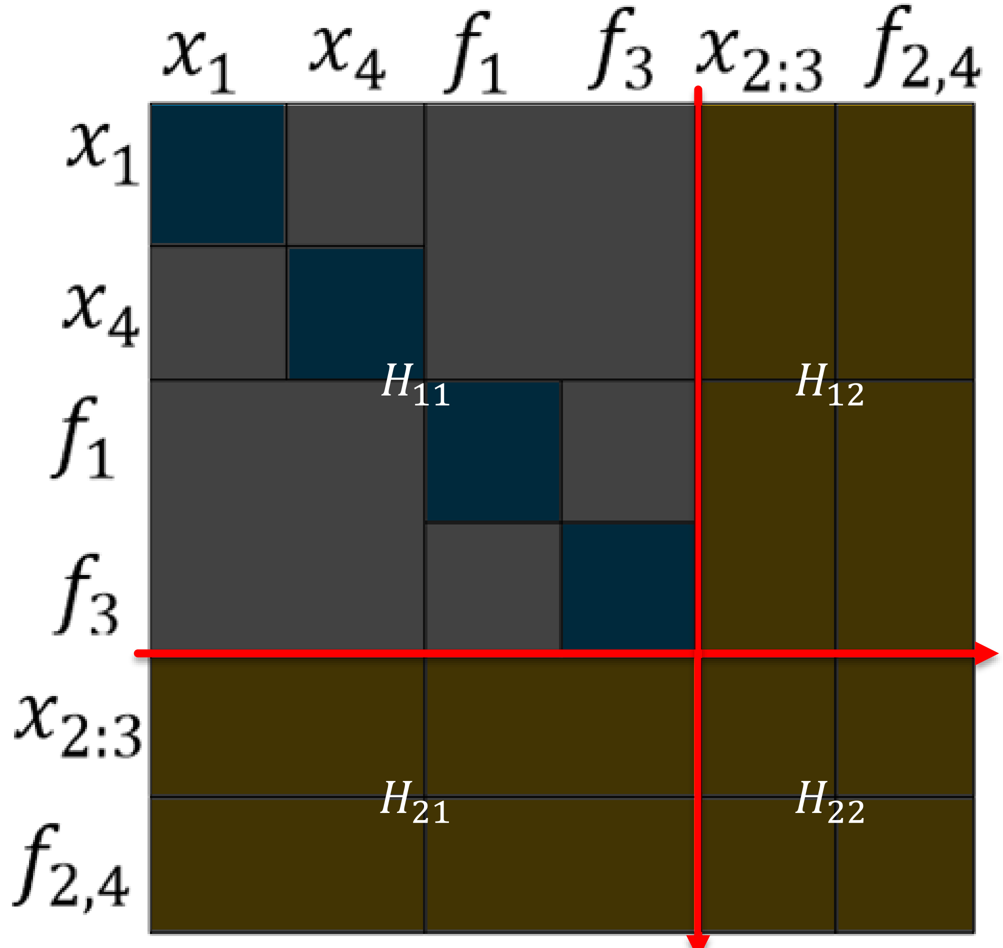
Hessian Matrix for Bundle Adjustment



CKLAM Sparsity

- Cross terms between f_1 and f_5 are created

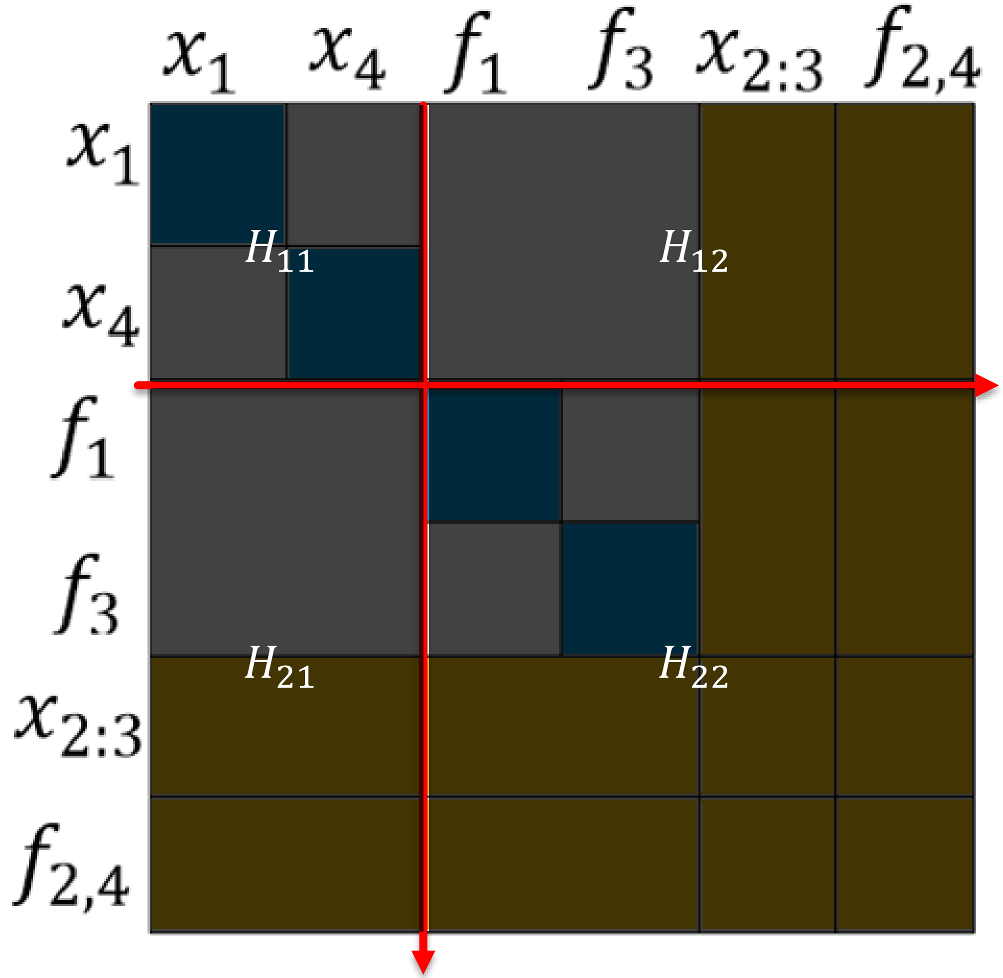
$H_{C_2} =$



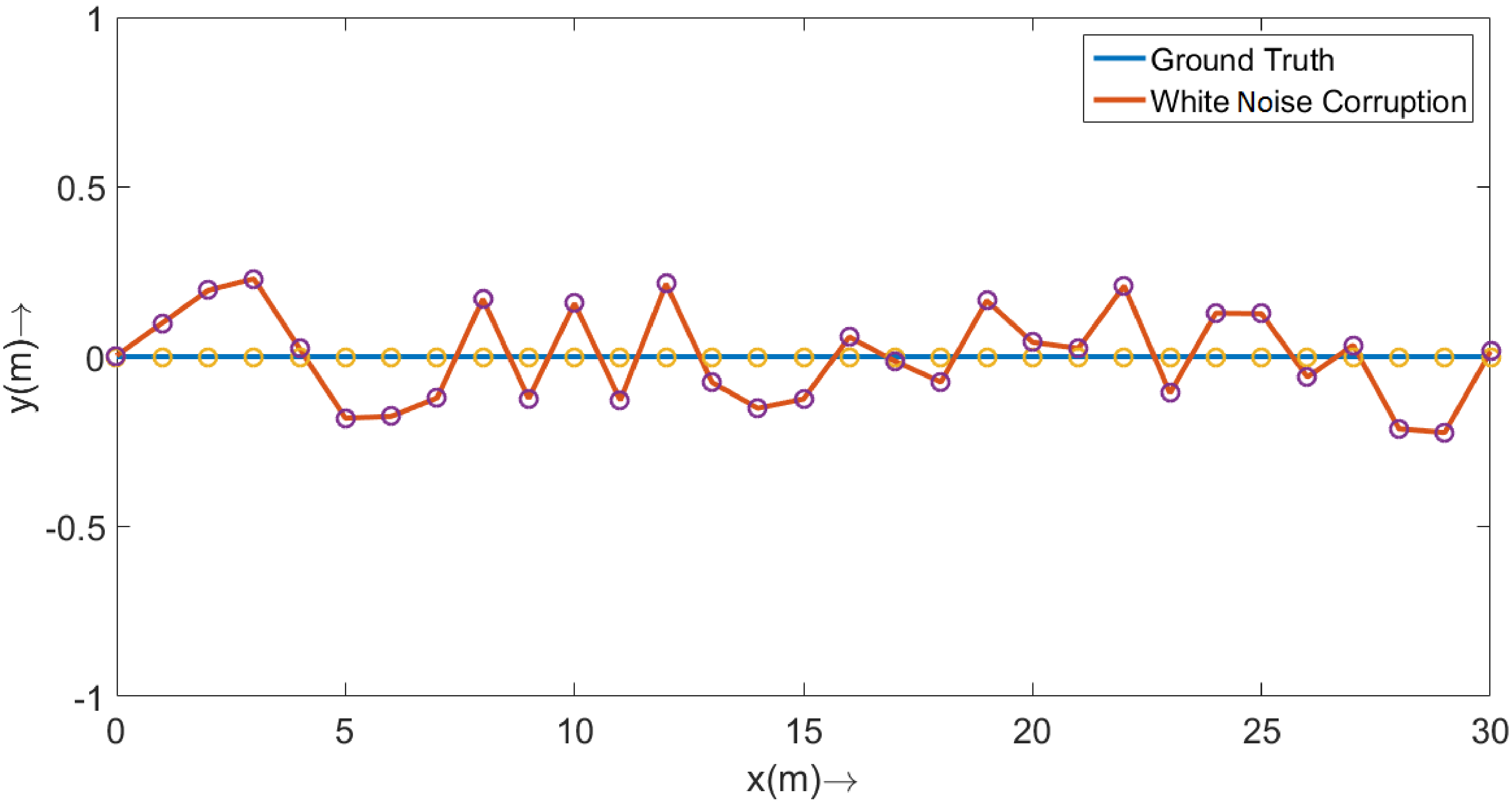
CKLAM Sparsity

- No cross dependency between f_1 and f_5

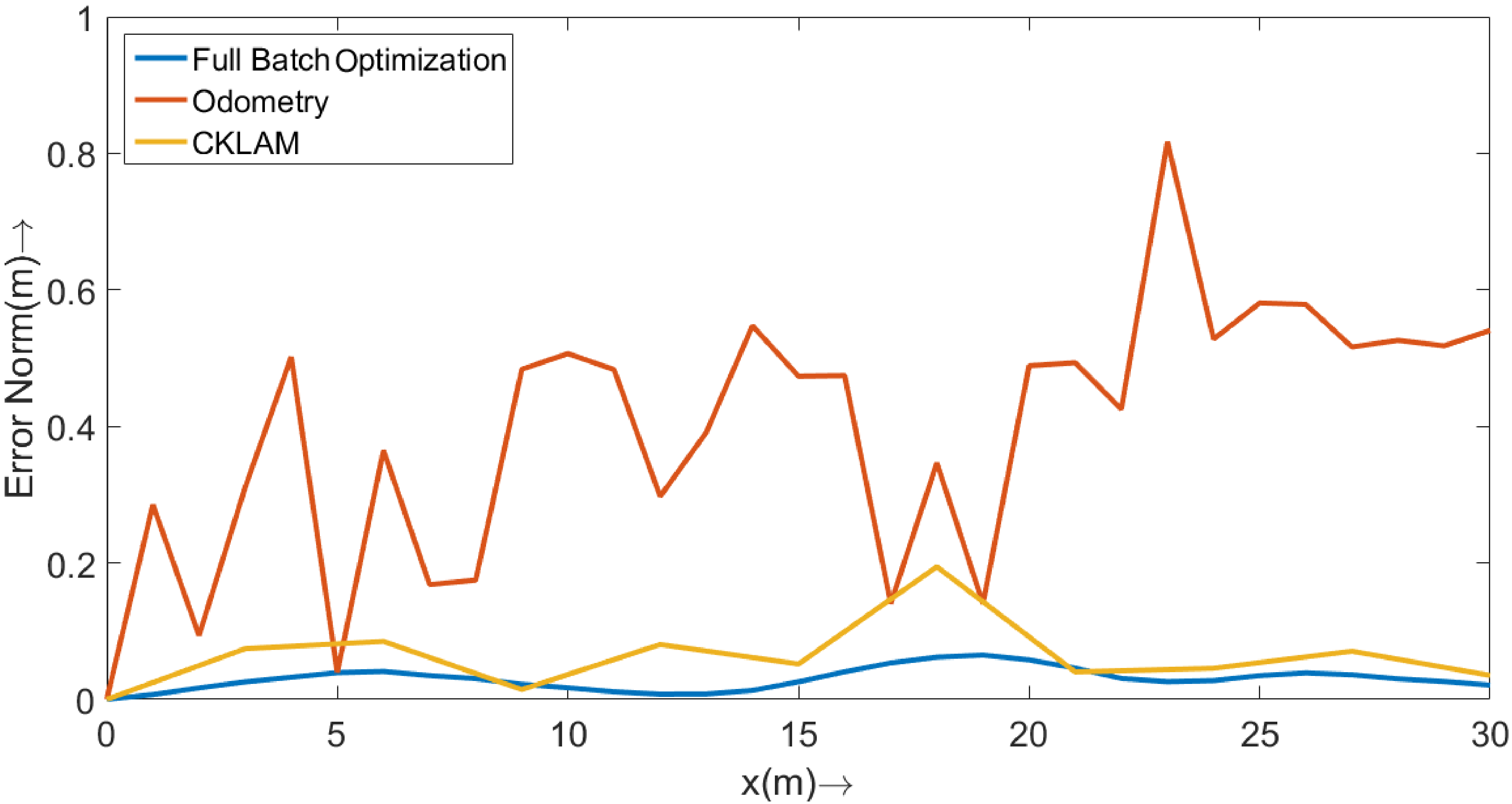
$$H_{C_2} =$$



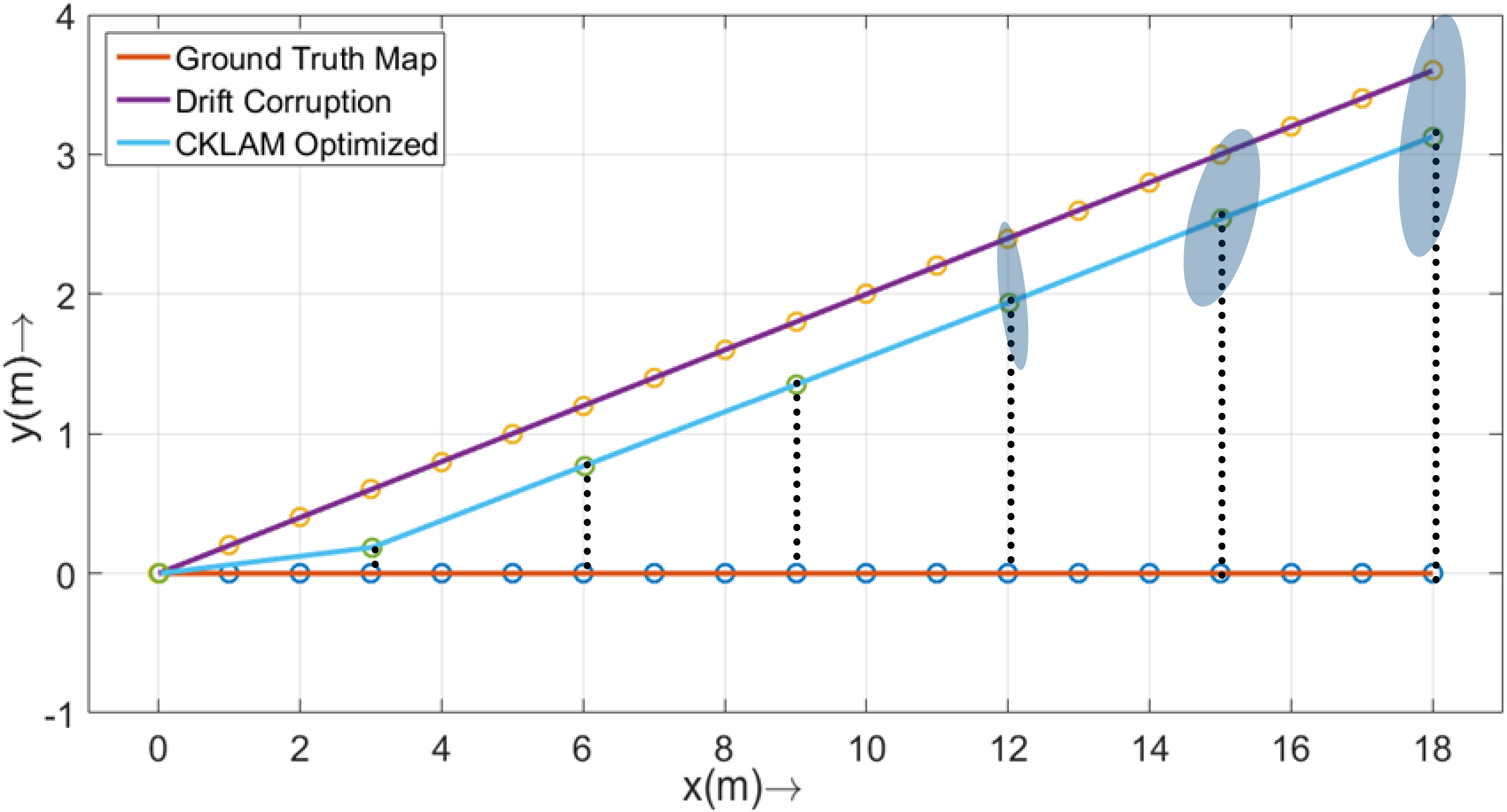
CKLAM Results (Simulated Map)



CKLAM vs Bundle Adjustment



CKLAM Results



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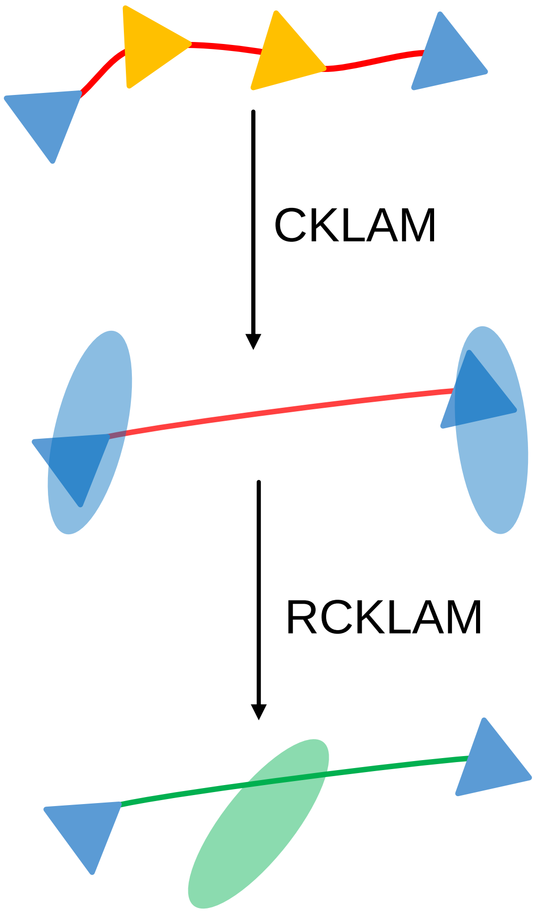
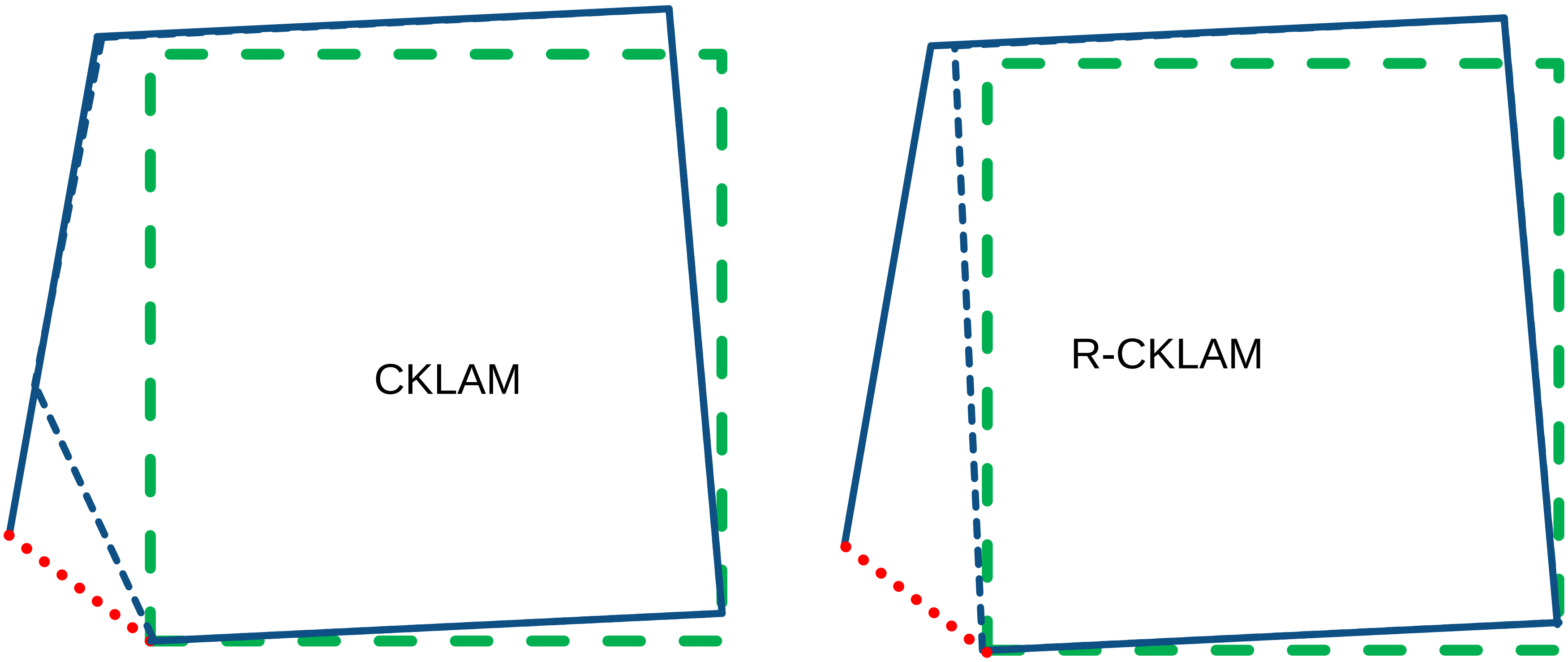
Relative CKLAM (RCKLAM) Motivation

- Modeling integrated error as absolute Gaussian is unnatural
- No substantial changes of individual vertices
- Hard to move local information to global frame



Model uncertainty of relative pose between consecutive key frames

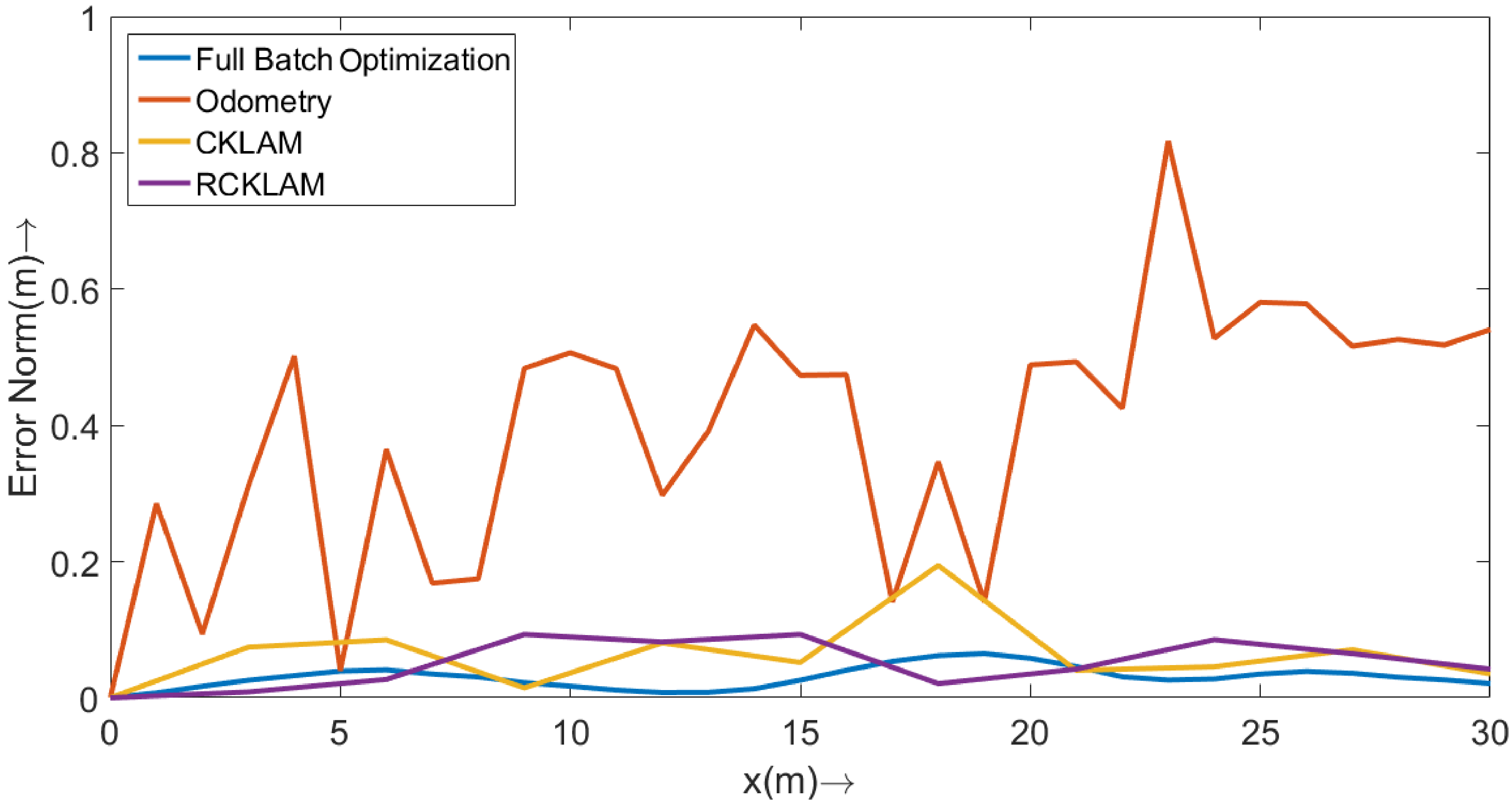
R-CKLAM vs CKLAM



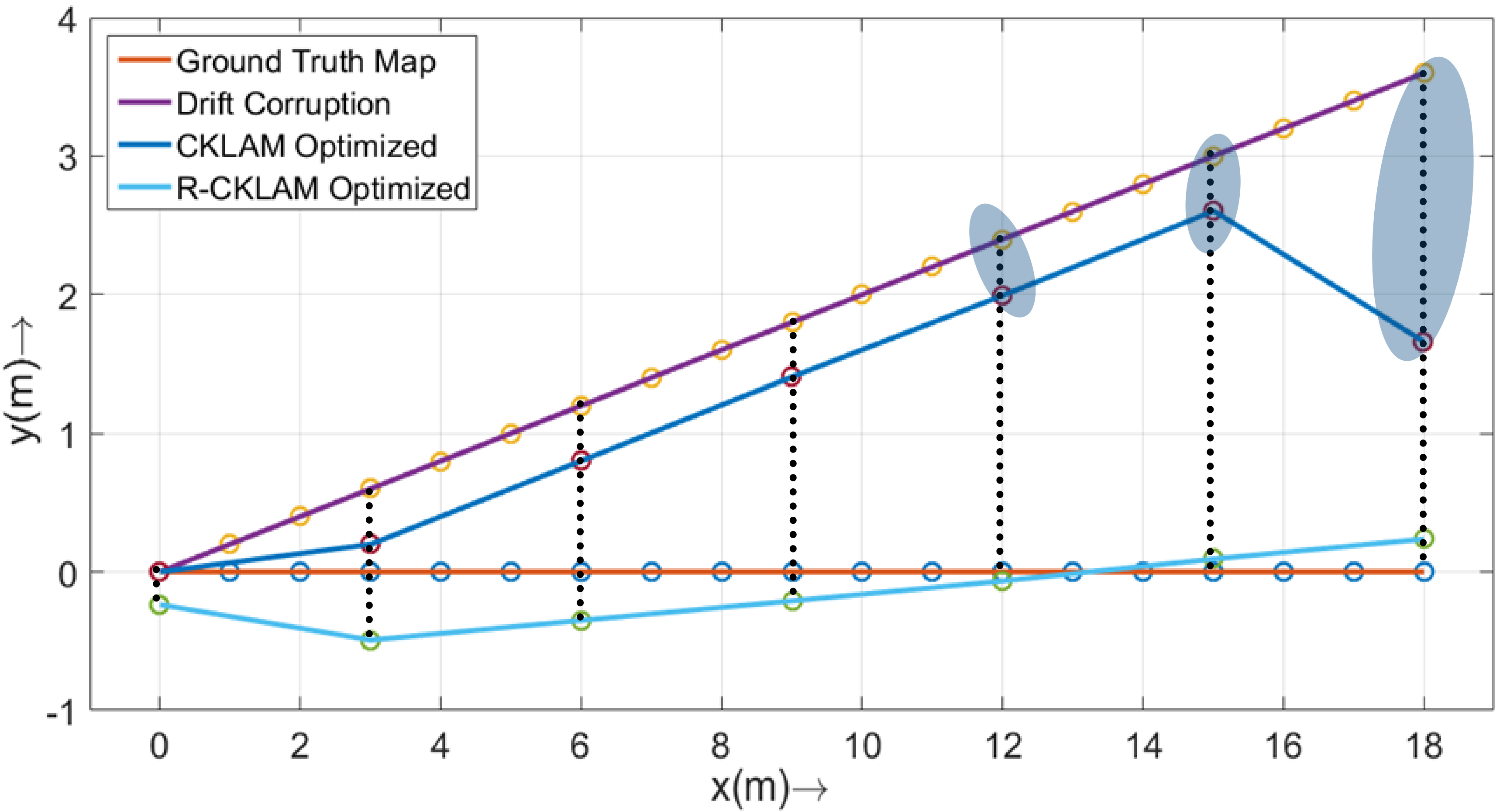
RCKLAM Formulation

- $C_{CKLAM} = f\left(T_{GB_1}, T_{GB_2}\right) \rightarrow \; C_{RCKLAM} = g(T_{B_1 B_2})$
  - $T_{B_1 B_2} = T_{GB_1}^{-1} T_{GB_2}$
- Linearize $T_{B_1 B_2}$
- $H = \begin{bmatrix} J_1 & J_2 \\ 0 & 1 \end{bmatrix}^T H' \begin{bmatrix} J_1 & J_2 \\ 0 & 1 \end{bmatrix}$

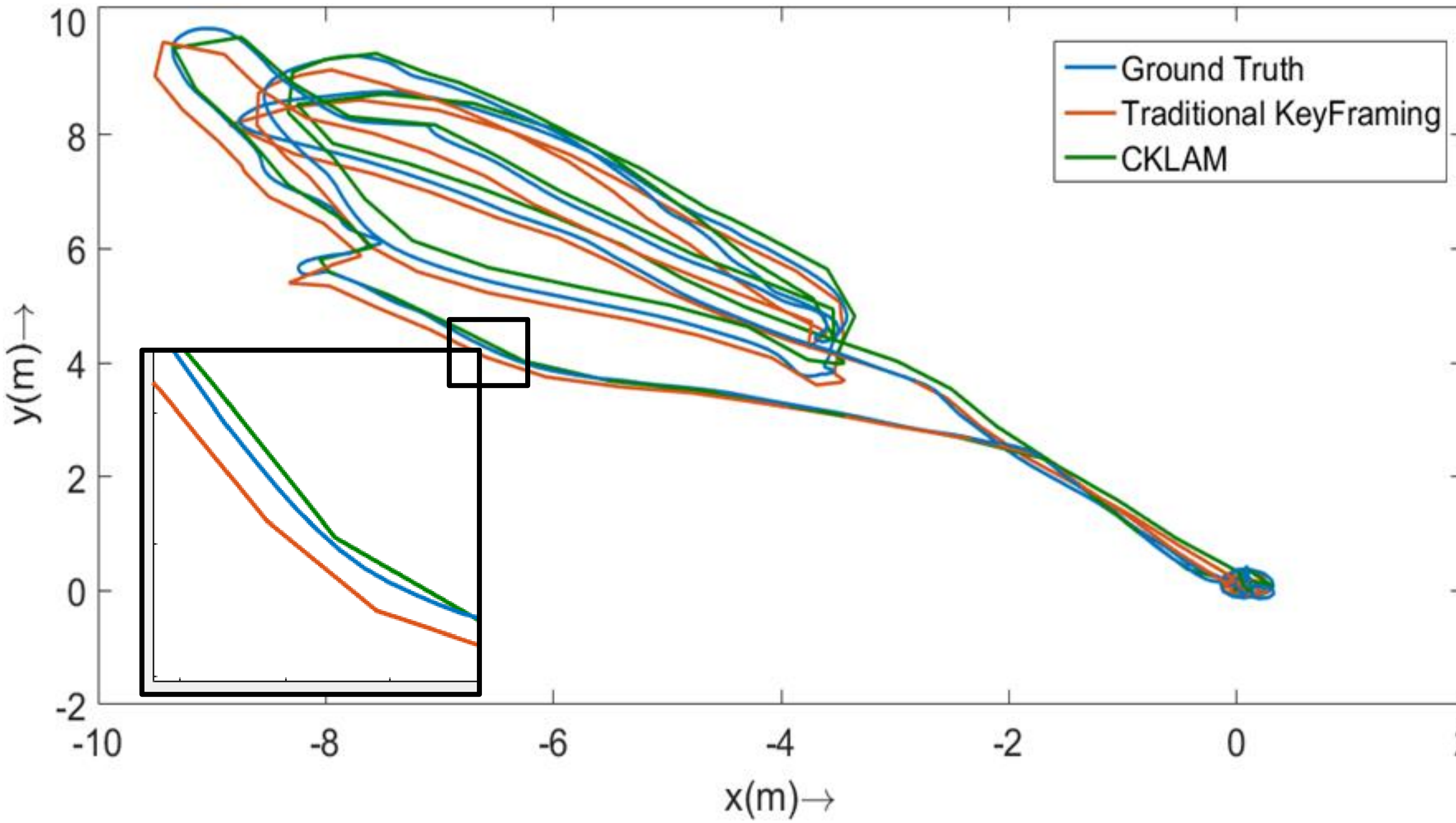
RCKLAM vs CKLAM (Simulated Map)



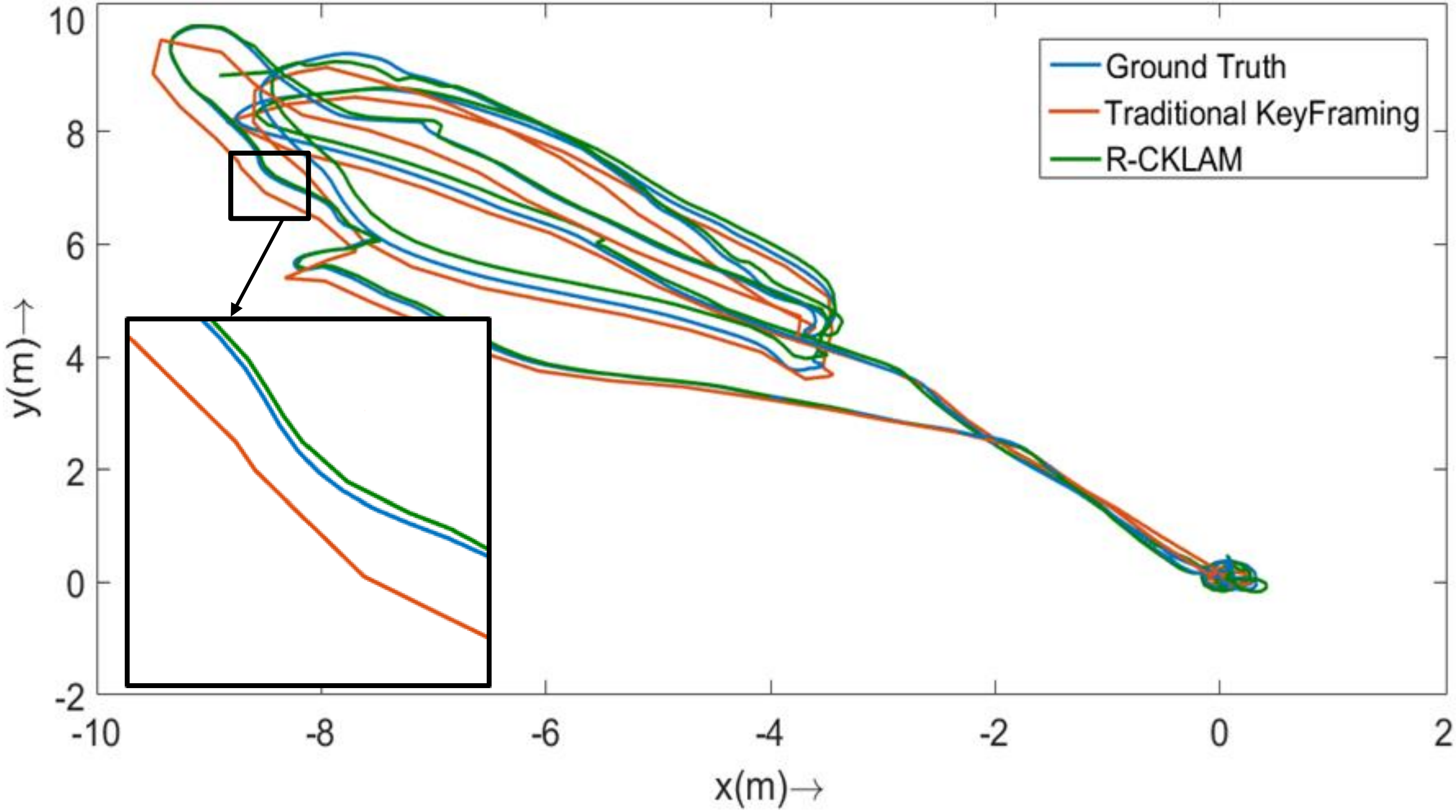
RCKLAM and Loop-closure



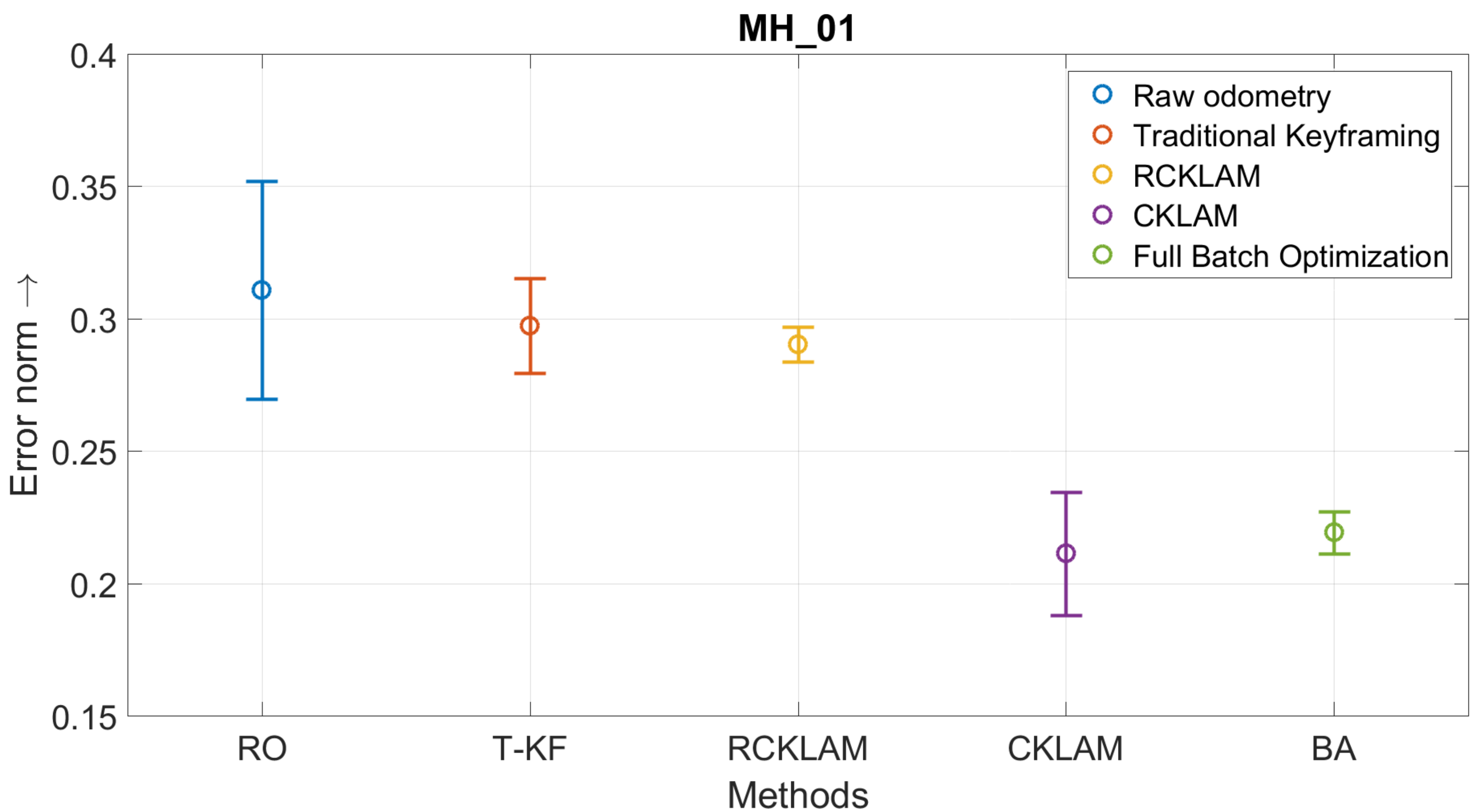
Evaluation on Euroc Datasets



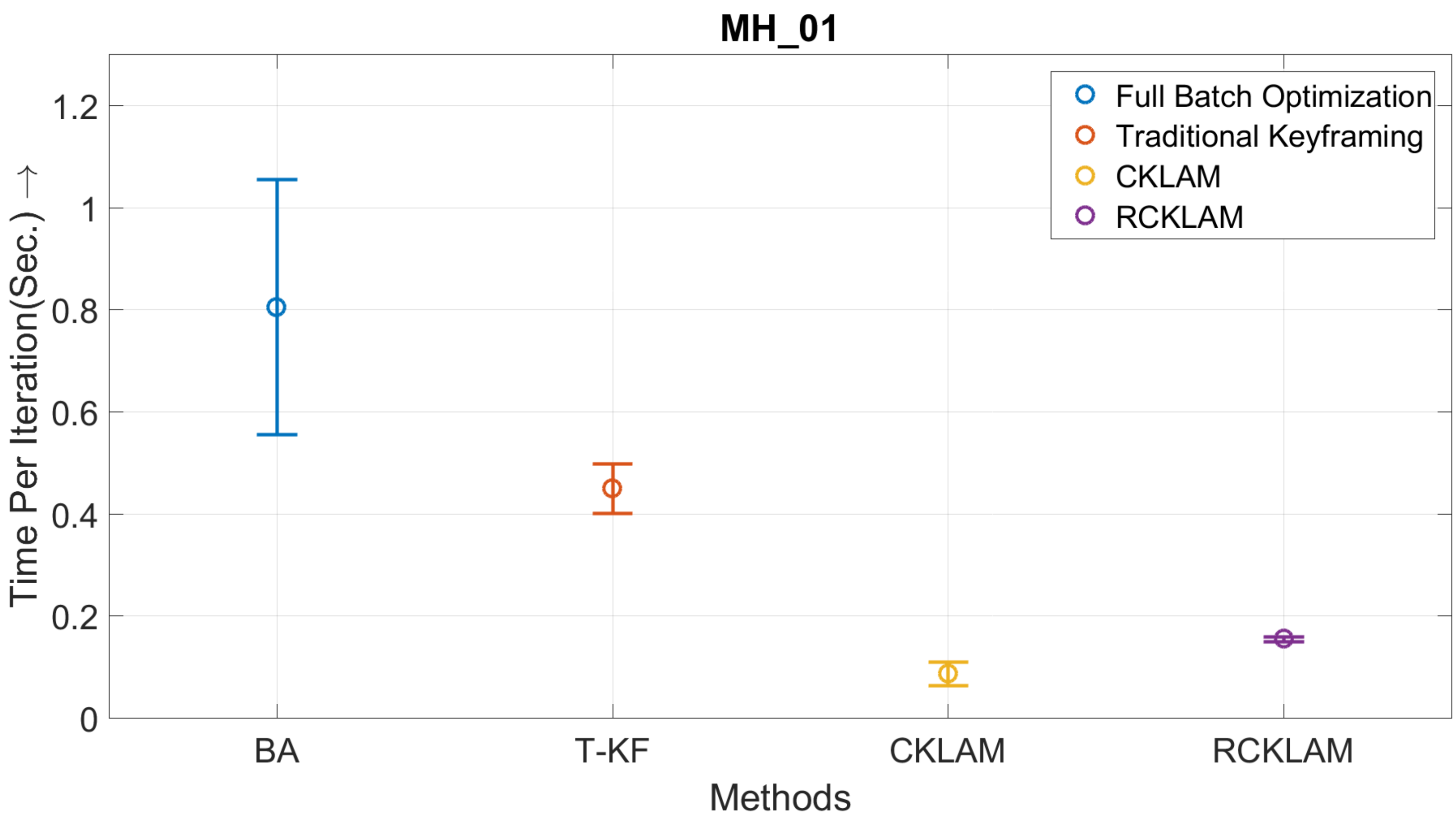
Evaluation on Euroc Datasets



Results Real Maps



Computational time advantage (Only Optimization time)

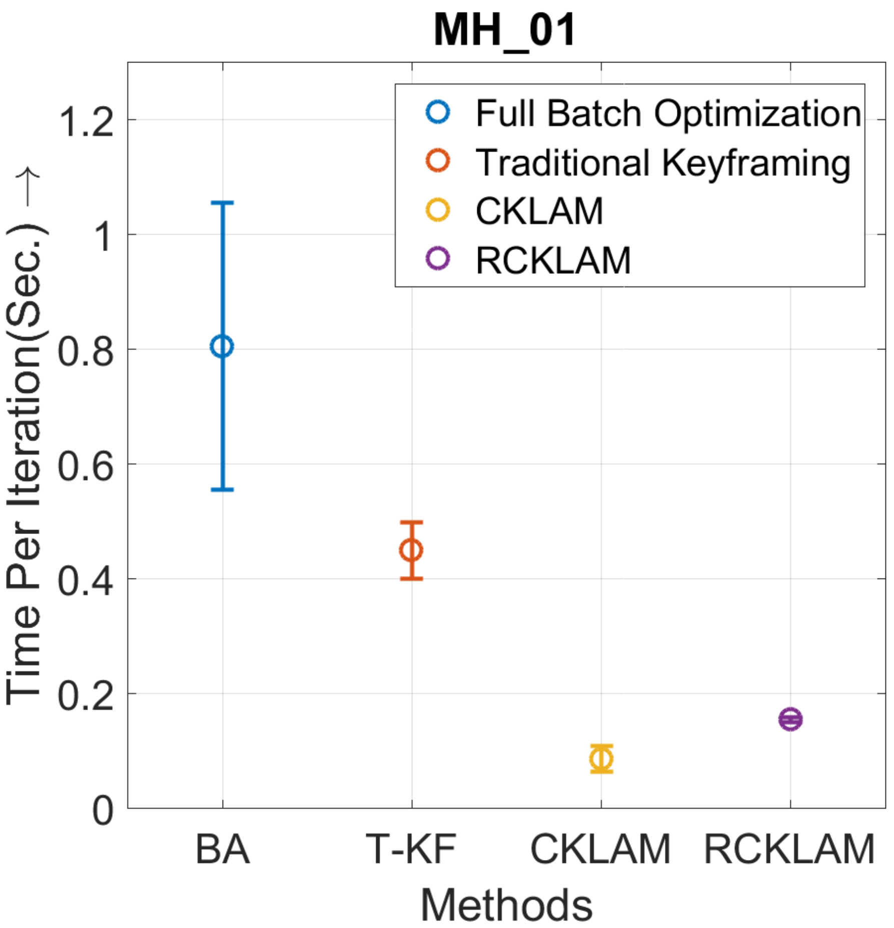


Conclusion

- A new method **R-CKLAM** has been proposed
- Flexibility significantly improved
- Advantages with loop closure shown

Future Work

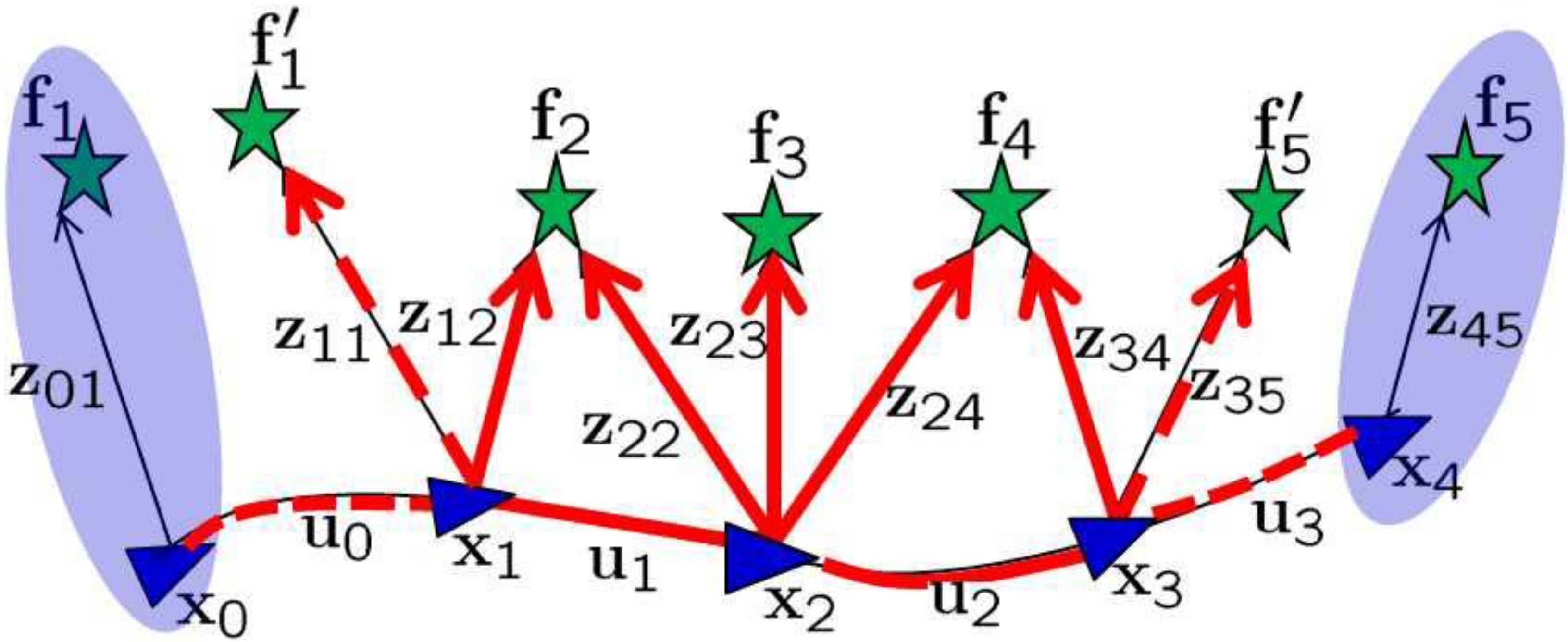
- Building online versions of CKLAM and RCKLAM
- Keyframe selection coupled with CKLAM



References

- 1. Esha D. Nerurkar , Kejian J. Wu , and Stergios I. Roumeliotis , “C-KLAM: Constrained Keyframe-Based Localization and Mapping”, In IEEE International Conference on Robotics and Automation Workshop on Long-term Autonomy, 2013.
- 2. G. Klein and D. Murray. Parallel tracking and mapping for small AR workspaces. In Proc. of the IEEE and ACM International Symposium on Mixed and Augmented Reality, pages 225–234, Nara, Japan, Nov. 13–16 2007.
- 3. J. Folkesson and H. Christensen, “Graphical slam - a self-correcting map,” in Proc. of the IEEE International Conference on Robotics and Automation, New Orleans, LA, Apr. 26 – May 1, 2004, pp. 383–390.

CKLAM Marginalization



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RCKLAM Formulation

- $C_{CKLAM} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} g_1 \\ g_2 \end{bmatrix}^T \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \alpha$

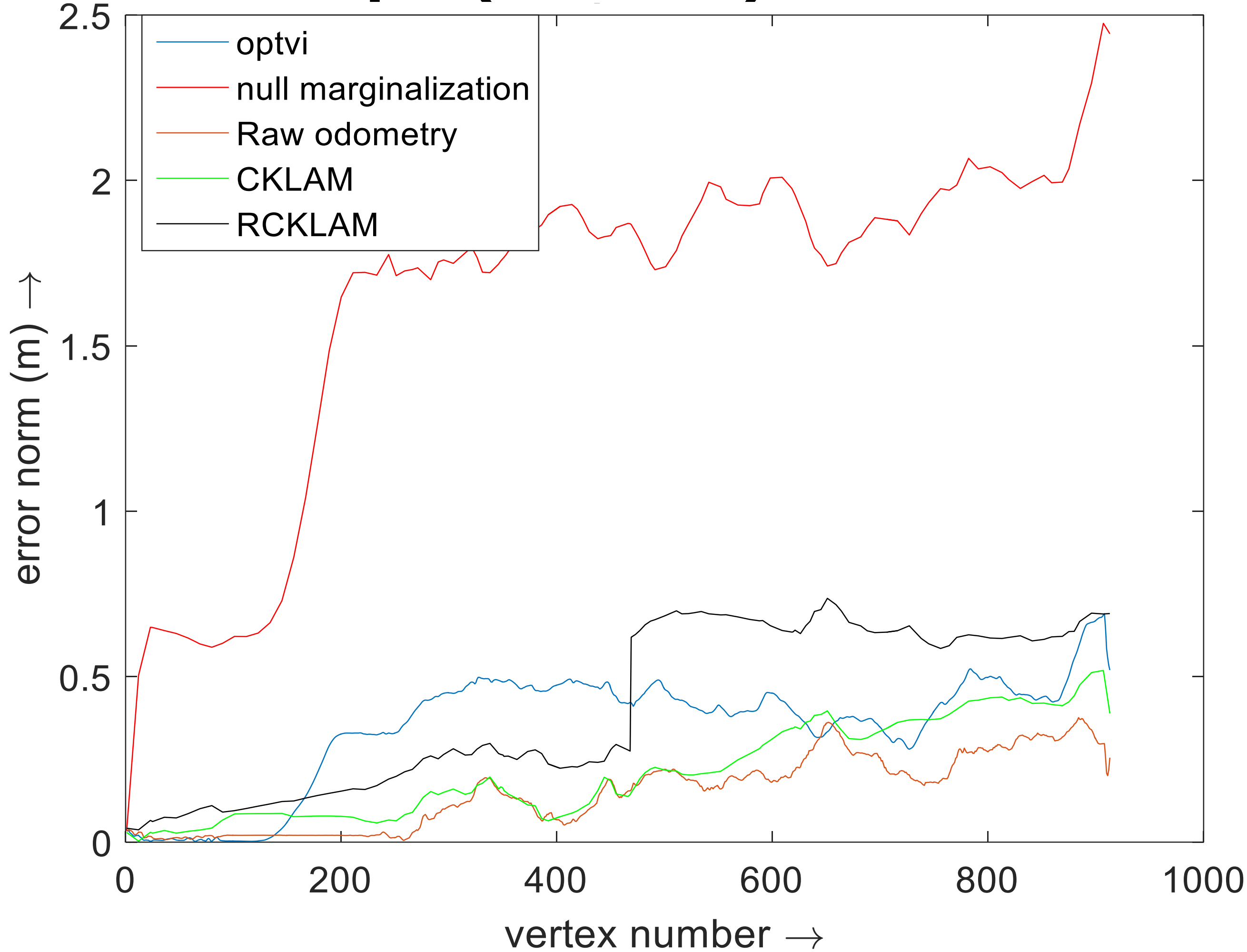
- $C_{RCKLAM} = \begin{bmatrix} f(x_2, x_1) \\ x_2 \end{bmatrix}^T \begin{bmatrix} H'_{11} & H'_{12} \\ H'_{21} & H'_{22} \end{bmatrix} \begin{bmatrix} f(x_2, x_1) \\ x_2 \end{bmatrix} + \begin{bmatrix} g'_1 \\ g'_2 \end{bmatrix}^T \begin{bmatrix} f(x_2, x_1) \\ x_2 \end{bmatrix} + \alpha$

- $\begin{bmatrix} x_2 - x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ then $H = \begin{bmatrix} J_1 & J_2 \\ 0 & 1 \end{bmatrix}^T H' \begin{bmatrix} J_1 & J_2 \\ 0 & 1 \end{bmatrix}$

RCKLAM Formulation

- Reformulate $C = \frac{1}{2}X^T HX + g^T X + \alpha$ as $C = (AX + b)^T (AX + b)$
- Linearize $f = f(x_{10}, x_{20}) + \frac{\partial f}{\partial x_1}(x_1 - x_{10}) + \frac{\partial f}{\partial x_2}(x_2 - x_{20})$
- Need $A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + b = A' \begin{bmatrix} f(x_2, x_1) \\ x_2 \end{bmatrix} + b'$ - replace linearization of f and reorder
- $A' = A \begin{bmatrix} J_1 & J_2 \\ 0 & 1 \end{bmatrix}^{-1}$ and $b' = b - A' \begin{bmatrix} \alpha_1 \\ 0 \end{bmatrix}$ where $\alpha_1 = f(x_{10}, x_{20}) - J_1 x_{10} - J_2 x_{20}$ with $J_1 = \frac{\partial f}{\partial x_1}$ and $\mathrm{J}_2 = \frac{\partial f}{\partial x_2}$

Results Real Maps (MH - 01)



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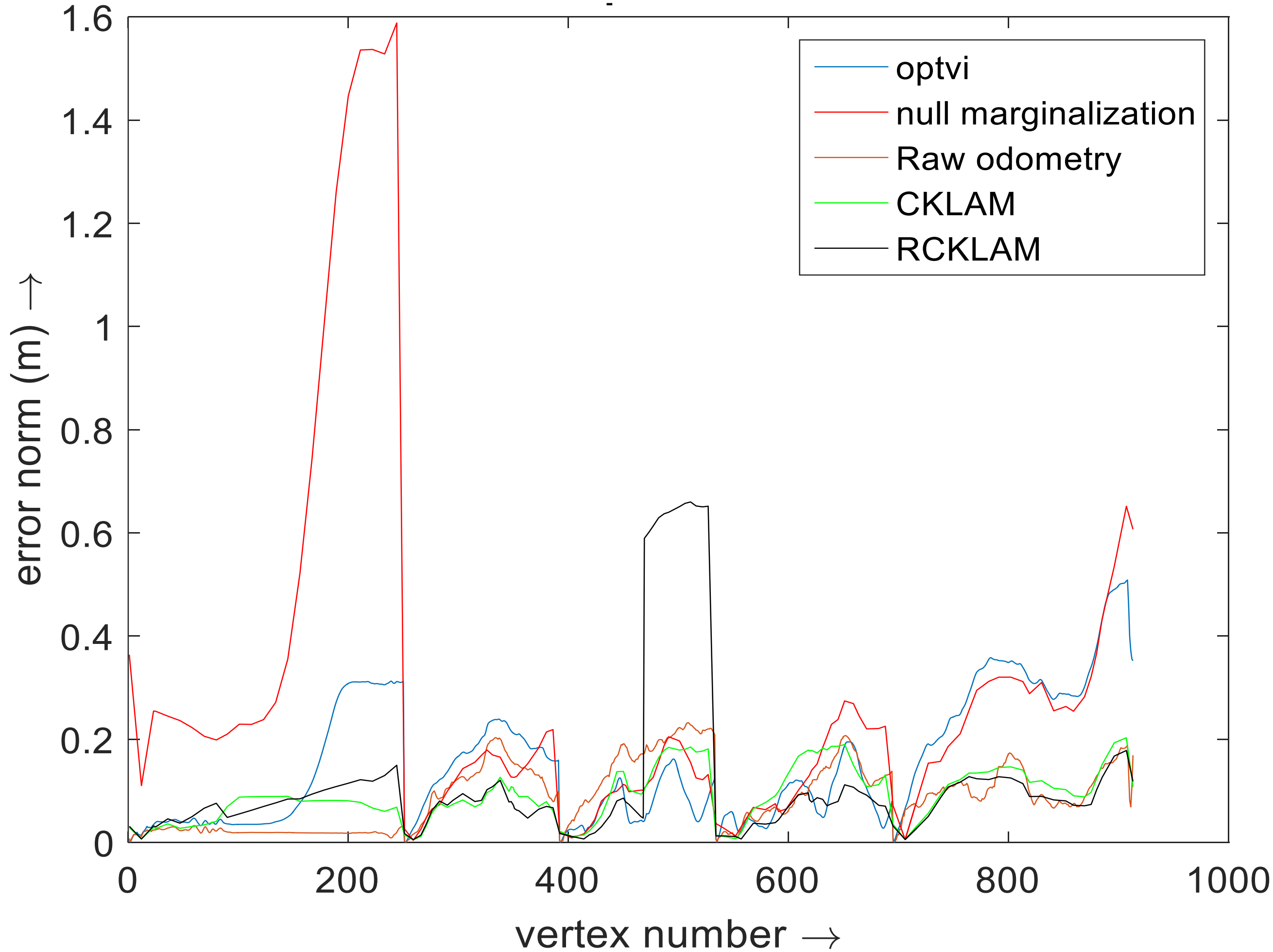
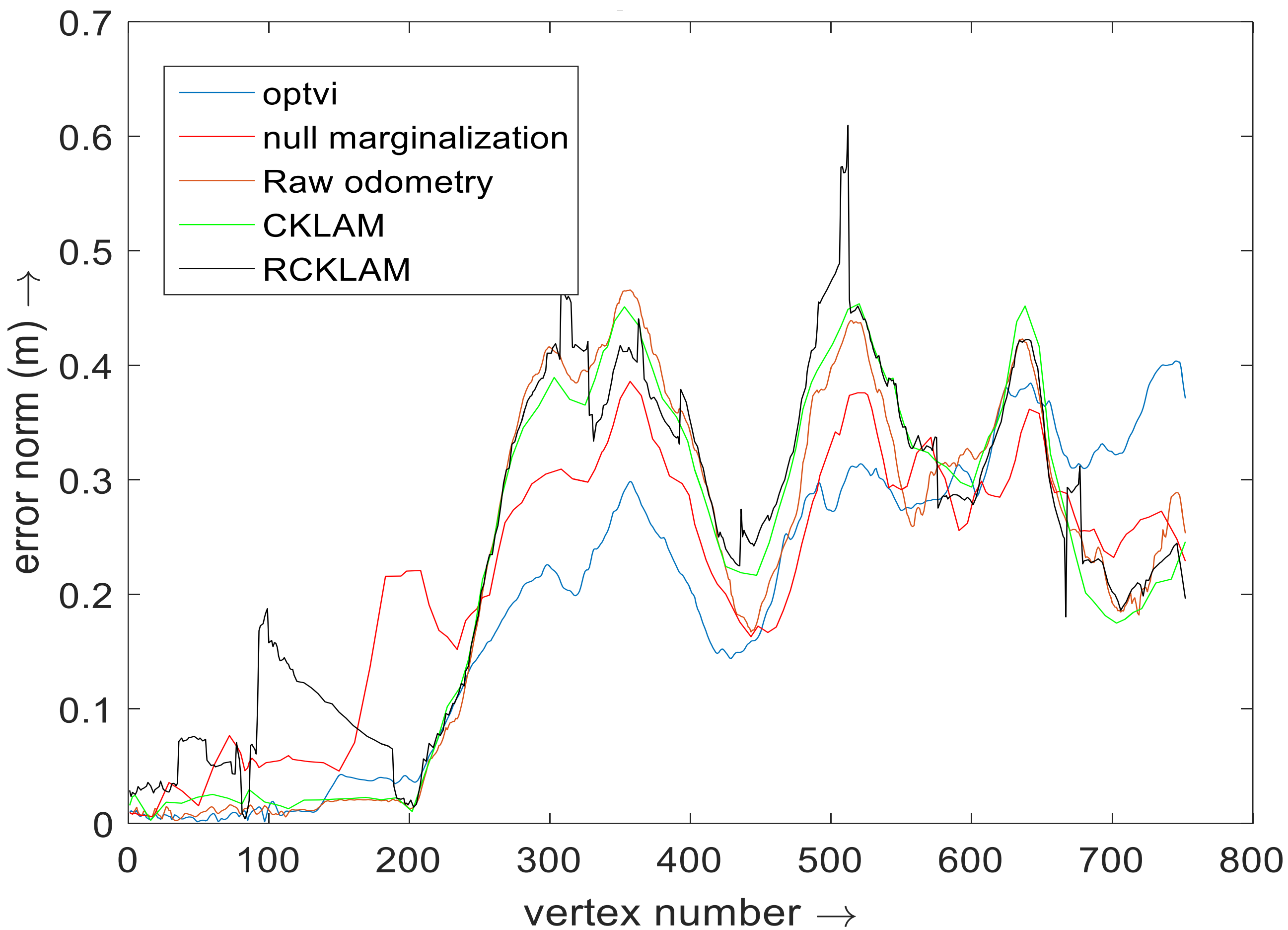
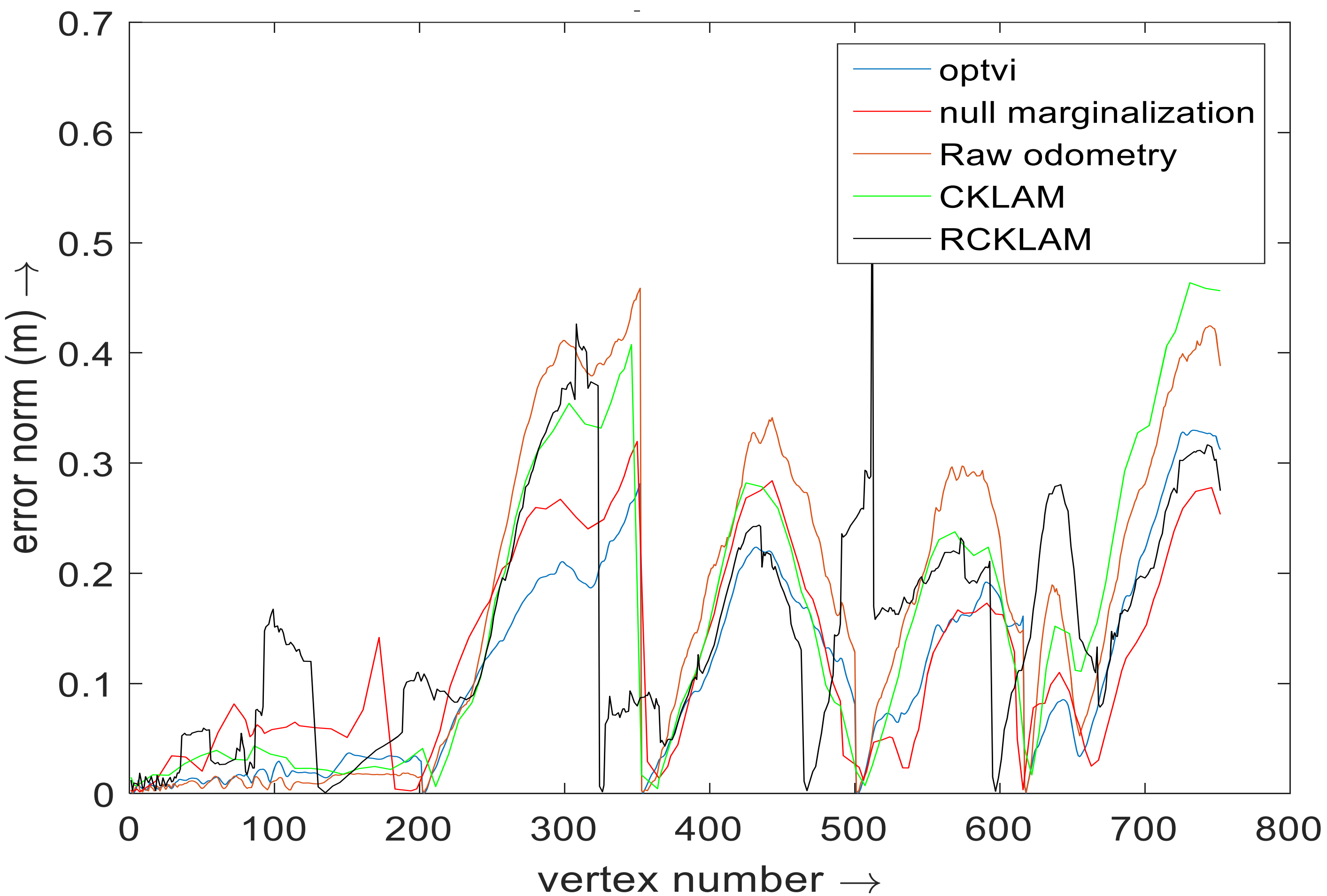


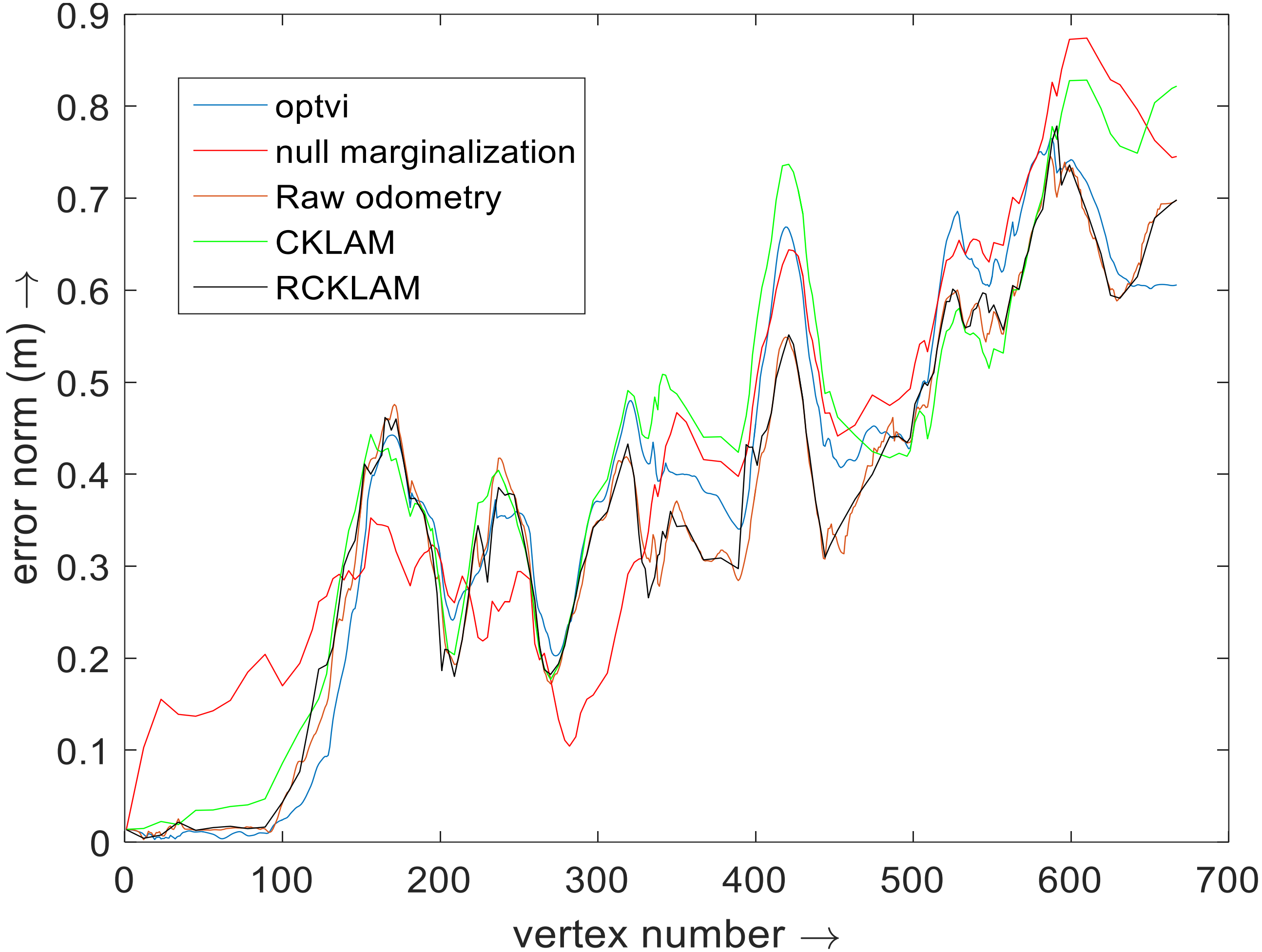
Results Real Maps (MH - 02)



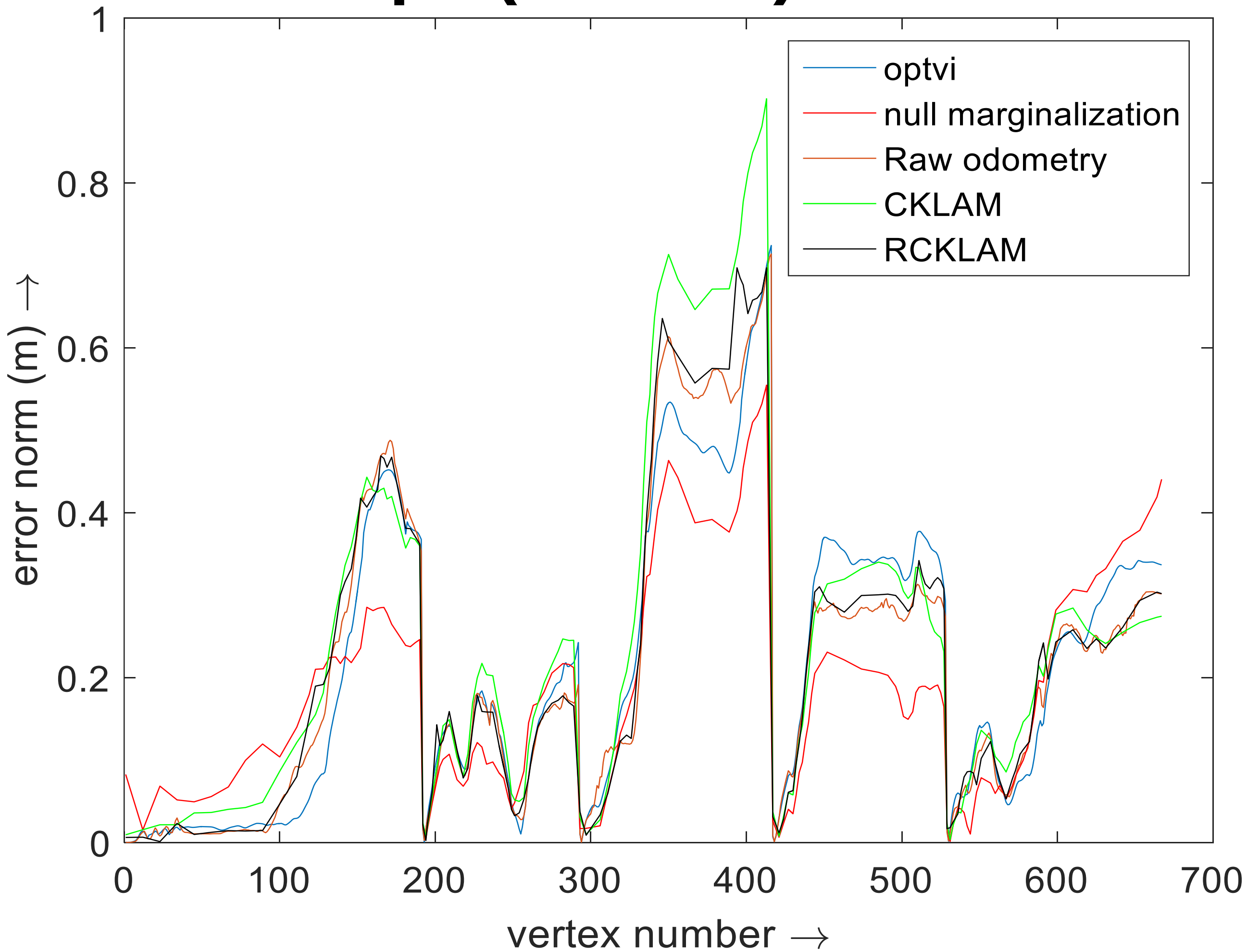
Results Real Maps (MH - 02)



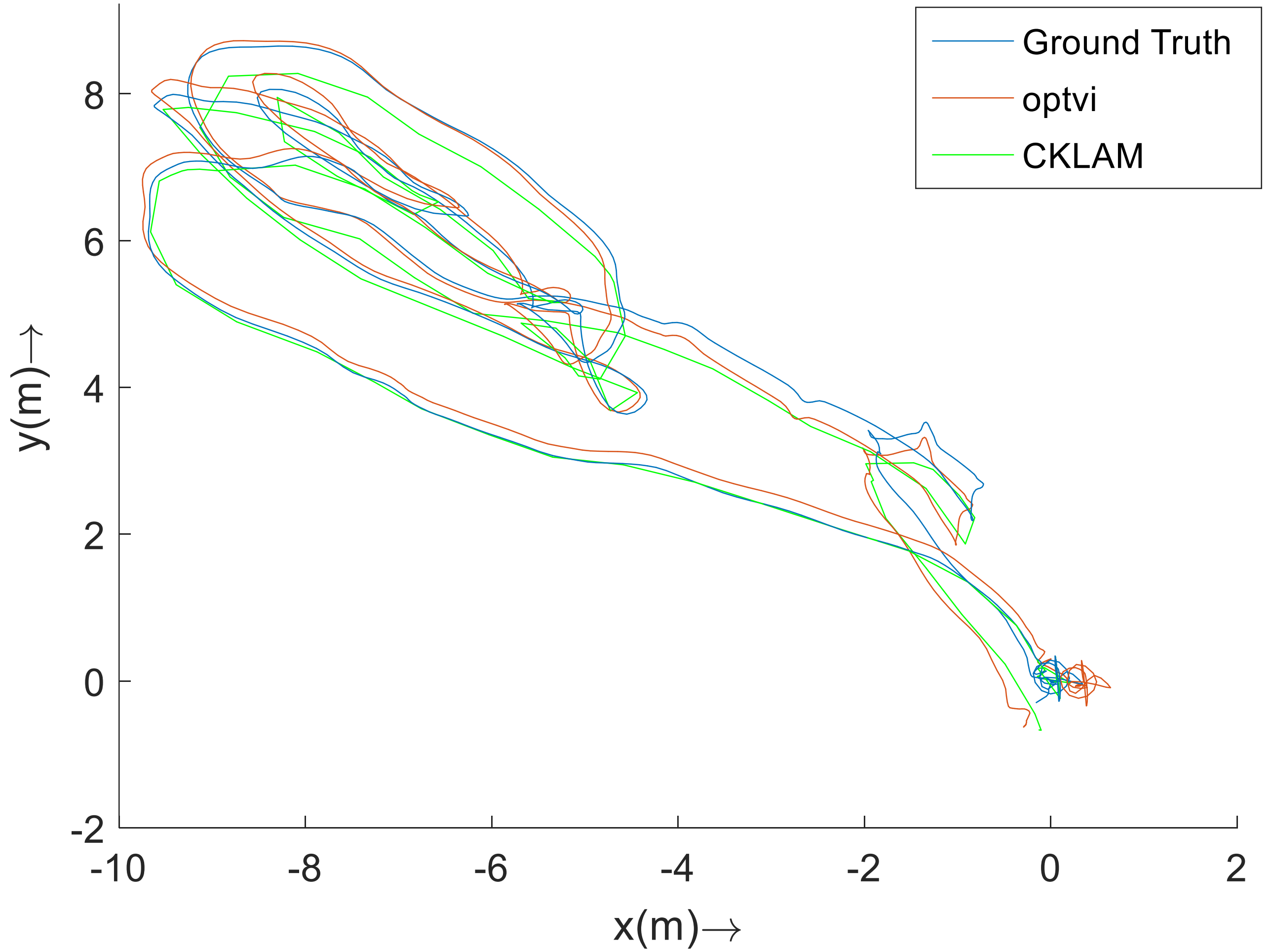
Results Real Maps (MH - 03)



Results Real Maps (MH - 03)



Results Real Maps (MH - 01)



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Results Real Maps (MH - 01)